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Contributions to the Empirics of Immigration, Redistribution and Social Mobility

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Zusammenfassung

Einwanderung, Umverteilung und soziale Mobilität haben als sozialpolitische Themenfelder in den letzten Jahren viel Aufmerksamkeit erfahren und bestimmten die politische und öffentliche Debatte in Deutschland. Sie werden seit dem Fall des Eisernen Vorhangs zunehmend von den Entwicklungen im internationalen Wirtschaftsgeflecht geprägt. Der internationale Handel, die Globalisierung, die internationale Migration und der qualifikationsverzerrende technische Fortschritt haben einen anwachsenden Einfluss auf die nationalen Arbeitsmärkte und auf die Tragfähigkeit des Sozialstaats. Diese Entwicklung wirft zum einen neue Fragen auf und begründet zum anderen die Überprüfung bisheriger Erkenntnisse: Wie wirkt sich die Immigration auf die nationalen Arbeitsmärkte und auf den Wohlfahrtstaat aus? Führt eine zunehmende ethnische und kulturelle Heterogenität in den europäischen Ländern zu einem Abbau des Sozialstaats? Bestimmt das Einkommen der Eltern das zukünftige Einkommen ihrer Kinder? Begünstigt der Strukturwandel die intragenerative Lohnmobilität? Diesen Fragestellungen widmet sich die vorliegende Dissertation.

Die internationale Migration hat in den letzten Jahrzehnten weltweit zugenommen. Der Zufluss an Menschen aus anderen Kulturen und Ethnien stellt neue Herausforderungen für den Arbeitsmarkt und den Sozialstaat dar und bewirkt Veränderungen im bestehenden sozialen Gefüge einer Gesellschaft. Für die Wirtschaft des Einwanderungslandes gehen mit der Immigration Wohlfahrtssteigerungen einher, wenn auch diese nicht gleichmäßig über die Einheimischen hinweg verteilt werden. Einheimische, die im direkten Wettbewerb zu den neuen Arbeitnehmern stehen, werden Lohnabschläge und den Verlust des Arbeitsplatzes erwarten, während die Übrigen entweder mit keinen Rückwirkungen oder sogar mit Lohnsteigerungen rechnen, da sie in relativen Größen knapper geworden sind. Der Sozialstaat hingegen profitiert, wenn hauptsächlich hochqualifizierte Arbeitnehmer einwandern. Die statistisch-ökonometrischen Untersuchungen für 20 europäische Länder in 2010 zeigen auf, dass der Unterschied in der Nachfrage nach Umverteilung zwischen hoch- und geringqualifizierten Einheimischen größer wird, je größer der Anteil an geringqualifizierten Einwanderern in der unmittelbaren Nachbarschaft ausfällt. Hochqualifizierte Einheimische opponieren stärker gegen eine Ausweitung des Sozialstaats, da zum einen der höhere Anteil an geringqualifizierten Immigranten den Wohlfahrtsstaat stärker belastet und zum anderen

die Löhne der Hochqualifizierten aufgrund eines geringeren relativen Arbeitsangebots steigen.

Neben den ökonomischen Konsequenzen der Einwanderung, geht mit dem Zufluss an neuen Bürgern auch die Angst vor Umwälzungen in der sozialen Umgebung und vor der Verwässerung bisher geltender Normen- und Wertevorstellungen einher. Letztere können eine Ablehnung von Immigranten seitens der Einheimischen nach sich ziehen und die Forderung nach einer restriktiven Einwanderungspolitik stärken. Andererseits kann der vermehrte Kontakt zu Mitgliedern anderer Ethnien dazu beitragen Informationslücken und Ressentiments abzubauen und im Gegenzug die Toleranz und Solidarität gegenüber Minderheiten stärken. Die statistisch-ökonometrischen Untersuchungen für 18 europäische Länder in 2014 zeigen auf, dass vermehrter interethnischer Kontakt im Alltag sowohl die soziale Distanz der Einheimischen zu Immigranten als auch ihre Ängste vor gesellschaftlichen Umwälzungen senkt. Allerdings schlägt sich die Größe der sozialen Distanz der Einheimischen nicht in ihrer Nachfrage nach Umverteilung nieder, sondern die abstrakten Ängste vor dem Verlust der nationalen Kultur und der Verschlechterung des sozialen Zusammenlebens senken die Präferenz für Umverteilung der Einheimischen. Dies ist insbesondere dahingehend interessant, dass nicht die Animositäten im Alltag, sondern die nicht fassbaren und allgemein-gesellschaftlichen Ängste die Treiber der persönlichen Solidarität und des Vertrauens gegenüber Immigranten sind.

Die Aufstiegschancen eines Bürgers über die Zeit hinweg oder im Vergleich zu den eigenen Eltern bestimmen mitunter seine Einstellung gegenüber dem Sozialstaat sowie die Weitergabe seiner Ansichten an die eigenen Kinder. Bezüglich der intergenerativen Einkommensmobilität befindet sich Deutschland im internationalen Mittelfeld; vor den Vereinigten Staaten (geringere Mobilität) und hinter den skandinavischen Ländern (höhere Mobilität). Fällt beispielsweise das Lebenseinkommen eines Vaters um 10 Prozent höher aus, so ist das Lebenseinkommen seines Sohnes in den Vereinigten Staaten um 4,9 Prozent und in Deutschland um 3,1 Prozent höher. Außerdem zeigt sich in Deutschland tendenziell ein zunehmender Einfluss des väterlichen Einkommens je höher das Einkommen des Sohnes ausfällt. In den Vereinigten Staaten ist der Einfluss des väterlichen Einkommens für Söhne mit geringem und hohem Einkommen höher als für Söhne mit einem mittleren Einkommen. Da diese Tendenzen jedoch nicht signifikant sind, ist der Einfluss des väterlichen Einkommens auf das Einkommen des Sohnes für einkommensschwache bzw. einkommensstarke Haushalte nicht unterschiedlich.

Richtet man den Fokus auf die intragenerative Lohnmobilität und die Lohnungleichheit sind die Entwicklungen am aktuellen Rand eher ernüchternd. Indes wird seit 2000 ein steter Rückgang der Lohnmobilität beobachtet. Auffällig ist, dass seit Beginn der 2000er Jahre die Lohnmobilität im Dienstleistungssektor signifikant kleiner als im Verarbeitenden Gewerbe ausfällt. Dieses Ergebnis ist hauptsächlich von einer sinkenden Lohnmobilität im Gesundheits- und Sozialwesen getrieben. Des Weiteren haben die Dauer der Arbeitslosigkeit und der ausgeübte Beruf eines Arbeitnehmers an Bedeutung gewonnen. Seit 2006 hat der Anstieg der Lohnungleichheit an Geschwindigkeit verloren und das Lohnwachstum zwischen 2006 und 2013 ist sogar polarisiert, d.h. die Löhne der Arbeitnehmer am unteren und am oberen Ende der Lohnverteilung sind relativ zu den Löhnen der Arbeitnehmer in der Mitte der Lohnverteilung stärker angestiegen. Diese Entwicklung ist jedoch nur teilweise auf die Computerisierung und die Automatisierung der Produktionsprozesse zurückzuführen. Zwar erfolgte zwischen 2001 und 2013 eine Verdrängung manueller Routinetätigkeiten, aber kognitive Routinetätigkeiten befinden sich weiterhin verstärkt am oberen Ende der Lohnverteilung und erfuhren sogar Zugewinne in ihrer Lohnmobilität. Manuelle nicht-routinemäßige Berufe wiederum befinden sich überproportional häufig am unteren Ende und in der Mitte der Lohnverteilung, so dass die Lohngewinne dieser Berufe am unteren Ende der Lohnverteilung durch die Lohneinbußen in der Mitte kompensiert wurden.

1

Skill Composition Matters: Immigration and Redistribution Preferences

The conditions of living together in a country, such as laws and regulations, as well as the structure of national institutions, affect the individual behavior of citizens in economic and societal terms. On the one hand, they create incentives for certain behavior. On the other hand, they impel voters to support parties which pledge to change or maintain the current institutional environment. The latter also applies to a country's tax and transfer system, which determines the extent of a citizen's net income by the end of the month or year. In turn, a redistribution system splits the society into two groups, a group of net contributors and a group of net beneficiaries. However, the tax and transfer system is not static in the long run, since the citizens have the possibility to change the design and the extent of redistribution in elections (at least in democractic countries). This raises the following question: what determines the individual preference for redistribution? In a pioneering work, Meltzer and Richard (1981) show that voters' demand for redistribution is driven by their financial self-interest. Net contributors will prefer less redistribution, whereas net beneficiaries will support more redistribution. The following chapter extends these reflections to the impact of immigration on natives' net income and shows that immigration has different effects on natives' preference for redistribution.

1.1 Introduction

Since the fall of the Iron Curtain, the movement of workers across national borders has gained much attention among policy makers and economists. After the collapse of the Soviet Union and Yugoslavia, the Western European countries experienced a stark increase in immigration from the states of the former Eastern bloc. In Germany, the net migration strongly increased between 1990 and 1992 due to the influx of ethnic

Germans from Eastern Europe and refugees from the former Yugoslavia. In turn, some southern European countries, such as Spain and Italy, showed increased immigration of North African refugees. Following the enlargement of the European Union in May 2004 and July 2007, Europe faced the next major movement of people across national boarders.[1] In particular, Ireland, the United Kingdom, Spain, and Italy were popular countries for immigrants from the new member states.[2] The last immigration peak occurred following the outbreak of the civil war in Syria in 2011. Afghan and Syrian refugees, among others, migrated through Turkey and the Balkans to Western Europe. Regardless of the causes of immigration, the influx of foreigners produces structural and compositional changes in the host country. On the one hand, the new residents enter the labor market and expand a country's labor force. On the other hand, the ethnic and cultural landscape of a country gets more diverse. In turn, these economic and societal shifts might cause concern among natives regarding potential consequences thereof. The economic literature commonly highlights natives' concern about immigration's impact on the labor market and on the welfare state. Regardless of whether these effects are real or merely perceived, they may affect natives' attitudes towards immigration and social policies. On the one hand, economic concern due to an influx of new workers can influence a native's support of immigration. On the other hand, immigration can change a native's attitude towards the welfare state and social policy. In the empirical literature, these two associations are widely investigated separately from one another.

This study brings these two strands of the literature together and examines the effects of immigration on a native's preference for redistribution, working through the labor market channel and the welfare state channel. Since immigrants' impact on the labor market as well as on the welfare state depends on their educational attainment, i.e. whether they are mainly skilled or unskilled, the impact of immigrants' skill mix relative to natives' skill mix on a native's preference for redistribution is investigated. For this purpose, a measure of the relative educational composition of immigrants and natives is constructed at the NUTS level 2 across European countries using data from the 2011 Population and Housing Census. Additionally, immigration might have different effects on a native's economic position according to his or her educational attainment. Thus, the regional relative skill composition is merged with individual-level data of natives using the European Social Survey 2010/2011. Therefore, the combination of regional and individual data adequately addresses the criticism by Hainmueller and Hiscox (2007, 2010) in two ways. First, using unbiased and harmonized regional data to construct the relative skill composition, a clear distinction can be made between skilled

[1] In May 2004, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, and Slovenia joined the European Union. In January 2007, Bulgaria and Romania became new member states of the European Union.

[2] With the exception of Ireland, Sweden, and the United Kingdom, the old member states of the European Union imposed transitional restrictions on the free movement of people from the new member states for several years.

and unskilled immigration within countries. Second, the observed regional relative skill composition is not influenced by natives' attitudes towards immigrants, at least in the short run.

Thus, this analysis outperforms previous studies that used respondents' perception about immigration's effect on the labor market and welfare state. Although natives' preference for redistribution might be determined by their perceptions, their survey responses could be biased due to their attitudes towards immigrants. Natives who disproportionally dislike immigrants or have xenophobic attitudes could tend to overestimate the economic effects of immigration. The opposite applies to natives who are more sympathetic towards immigrants. In both cases, natives' survey responses no longer measure their perceptions of immigrations' economic effect exclusively, but rather are biased due to their attitudes towards immigrants. Thus, it is not possible to attribute the estimated effects on natives' redistribution preference solely to their economic concern, since the estimated coefficients also cover the effect of societal concern on natives' redistribution preference. Furthermore, the empirical analysis is based on a theoretical framework which derives immigrants' impact on both the labor market and the welfare state. First, the labor market effects depend on immigrants' skill composition. Assuming that skilled and unskilled workers are complements, skilled (unskilled) immigration should have a negative impact on labor market outcomes of skilled (unskilled) natives. Second, immigration's effect on the welfare state depends on immigrants' skill composition relative to natives' skill composition. If immigrants are more skilled (less skilled), on average, than natives, they are more likely to be net contributors to (net recipients of) the welfare state in the host country. The former should induce either a lower tax rate or more social benefits, whereas the latter should lead either to a raise in the tax rate or a cut to social benefits. Thus, the adjustment of the government budget can occur through a change in taxes or benefits. Taking the labor market and welfare channel into account and linking them to a Meltzer and Richard (1981) model of natives' preference for redistribution, different effects can be predicted for skilled and unskilled natives. On the one hand, skilled (unskilled) immigration results in a rise (reduction) of natives' disposable income, which, in turn, decreases (increases) their preference for redistribution. On the other hand, the labor market effect of skilled or unskilled immigration depends on a native's educational attainment. Whereas unskilled immigration encourages unskilled natives to support more redistribution due to lower wages or higher unemployment risk for unskilled workers, skilled natives show a lower preference for redistribution due to higher wages and lower unemployment risk for skilled workers. The opposite applies if immigration is mainly skilled. Combining immigrant's impact through both channels, unskilled (skilled) immigration motivates skilled natives to prefer less (more) redistribution. However, the labor market effect and the welfare state effect compensate for one another for unskilled natives. Therefore, the total effect on unskilled natives' support of redistribution is a priori unclear.

Using information on natives' preference for redistribution and a common measure of regional relative skill ratio, the empirical assessment confirms the predictions of the theoretical framework. Skilled natives prefer more redistribution if the relative skill ratio is higher in a region, i.e. the proportion of skilled immigrants increases relative to the proportion of skilled natives. However, there is no unambiguous effect on unskilled natives depending on the relative skill ratio. Skilled natives' probability of a high redistribution preference increases by 5.5 percentage points more than unskilled natives' probability if the regional relative skill ratio increases by one percent. The effect of the relative skill ratio on the unskilled, however, is not significantly different from zero. These results are robust to IV estimation approaches which consider the possibility of selective in- and out-migration at the regional level. Controlling for the regional share of immigrants, the primary results are maintained, even after adjusting for natives' self-selection into regions based on their attitudes towards immigrants. Finally, the effect of the relative skill ratio on skilled natives is still significant after controlling for regional income inequality using the at-risk-of-poverty rate. The rest of the chapter is organized as follows: Section 1.2 provides a literature review and Section 1.3 describes the theoretical framework which determines the individual preference for redistribution, dependent on the educational attainment of natives and the relative skill composition of immigrants and natives. Section 1.4 presents the data sources of the employed variables and Section 1.5 describes the estimation strategy. Section 1.6 gives the basic results and empirical extensions using the regional share of immigrants and the regional at-risk-of-poverty rate as additional control variables. Finally, Section 1.7 concludes.

1.2 Related Literature

In migration literature, particular attention has been given to natives' concern about immigration's effect on the labor market and welfare state. Considering the labor market effects, immigration leads to a more intense labor market competition among residents in the host country due to the expansion of labor supply. In general, immigration benefits the native population as a whole according to the the *factor-proportions model*. However, these gains from immigration are unevenly distributed among the native population (Borjas et al., 1996, 1997). Thus, the direction of labor market effects depends on whether some natives are substitutes for or complements to immigrants. Assuming that unskilled and skilled workers are complements to one another, immigration of unskilled workers causes a reduction in wages (a higher unemployment rate) of unskilled natives, whereas the wages (unemployment rate) of skilled natives increase (decreases). The opposite applies for the influx of mainly skilled immigrants (see Borjas, 1999, 2014, for an overview). There are several studies confirming the effect on the labor market as an important driver of natives' attitudes towards immigration policy. Examining different immigration models, Scheve and Slaughter (2001) and Dustmann and Preston (2007) notice that natives' concern about job security and wages affect their support of immigration in the United States and England, respectively. Using diverse measures of the relative skill composition between immigrants and natives, Mayda (2006) shows that skilled natives favor more free movement in countries where natives are more skilled than immigrants (see also O'Rourke and Sinnott, 2006, for similar results). The opposite is true with respect to unskilled natives' support of immigration. These results can be traced back to the predictions of international migration theory. Countries which have a mainly skilled labor force show a high inflow of unskilled immigrants, since skilled labor is the abundant production factor there. Thus, skilled natives' wages increase, whereas unskilled natives' wages decrease.

Moreover, in their attitudes towards immigration, natives take into account that the free movement of people has an impact on the welfare state. Since unskilled workers are more likely to be net recipients of the welfare system and skilled workers are more likely to be net contributors to the welfare system, an inflow of unskilled or skilled immigrants results in different adjustments of the host country's tax and transfer system. If adjustment occurs through taxation, immigration affects skilled natives' income more strongly. Therefore, they should oppose (support) immigration more if a large proportion of immigrants is unskilled (skilled). If, however, adjustment is made through social benefits, immigration affects unskilled natives more strongly. They will vote against (for) immigration more if immigrants are mainly unskilled (skilled) (see Dustmann and Preston, 2007; Facchini and Mayda, 2008, 2009, 2012). In the United States, Hanson et al. (2007) show that a rise in fiscal burden caused by immigration reduces natives' support for the free movement of workers, especially among more educated natives. In England, Dustmann and Preston (2007) demonstrate that welfare concerns are even more important than labor market concerns in determining natives' immigration attitudes. Based on individual and aggregated data from European countries, Boeri (2010) shows that a higher share of immigrants who receive social benefits is associated with stronger economic concerns among natives. Taking both economic channels of immigration, the labor market and welfare state channel, into account, Facchini and Mayda (2012) detect that unskilled natives support skilled immigration more than skilled natives.

In contrast, some studies ascertain that highly educated natives are more likely to favor any type of immigration, irrespective of immigrants' educational composition (Hainmueller and Hiscox, 2007, 2010), natives' labor market outcomes (Gang et al., 2013; Hainmueller and Hiscox, 2007; Hainmueller et al., 2015), or the fiscal threat presented by immigration (Tingley, 2013).[3] In particular, Hainmueller and Hiscox (2007) criticize previous studies which employed survey questions to estimate the labor market and welfare state effects without directly differentiating between unskilled and skilled immigration. Furthermore, Hainmueller and Hiscox (2010) point out that the correlation between natives' educational attainment and support for immigration might be more strongly driven by natives' perception about immigration's impact on the host country's social fabric. Card et al. (2012) show that natives' concerns about the ethnic composition of the neighborhood is two to five times more important of shaping the attitudes towards immigration policy than economic concerns, such as the labor market and welfare state effects.

The second strand of the literature which is related to this study examines the association between immigration or ethnic heterogeneity and natives' redistribution preference (see Stichnoth and Van der Straeten, 2013; Alesina and La Ferrara, 2005a, for an overview). There is some cross-country evidence supporting the hypothesis that a rise in heterogeneity diminishes redistribution. Alesina et al. (2001) show that social spending correlates significantly negatively with ethnic fractionalization, where the fractionalization index yields the probability that two randomly picked persons belong to different groups. A negative link between ethno-linguistic fractionalization and government spending on health or education is detected in Kuijs (2000). Soroka et al. (2006) focus on the change in ethnic heterogeneity and determine that a change in the proportion of immigrants is negatively correlated with the change in a country's social spending. However, Senik et al. (2009) find a weak link between the perceived presence of immigrants and natives' redistribution preference across European countries. Stichnoth and Van der Straeten (2013) present similar results for public support of unemployment benefits in Germany. In turn, Dahlberg et al. (2012) substantiate that in Denmark, a higher refugee inflow rate lowers natives' preferred level of social spending at the regional level. For Sweden, Eger (2010) shows similar findings with regard to the share of immigrants at the county level. Additionally, Burgoon et al. (2012) ascertain a moderate effect on natives' redistribution preference. However, they note that immigrants who enter a worker's occupation increase his or her economic insecurity and thus increase the support of more governmental redistribution. Investigating the labor market compensation hypothesis, Finseraas (2008) shows that economic risk due to immigration has a positive impact on natives' preference for redistribution. Based on the welfare effect of immigration, Magni-Berton (2014) points out that if citizens perceive immigrants as net recipients of the welfare state, they support less redistribution. Furthermore, this effect is even stronger if citizens mention that there are "too many" immigrants in the country.

[3] For a critical review of the labor market and welfare state effect on natives' attitudes towards immigration policy, see Hainmueller and Hopkins (2014).

1.3 Immigration and Natives' Financial Self-Interest

The individual preference for redistribution depends on the financial self-interest of voters. While net recipients of governmental redistribution will vote for an expansion, net contributors will dissent an expansion. Meltzer and Richard (1981) show, based on Romer (1975) and Roberts (1977), that the current income position of a voter is decisive for his or her preferred income tax rate and thus the extent of governmental redistribution. Immigration, in turn, affects the wage trend on the labor market as well as the relevant components of the tax and transfer system. Therefore, the individual financial self-interest can be combined with the real or perceived effects of immigration within a simple equilibrium model based on Facchini and Mayda (2009) and Dustmann and Preston (2006).[4]

Two production factors, unskilled (L_U) and skilled labor (L_S), are considered in the model. They are combined using a constant returns to scale technology $y = f(L_U, L_S)$ to produce the aggregate output, the price of which is normalized to one. The economy is populated by a set of N natives, indexed by n, and by a set of M immigrants, indexed by m. The total supply of each skill is expressed by

$$L_j = \phi_j N + \psi_j M \,, \quad j \in \{S, U\} \,, \tag{1.1}$$

where ϕ_j and ψ_j are, respectively, the share of workers with the skill profile j in the native and immigrant population. The immigrant-to-native population is defined by $\pi = M/N$ and assumed to be very low initially. In addition, the native population is assumed to be constant throughout the analysis. Thus, changes in the relative skill shares for skill profile j between immigrants and natives follow from

$$\frac{d \ln L_j}{d\pi} = \frac{\psi_j}{\phi_j} = \beta_j \,, \quad j \in \{S, U\} \,. \tag{1.2}$$

Next, let w_j be the before-tax wage rate for skill profile j with $w_S > w_U$ and $c(w_S, w_U)$ the unit cost function of the aggregate output. Therefore, wages and outputs are determined by two sets of equilibrium conditions. First, the equilibrium in the factor market requires labor supply to be equal to labor demand for each skill type:

$$L_j = y \frac{\partial c(w_U, w_S)}{\partial w_j} \,, \qquad j \in \{S, U\} \,. \tag{1.3}$$

Second, perfect competition on the product markets implies that firms earn non-positive

[4] Facchini and Mayda (2009) consider a simple two-factor Heckscher-Ohlin model of a small open economy and abstract from the potential price effects of immigration. Conclusions are drawn on the basis of a single aggregate output sector according to Dustmann and Preston (2006).

profits in equilibrium. That is

$$c(w_U, w_S) = 1 \; . \tag{1.4}$$

The governmental redistribution works through a linear tax and transfer system with a uniform tax rate $\tau \in (0,1)$ and a lump-sum social benefit b.[5] The tax rate is assumed to be exogenous and does not affect the labor supply decisions of an individual. Both natives and immigrants are taxed and entitled to social benefits. Thus, the government budget constraint can represented by

$$\tau \overline{w} = b \; , \tag{1.5}$$

where $\overline{w} = \frac{w_U L_U + w_S L_S}{L_U + L_S}$ is the average wage of the entire population. The net income of a native n with skill level j is given by

$$I_j = (1-\tau) w_j + b \; . \tag{1.6}$$

Furthermore, the change in the net income of a native with skill level j can be decomposed into three parts:

$$dI_j = (1-\tau)\, dw_j - w_j\, d\tau + db \; . \tag{1.7}$$

Thus, there are three potential channels for immigration to influence a native's net income: (i) the before-tax wage, (ii) the tax rate, and (iii) social benefits.

1.3.1 Effect of Immigration on Skilled and Unskilled Wages

Totally differentiating the equilibrium conditions, it is easy to show that the effect of immigration on wages is expressed by[6]

$$\frac{d \ln w_U}{d\pi} = \frac{\beta_U - \beta_S}{\epsilon_{UU} - \left(\epsilon_{SU} + \frac{\theta_U}{\theta_S}\epsilon_{US}\right) + \epsilon_{SS}\frac{\theta_U}{\theta_S}}, \tag{1.8}$$

$$\frac{d \ln w_S}{d\pi} = -\frac{\theta_U}{\theta_S} \cdot \frac{\beta_U - \beta_S}{\epsilon_{UU} - \left(\epsilon_{SU} + \frac{\theta_U}{\theta_S}\epsilon_{US}\right) + \epsilon_{SS}\frac{\theta_U}{\theta_S}}, \tag{1.9}$$

where $\epsilon_{ij} = \frac{\partial \ln c_i}{\partial \ln w_j} = \frac{\partial L_i}{\partial w_j}\frac{w_j}{L_i}$ denotes the labor demand elasticity with $c_i = \frac{\partial c}{\partial w_i}$ and the factor share in the production of skill level j is expressed by $\theta_j = \frac{\partial c}{\partial \ln w_j}$. The differentiations show that there is no wage effect if immigrants have the same skill composition as natives ($\beta_U = \beta_S$). Due to the negativity of the denominator in (1.8) and (1.9), which

[5] The literature suggests that the best egalitarian income tax scheme can be approximated by a linear tax system (Mirrlees, 1971). This strategy was pursued by Razin et al. (2002), among others.

[6] A detailed derivation is given by Dustmann and Preston (2006).

follows from the concavity of the cost function, immigration is expected to depress the wages of workers competing with the skill level which is relatively more abundant in immigrant labor and to raise the wages of native workers with different skill level.[7] Therefore, unskilled immigration ($\beta_U > \beta_S$) depresses the wages of unskilled natives due to labor market competition and raises the wages of skilled natives due to complementarity. The opposite is true in the case of skilled immigration ($\beta_S > \beta_U$).

1.3.2 Effect of Immigration on the Welfare State

If immigration entails changes of wages on the labor market, the tax and transfer system is also affected through a change in average wages. In order to examine the welfare state effects of immigration, the governmental budget constraint is totally differentiated[8]

$$d\ln\tau + d\ln\overline{w} = d\ln b\,. \tag{1.10}$$

Thus, the adjustment of the redistribution system due to immigrations' impact on wages depends on whether immigrants are a net fiscal burden or net fiscal gain for the welfare state. As already underlined in Facchini and Mayda (2009), there are two potential channels for adjustment. On the one hand, the government can reduce social benefit expenditure and maintain the same tax rate (benefit adjustment model). On the other hand, the uniform tax rate is increased and the social benefit expenditure is maintained (tax adjustment model). The effect of a marginal inflow of immigrants on the welfare state in the tax adjustment model ($d\ln b = 0$) and in the benefit adjustment model ($d\ln\tau = 0$) can represented by[9]

$$\frac{d\ln\tau}{d\pi} = \frac{(\phi_U - \theta_U)(\beta_U - 1)}{1-\phi_U}, \tag{1.11}$$

$$\frac{d\ln b}{d\pi} = \frac{(\phi_U - \theta_U)(1-\beta_U)}{1-\phi_U}, \tag{1.12}$$

where $\phi_U - \theta_U$ is the difference between the share of the unskilled in the native population and their share in the native GDP. Since $w_U < w_S$, it follows that $\phi_U > \theta_U$. If the native and immigrant skill compositions are identical ($\beta_U = 1$), an inflow of immigrants neither alters the current tax rate nor the social benefit expenditure. If, instead, immigrants are less skilled, on average, than natives ($\beta_U > 1$), the tax rate will increase or social benefits will decrease. The opposite is true for skilled immigration.

[7] Dustmann and Preston (2006) provide the mathematical proof of this relationship.

[8] The total differential $db = \tau \cdot d\overline{w} + d\tau \cdot \overline{w}$ can be converted into equation (1.10) using the property $\frac{dx}{x} \approx d\ln x$.

[9] Facchini and Mayda (2009) provide a proof and more detailed analysis.

Nevertheless, the net income of a native with skill level j is affected in a similar manner in each of the adjustment models:

$$dI_j = (1-\tau)dw_j - w_j\tau \cdot d\ln\tau \qquad \text{(tax adjustment model)} \qquad (1.13)$$

$$dI_j = (1-\tau)dw_j + b \cdot d\ln b \qquad \text{(benefit adjustment model)} \qquad (1.14)$$

The first terms on the right hand side yield the impact of immigration on a native's wage due to competition or complementarity of his or her skill type. The second terms give the change in a native's net income due to adjustments to the redistribution system which is affected by the impact of immigration on public services. In both adjustment models, unskilled immigration decreases (increases) unskilled (skilled) natives' wages. The tax rate rises in the tax adjustment model, whereas social benefits decrease in the benefit adjustment model. The opposite occurs in the case of skilled immigration. Therefore, unskilled natives disfavor unskilled immigration because their wages and their social benefits decrease (or the tax rate increases). However, they favor skilled immigration because their wages and social benefit increase (or the tax rate decrease). In turn, skilled natives are ambivalent in their attitudes towards both skilled and unskilled immigration. On the one hand, unskilled immigration increases their wages due to complementarity on the labor market while increasing their fiscal burden through an increase in the tax rate (or a decrease in social benefits). On the other hand, skilled immigration decreases their wages due to competition on the labor market, while decreasing their fiscal burden through a decrease of the tax rate (or an increase of social benefits).

1.3.3 Effect of Immigration on Natives' Preference for Redistribution

In order to combine the labor market and welfare state effects of immigration on natives' preference for redistribution, the net income function of a native with particular skill level j in the tax adjustment model is applied:

$$I_j = (1-\tau)w_j + \tau\overline{w}\,. \qquad (1.15)$$

Hence, the effect of an increase in the amount of redistribution on the well-being of a native with skill level j can represented by

$$\frac{dI_j}{d\tau} = \overline{w} - w_j\,. \qquad (1.16)$$

Therefore, if a native's wage is less than the average wage of the entire population, a higher tax rate would raise his or her net income. The opposite is true if a native's wage exceeds the average. Thus, the impact of immigration on a native's preference for redistribution can be expressed by[10]

$$\frac{d}{d\pi}\left(\frac{dI_j}{d\tau}\right) = -\overline{w}\frac{d\ln\tau}{d\pi} - w_j\frac{d\ln w_j}{d\pi} \,. \tag{1.17}$$

Based on immigration's labor market effects, derived in the Equations (1.8) and (1.9), as well as welfare state effects, derived in Equation (1.11), Equation (1.17) allows the calculation of the overall impact of immigration on a native's preference for redistribution differentiated by two types of immigration (skilled and unskilled) and two types of native workers (skilled and unskilled). Whereas the first term captures immigration's effect on the welfare state, the second term yields the change in natives' wages due to immigration. The former becomes negative if unskilled immigration occurs, because the derivative is positive due to the need for a higher tax rate. Therefore, a native's preference for redistribution decreases regardless of his or her skill type, since immigrants receive more in social benefits than they pay in taxes and benefit disproportionally from the additional revenue. This relationship is commonly termed the *fiscal leakage effect* (Razin et al., 2002). The opposite effect occurs if skilled immigration takes place. The sign of the second term depends on whether the wage of a native with skill level j increases or decreases due to immigration. If there is unskilled immigration, unskilled natives' wages decrease, whereas skilled natives' wages increase. Therefore, the second term becomes positive for unskilled natives and negative for skilled natives. The former prefer more redistribution due to the downward pressure on their wages, whilst the latter prefer less redistribution, since their wages increase. However, immigration's labor market effect might be weaker if natives and immigrants with the same skill type are imperfect substitutes for one another (Magni-Berton, 2014). Combining both the welfare and labor market effects, skilled (unskilled) immigration heightens (diminishes) the skilled natives' support of redistribution. Unskilled natives, however, are indecisive (see Table 1.1). On the one hand, if unskilled immigration is present,

Table 1.1: Predicted effects of immigrants' skill composition on natives' redistribution preference

	Unskilled Immigration		**Skilled Immigration**	
	Labor Market Effect	*Welfare State Effect*	*Labor Market Effect*	*Welfare State Effect*
Unskilled Natives	positive	negative	negative	positive
Skilled Natives	negative	negative	positive	positive

they favor less redistribution due to the fiscal leakage effect absorbing natives' taxes. On the other hand, they prefer more redistribution as a compensation mechanism for

[10] In order to derive Equation (1.17), $d\ln\overline{w} = -d\ln\tau$ as a property of the government budget constraint in the tax adjustment model is used. Moreover, the effect of immigration on redistribution preferences in a benefit adjustment model yields the same results. The corresponding derivation is in the appendix of this chapter.

stronger competition and lower wages on the labor market (Finseraas, 2008). The same unclear pattern appears if skilled immigration occurs. On the one hand, unskilled natives favor less redistribution due to increased wages and less dependency on social benefits. On the other hand, skilled immigration creates additional fiscal gains, which are disproportionally distributed to unskilled natives and increase their support on more redistribution.

The empirical literature is divided with respect to the wage effects of unskilled immigration (see Borjas, 2003; Ottaviano and Peri, 2006, among others, for diverging results). Since several European countries have national minimum wages and exhibit rigid wage structures, the adjustment to unskilled immigration is confined to changes of the unemployment rate rather than to wage changes.[11] Therefore, if unskilled immigration occurs, the unskilled natives experience no wage changes, but exhibit a higher probability of being unemployed. Adding this probability as an uncertainty parameter $\lambda \in (0,1)$ into the net income equation of an unskilled native yields

$$I_U = (1-\lambda)(1-\tau)w_U + \tau\overline{w}\,. \tag{1.18}$$

Accordingly, unskilled immigration's effect on an unskilled native's preference for redistribution can be expressed by[12]

$$\frac{d}{d\pi}\left(\frac{dI_U}{d\tau}\right) = \overline{w}\frac{d\ln\overline{w}}{d\pi} + w_U\frac{d\lambda}{d\pi} \tag{1.19}$$

Whereas the first term represents the welfare state effects and is equivalent to the expression in Equation (1.17), the second term captures immigration's impact on an unskilled native's probability of being unemployed. If unskilled immigration occurs, some unskilled natives become unemployed due to excess supply of unskilled labor and the overall average wage declines, since more citizens earn zero wages. In turn, a lower average wage demands an adjustment of the government budget by either raising the taxes or lowering social benefits. Thus, the first term becomes negative in both adjustment models. Since unskilled immigration increases an unskilled native's probability of being unemployed, the second term becomes positive. In total, the effect of unskilled immigration on unskilled natives' redistribution preferences remains unclear because of the counterbalance of its effects.

[11] These institutional conditions set a lower limit for wages on the labor market. Therefore, if skilled immigration occurs, they do not affect the development of wages, since unskilled workers' wages increase. On the other hand, skilled workers' wage cuts will not be sufficient to make the lower limit work.

[12] Due to the fact that wages of unskilled workers remain unchanged, $\frac{d\ln w_U}{d\pi} = 0$ holds.

1.4 Data and Variables

In order to examine the theoretical effects of immigration on the demand for redistribution, individual data on preferences for redistribution and aggregated data on the relative skill ratio between immigrants and natives at the regional level are combined. On the individual level, the 5th wave of the European Social Survey is used. This cross-national survey covers 27 countries (26 European countries plus Israel) as the ultimate sampling unit and contains persons aged 15 and over who are residents of private households (European Social Survey, 2012). It provides detailed information on the socio-economic and demographic characteristics of the respondents as well as on individual attitudes towards several sociopolitical issues. In particular, respondents are asked to which extent they agree or disagree with the following statement:"*The government should take measures to reduce differences in income levels*". Respondents can choose between five ordered categories: "strongly agree", "agree", "neither agree nor disagree", "disagree", and "strongly disagree". The answers to this question constitute the empirical variable in order to measure a respondent's preference for redistribution in the following examination.[13] In general, there is a high demand for redistribution in the European countries. Almost 73 percent of respondents choose the top categories "agree" and "strongly agree" (see Table 1.2). There is some variation in the preference

Table 1.2: Preference for redistribution based on the responses to the question: *"The government should take measures to reduce differences in income levels"* (in percent)

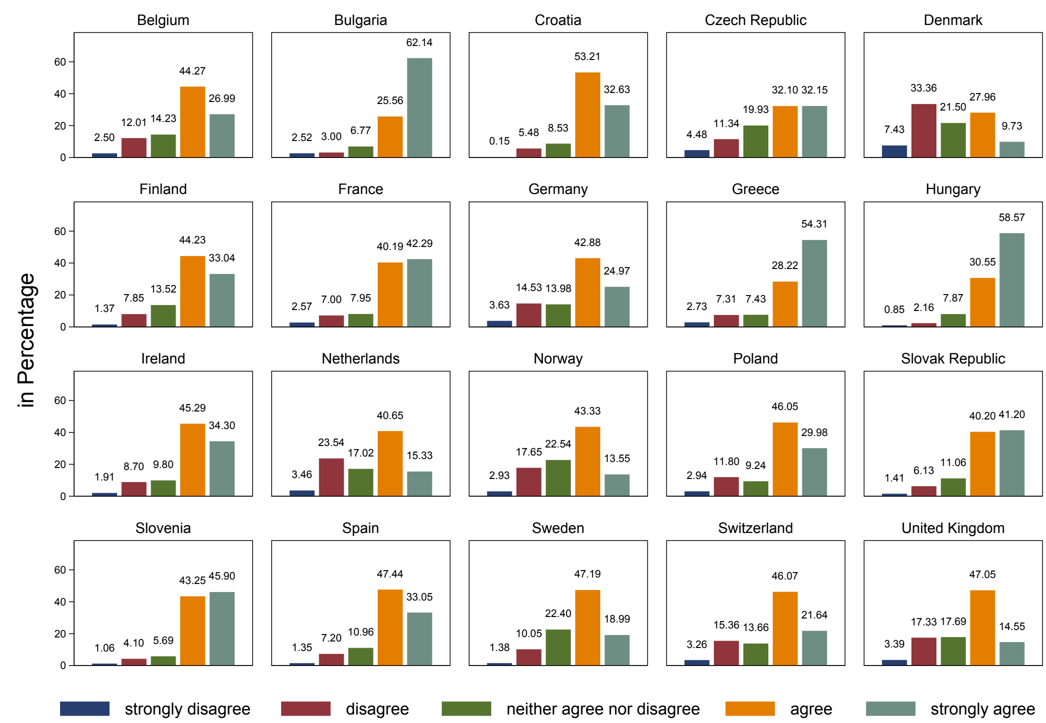
Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
2.61	11.23	13.17	39.86	33.12

Notes: Calculations are based on responses of the final born sample, weighted with design and population weights.

for redistribution across European countries. For example, in Denmark the respondents generally disagree with the statement, whereas the Bulgarian and Hungarian respondents agree, on average. Furthermore, the European countries differ with respect to the distribution of redistribution preferences within the countries (see Figure 1.1). Whilst the population share of the highest preference for redistribution is 62.14 percent in Bulgaria, merely 15.33 percent of the Dutch respondents have a very high preference for redistribution. In particular, some former Eastern bloc countries, such as Slovakia, Hungary, and Bulgaria, as well as the post-communist countries of Slovenia and Croatia, have a very high preference for redistribution. Nevertheless, the smaller population shares in the top two outcome categories in Poland and the Czech Republic indicate

[13] In the empirical literature, this question has emerged as an appropriate measure for the individual preference for redistribution (see, among others, Burgoon, 2014; Corneo and Grüner, 2000, 2002; Finseraas, 2008; Senik et al., 2009).

Figure 1.1: Distribution of preferences for redistribution across European countries



Notes: Responses of the final born sample weighted with country-specific design weights.

that the transformation process in these countries is already well advanced and peoples' attitudes and expectations towards governmental redistribution are approaching the perceptions of the Western European countries. This is in line with the results provided by Alesina and Fuchs-Schundeln (2007). They show that, on average, citizens from countries of the former Eastern block initially have a higher preference for state intervention and redistribution than citizens from Western Europe. Employing the German reunification as a natural experiment, the authors detect that it takes one to two generations (20-40 years) until the average attitudes of former East German citizens converge with the average attitudes of the West German citizens.

Since socio-economic and demographic characteristics are important determinants of redistribution preferences, a basic set of exogenous variables is prepared. This includes the respondent's age, gender, educational attainment, partnership status, labor force status, household size, household income, size of the place of residence, parental status, and current or former sector of employment. The labor force status of a respondent is summarized by the categories "employed", "unemployed", and "not in labor force", where the latter includes "ill", "disabled", "stay-at-home", and "retired" persons.[14] The information on the size of the place of residence is grouped into the

[14]Respondents who are currently studying are not taken into account, as most of them are not entitled to vote.

binary variable *urban*, whereby "big city" and "suburb of big city" have the value 1 and "town/small city", "country/village" and "farm/countryside home" have the value 0. *Partnership status* is measured by means of a binary variable which indicates whether the respondent shares his or her household with a life partner or not.[15] In addition, the variable for the employment sector indicates whether the respondent works or worked in the "public sector", "private sector", was "self-employed", or "other". Individual data on Portugal are excluded from the analysis because there is no information on the household income of respondents. The ESS harmonized version of the International Standard Classification of Education (ISCED) is used to measure a respondent's educational attainment, whereby the following grouping is performed : (i) primary and lower secondary level (ISCED 1,2); (ii) upper secondary and advanced vocational level (ISCED 3a,3b,4); (iii) tertiary level (ISCED 5,6). In order to link the individual educational attainment with the relative skill ratio at the regional level, a binary education variable is created. Respondents with education level (iii) correspond to the *skilled* and take the value 1, whilst the remaining belong to the *unskilled* and take the value 0. Since the purpose of the study is the estimation of immigration's impact on a native's preference for redistribution, all respondents whose place of birth is outside the country of data collection were dropped from the original sample.

Moreover, the 2011 Population and Housing Census is used in order to calculate the relative skill compositions at the NUTS level 2 (European Commission, 2016). The data include detailed information on the number of immigrants and natives by educational attainment which is measured according to the ISCED classification. In turn, education levels are grouped into skilled and unskilled according to the above recoding scheme for both natives and immigrants, respectively. Thus, the relative skill composition is calculated for both the skilled (RSC) and the unskilled (RUC) population at the regional level r by

$$\mathrm{RSC}_r = \frac{\text{Share of skilled immigrants in immigrant population}}{\text{Share of skilled natives in native population}}\,, \tag{1.20}$$

$$\mathrm{RUC}_r = \frac{\text{Share of unskilled immigrants in immigrant population}}{\text{Share of unskilled natives in native population}}\,, \tag{1.21}$$

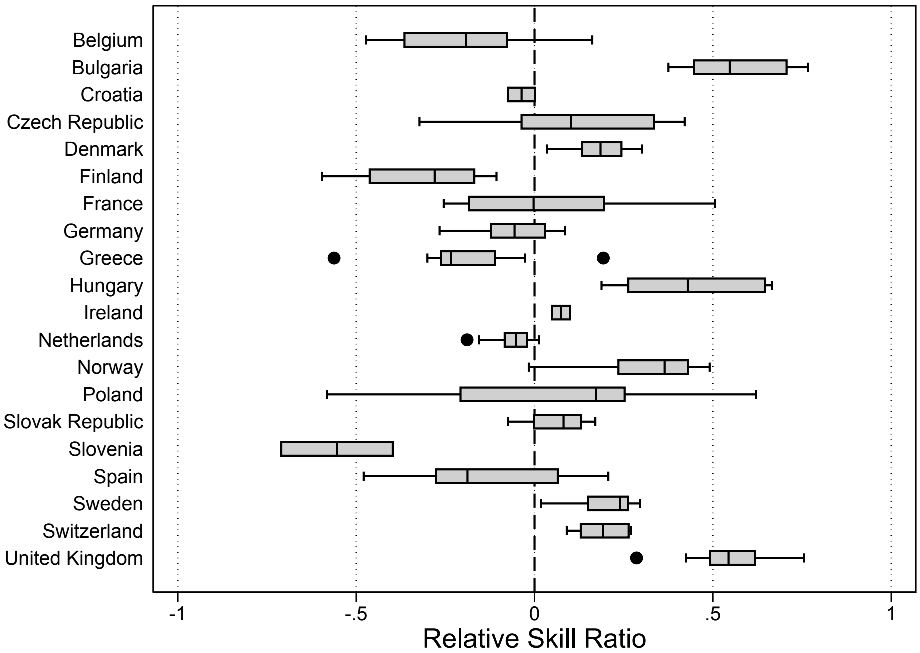
where RSC and RUC are equivalent to β_S and β_U in the theoretical framework, respectively. Since an increase of RUC essentially entails a decline of RSC due to the binary coding of skills, only one of the two measures has to be considered in the estimations. In particular, the logarithm of the relative skilled composition is employed in the estimations and denoted as *relative skill ratio (rsr)*.[16] The greater the relative skill ratio in

[15]Since the Finnish sample does not provide any information on family status, but on partnership status, the latter is used to prevent the loss of observations. Estimations without Finland showed that the coefficients and standard errors of the other covariates vary only slightly, regardless of whether family status or partnership status is used.

[16]Facchini and Mayda (2009) use a similar measure: $\log\left(1 + \frac{RUC_r}{RSC_r}\right)$.

a region, the higher the share of skilled immigrants compared to natives. If the ratio equals zero, the share of skilled immigrants and the share of skilled natives in their respective population are even. Once the ratio takes a positive value, the share of the skilled is higher in the immigrant population than in the native population *(skilled immigration)*. In turn, if the ratio is negative, the share of the skilled is lower in the immigrant population than in the native population *(unskilled immigration)*. Since no data on educational composition of the population are available for Russia, Israel, and Ukraine at the regional level, these countries are not considered in the analysis. Additionally, Lithuania, Cyprus, and Estonia are not taken into account, as these countries have no variation in the relative skill ratio at the NUTS level 2.[17] In order to prevent distortions in the estimations by an insufficient number of valid observations within regions, regions with less than 30 observations are not taken into account. Thus, the final sample includes 20 European countries and the relative skill ratio for 160 regions.[18] In some countries, such as the United Kingdom and Switzerland, the regional relative skill ratios are, without exception, positive (see Figure 1.2). Thus, these countries exhibit

Figure 1.2: Box-Whisker plot of regional relative skill ratios across European countries



Source: European Commission (2016), own calculations.

skilled immigration. In contrast, the regions in Finland and Slovenia experience entirely unskilled immigration. In most countries, there is a great variation of the relative skill

[17]In Germany and the United Kingdom, the respondents' place of residence is given on the NUTS level 1. Accordingly, the relative skill ratios are calculated at the NUTS level 1 for these two countries.

[18]The summary statistics of the main variables used in the analysis are presented in Table 1.10 in the appendix of this chapter.

ratio across regions, where some regions exhibit skilled immigration and other regions evince unskilled immigration.

1.5 Econometric Specification

Since the dependent variable *preference for redistribution* includes five ordered categories, the application of ordered response models is appropriate. Furthermore, the categories, "strongly disagree" and "disagree", are collapsed, because only 2.5 percent of the natives constituted the former (see Table 1.2). Since ordered response models are equivalent to a series of binary regressions due to the *proportional odds assumption*, the estimation of a binary response model which shows a value of one in the dependent variable for only 2.5 percent of the observations is not recommended (Hamilton, 1992). Therefore, the employed dependent variable in the analysis has four categories. Ultimately, ordered logit regressions of natives' preference for redistribution y are applied and derived from a latent variable model. Thus, a native's unobserved attitude towards the welfare state y_i^* can be expressed by

$$y_i^* = \boldsymbol{x_i'}\boldsymbol{\beta} + \gamma_1 \cdot \text{skilled}_i + \gamma_2 \cdot \text{rsr}_{r(i)} + \gamma_3 \cdot \text{skilled}_i \cdot \text{rsr}_{r(i)} + u_i, \tag{1.22}$$

where $\boldsymbol{x_i'}$ is a vector of individual socio-economic and demographic determinants, including the basic set of covariates described above. The binary variable *skilled* indicates whether the native i is skilled or unskilled. The variable $rsr_{r(i)}$ represents the relative skill ratio in the region r of native i. Finally, the interaction term $skilled_i \cdot rsr_{r(i)}$ determines whether the relative skill ratio of the region has an additional impact on the redistribution preference of a skilled native compared to an unskilled native in the same region. According to the theoretical framework, the coefficient of the interaction term γ_3 should be positive, since an increased regional relative skill ratio has a positive effect on the redistribution preference of skilled natives due to both the labor market and welfare state effects.

Furthermore, the model includes a full set of country dummies in order to capture country-specific effects, whereby the intercept in $\boldsymbol{x_i'}$ varies across countries. This is required since both unobservable and observable measures, e.g. the current level of income inequality and governmental redistribution, may have an effect on a native's preference for redistribution. Employing country-specific intercepts enables the exclusion of country-level variables' influence, which is assumed to be homogenous across fellow natives.[19] The fixed effect estimation of an ordered response model may give rise

[19]Thus, no additional country-level variables can be considered in the estimations, since the fixed effects already capture both observable and unobservable country effects. In principle, however, country-specific variables can be integrated within interaction terms with individual variables, without taking the main effect into account.

to the incidental parameter problem (Chamberlain, 1984). The maximum likelihood estimator of the incidental parameters (fixed effects) is consistent as long as $T \to \infty$, for given N (assuming that there are T observations for each individual unit $i = 1, \ldots, N$). However, the estimator is inconsistent for given T, as $N \to \infty$. Since country fixed effects are included, the parsed panel is very long. N is small and T is high, as there are many observations within each country. Given these properties of the data, the incidental parameters problem is not an issue for the estimation results.

The error terms ϵ_{ic} follow a standard logistic distribution and are independent across, but not within, countries. Thus, the asymptotic robust standard errors are adjusted for clustering at the country level in order to address heteroscedasticity and allow for correlation between individual observations within the same country. Since the dependent variable is ordered, the underlying latent variable can be divided into four ordinal categories

$$y_i = m \qquad \text{if } \kappa_{m-1} \le y_i^* < \kappa_m \qquad \text{for } m = 1, \ldots, 4\,, \tag{1.23}$$

where the thresholds (or cutoff points) κ_1 through κ_3 are estimated together with the coefficients of the model by maximum likelihood, whereby $\kappa_0 = -\infty$ and $\kappa_4 = \infty$ are fixed. Thus, the observed response categories are tied to the latent variable by the measurement model

$$y_i = \begin{cases} 1 \ \text{(“strongly disagree” or “disagree”)}, & \text{if } \ -\infty \le y_i^* < \kappa_1 \\ 2 \ \text{(“neither agree nor disagree”)}, & \text{if } \ \kappa_1 \le y_i^* < \kappa_2 \\ 3 \ \text{(“agree”)}, & \text{if } \ \kappa_2 \le y_i^* < \kappa_3 \\ 4 \ \text{(“strongly agree”)}, & \text{if } \ \kappa_3 \le y_i^* < \infty \end{cases} \tag{1.24}$$

The probability of $y_i = m$ is given by

$$\begin{aligned} \Pr(y = m|\boldsymbol{x}, \boldsymbol{\Psi}) &= \Pr(\kappa_{m-1} \le y^* < \kappa_m|\boldsymbol{x}, \boldsymbol{\Psi}, u_c) \\ &= F(\kappa_m - \boldsymbol{x}'\boldsymbol{\beta} - \boldsymbol{\Psi}'\boldsymbol{\gamma}) - F(\kappa_{m-1} - \boldsymbol{x}'\boldsymbol{\beta} - \boldsymbol{\Psi}'\boldsymbol{\gamma}), \end{aligned} \tag{1.25}$$

$$\text{with} \qquad \boldsymbol{\Psi} = \begin{pmatrix} \text{skilled} \\ \text{rsr} \\ \text{skilled} \cdot \text{rsr} \end{pmatrix} \qquad \text{and} \qquad \boldsymbol{\gamma} = \begin{pmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{pmatrix} \qquad ,$$

where $F(\cdot)$ is the cumulative density function which is either the logistic distribution or the standard normal distribution in the following estimations as required. In order to provide a better interpretation and graphical illustration of the empirical results, the average marginal effects on a high preference for redistribution are calculated in addition to the raw estimation results. A high preference for redistribution is defined as the probability of selecting the two top categories “agree” and “strongly agree” of the ordered dependent variable. The corresponding probability is

$$\Pr(y \geq 3|\boldsymbol{x}, \boldsymbol{\Psi}) = 1 - F(\kappa_2 - \boldsymbol{x}'\boldsymbol{\beta} - \boldsymbol{\Psi}'\boldsymbol{\gamma}) \tag{1.26}$$

and the average marginal effect AME_k of a particular variable x_k (or Ψ_k) is obtained by

$$AME_k = \frac{\partial \Pr(y \geq 3|\boldsymbol{x} = \boldsymbol{x_i}, \boldsymbol{\Psi} = \boldsymbol{\Psi_i})}{\partial x_k} = \hat{\beta}_k \left[\frac{1}{n} \sum_{i=1}^{n} f(\kappa_2 - \boldsymbol{x_i'}\hat{\boldsymbol{\beta}} - \boldsymbol{\Psi_i'}\hat{\boldsymbol{\gamma}}) \right], \tag{1.27}$$

where f is the probability density function and n is the number of total observations. Since the effect of the regional relative skill ratio on skilled and unskilled natives is the focal point of this study, the contrast of the average marginal effect of the relative skill ratio between skilled and unskilled natives $CAME_{rsr}$ is obtained by

$$\begin{aligned} CAME_{rsr} &= \frac{\partial \Pr(y \geq 3|\boldsymbol{x} = \boldsymbol{x_i}, \text{skilled}, \text{rsr}_i, \text{skilled} \cdot \text{rsr}_i)}{\partial rsr} - \frac{\partial \Pr(y \geq 3|\boldsymbol{x} = \boldsymbol{x_i}, \text{rsr}_i)}{\partial rsr} \\ &= (\hat{\gamma}_2 + \hat{\gamma}_3) \cdot \left[\frac{1}{n} \sum_{i=1}^{n} f(\kappa_2 - \boldsymbol{x_i'}\hat{\boldsymbol{\beta}} - \hat{\gamma}_1 - \hat{\gamma}_2 \cdot \text{rsr}_i - \hat{\gamma}_3 \cdot \text{rsr}_i) \right] \\ &- \hat{\gamma}_2 \cdot \left[\frac{1}{n} \sum_{i=1}^{n} f(\kappa_2 - \boldsymbol{x_i'}\hat{\boldsymbol{\beta}} - \hat{\gamma}_2 \cdot \text{rsr}_i \right]. \end{aligned} \tag{1.28}$$

Furthermore, design and population weights are applied, since the observations are pooled and all parameters are constrained to be the same across countries. Finally, a number of checks are carried out to explore the robustness of the results.

1.6 Empirical Results

The theoretical framework predicts that the preference for redistribution is a function of a person's individual income. Immigration, in turn, affects natives' net income through the labor market channel and welfare channel. The overall effect depends on the skill-type of immigration and the natives' skill level. The raw coefficients of the ordered logit regressions indicate that higher household income decreases the preference for redistribution (see Table 1.3). Skilled respondents have, on average, a lower preference for redistribution. Furthermore, the utilized control variables are almost continuously significantly associated with a native's preference for redistribution and confirm the common findings in the empirical literature.[20] The coefficient's magnitude as well as the standard errors differ only slightly between the born and citizen sample. The main effect of the regional relative skill ratio is weakly significant in the born sample. Therefore, an increasing relative skill ratio refers to a higher redistribution preference

[20]For an overview of the determinants of preferences for redistribution, see Alesina and Giuliano (2009), among others.

Table 1.3: Ordered logit estimation results

	Born Sample		Citizen Sample	
age	0.0339	(0.0062)***	0.0328	(0.0064)***
age^2	-0.0003	(0.0001)***	-0.0003	(0.0001)***
female	0.1479	(0.0301)***	0.1456	(0.0271)***
life partner	0.0484	(0.0462)	0.0603	(0.0465)
household member	0.0776	(0.0216)***	0.0652	(0.0186)***
kids at home	-0.1994	(0.0183)***	-0.1906	(0.0255)***
(sub-)urban	-0.0278	(0.0543)	-0.0216	(0.0472)
employed		*reference*		
unemployed	0.1626	(0.0627)***	0.1502	(0.0685)**
not in labor force	0.0792	(0.0275)***	0.0947	(0.0285)***
public sector		*reference*		
private sector	-0.0980	(0.0404)**	-0.0915	(0.0437)**
self-employed	-0.3105	(0.0657)***	-0.3001	(0.0619)***
other	0.0151	(0.1351)	0.0007	(0.1218)
household income	-0.1218	(0.0129)***	-0.1200	(0.0128)***
skilled	-0.4285	(0.0598)***	-0.4046	(0.0661)***
rsr	0.3006	(0.1785)*	0.2594	(0.1666)
skilled × rsr	0.3828	(0.1721)**	0.3310	(0.1727)*
no migration background		*reference*		
migration background			-0.0052	(0.1153)
migration experience			-0.0199	(0.0512)
Obs.	24018		25145	
McFadden R^2	0.057		0.055	
AIC	50278.65		53083.16	
BIC	50424.20		53237.68	
Log Likelihood	-25121.32		-26522.58	

Source: ESS 2010/2011, 2011 Population and Housing Census.
Note: Dependent variable is a native's preference for redistribution. Raw coefficients of the ordered logit estimations are reported. Migrational background applies to respondents who were not born abroad, but rather who have at least one parent who was born abroad. Migrational experience, in turn, describes those respondents who were born abroad and migrated to the respective country. Country fixed effects are included, but not reported. Standard errors are reported in parentheses and clustered at the country level. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

regardless of the the natives' skill level. Thus, the effect of immigration through the welfare channel overcompensates for the effect of immigration through the labor market channel for unskilled natives. However, it must be taken into account that this effect is weak and even insignificant for the citizen sample.

Additionally, the interaction term between the relative skill ratio and the binary skill variable is significant in both samples. Therefore, the positive effect of the relative skill ratio is higher for skilled natives than for unskilled natives. Thus, the redistribution preference increases more strongly with a rising relative skill for skilled natives than for unskilled natives. Both the main effect and the interaction effect jointly confirm the theoretical predictions, since the observed regional relative skill ratio serves as a proxy for the type of immigration that is experienced by a region. In European regions where the proportion of skilled immigrants is greater than the proportion of skilled natives, skilled natives have, on average, a higher preference for redistribution than skilled natives in regions with an inverse ratio.[21]

Considering the difference in the average marginal effect of the relative skill ratio on particular probabilities of the ordered dependent variable between unskilled and skilled natives, the results so far are reinforced (see Table 1.4).[22] Since the main effect

Table 1.4: Contrast of average marginal effects of relative skill ratio between skilled und unskilled natives on outcome probabilities

	Born Sample		**Citizen Sample**	
strongly disagree or disagree	-0.0637	(0.0231)***	-0.0544	(0.0235)**
neither agree nor disagree	-0.0225	(0.0118)*	-0.0199	(0.0119)*
agree	0.0311	(0.0104)***	0.0258	(0.0106)**
strongly agree	0.0552	(0.0294)*	0.0485	(0.0294)*

Source: ESS 2010/2011, 2011 Population and Housing Census.
Note: Dependent variable is a native's preference for redistribution. Standard errors are reported in parentheses and clustered at the country level. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

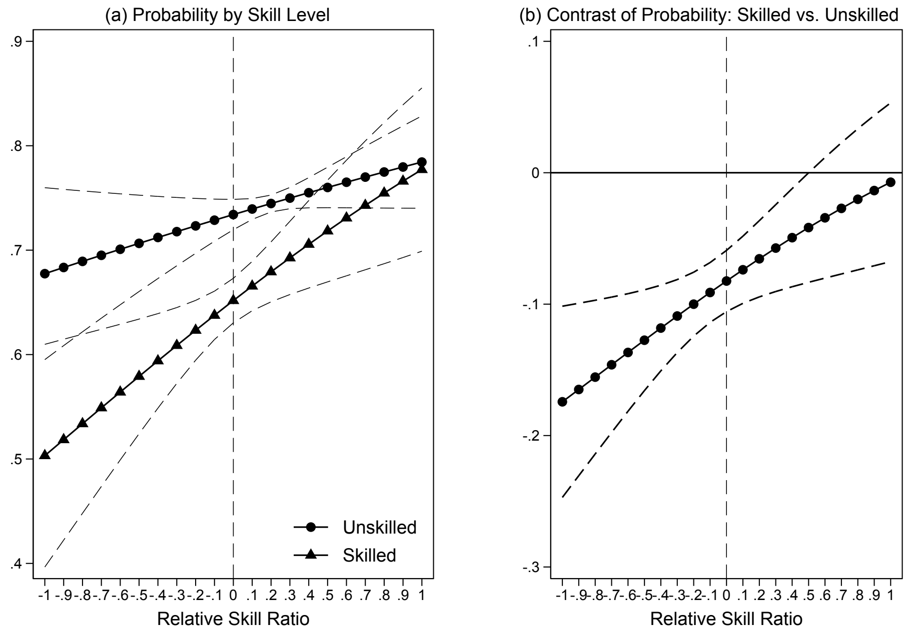
of the relative skill ratio is positive, an increase in the relative skill ratio raises the preference for redistribution for both unskilled and skilled natives. However, if the relative skill ratio increases by one percent, the probability of checking "strongly agree" increases for skilled natives by 5.5 percentage points more than for unskilled natives. In turn, the probability of checking "strongly disagree or disagree" decreases for the skilled by 6.4 percentage points more than for unskilled natives. The effects are similar for the citizen sample.

Thus, if the relative skill ratio increases, the redistribution preference of skilled and unskilled natives converges. The opposite occurs if the ratio diminishes (see Figure 1.3, Panel (b)). In regions which have a negative relative skill ratio and, thus, experience unskilled immigration, the skilled natives have a significantly lower redistribution preference than unskilled natives. In turn, in regions which have a positive ratio and

[21] Since Portugal was excluded from the analysis due to the lack of household income information, the same estimation is repeated with information for the main household income resource. This is done for a born sample both with and without Portugal. The coefficients' sign and standard errors remain almost the same; particularly, the interaction term between the regional relative skill ratio and the skilled dummy remains significantly positive. The raw coefficients are given in Table 1.11 in the appendix of this chapter.

[22] Average marginal effects of all basic covariates on the probability of each category of the dependent variable are given in Table 1.12 in the appendix of this chapter.

Figure 1.3: Average marginal effect of relative skill ratio for skilled and unskilled natives on the probability of a high preference for redistribution



Source: ESS 2010/2011, 2011 Population and Housing Census.
Notes: A high preference for redistribution is defined as the probability of selecting the two top categories "agree" and "strongly agree" of the ordered dependent variable. Thin lines around the predicted values represent the 95 percent confidence intervals.

experience skilled immigration, the skilled natives still have a lower preference for redistribution than unskilled natives, but this difference gradually diminishes with an increasing relative skill ratio (see Figure 1.3, Panel (a)). Once the regional relative skill ratio exceeds a value of around 0.4, these differences are no longer significantly different from zero.

Moreover, this impact of the relative skill ratio cannot be driven by an income disparity between different European regions, since the estimations take into account a respondent's household income measured in deciles of a country's income distribution. Thus, respondents from different regions may have different incomes and still be members of the same decile. Since the relative income of a person is decisive for his or her redistribution preference, the income effect is driven by his or her position along the income distribution. Thus, applying household income deciles directly in the estimation enables the comparison of respondents who share the same income position within their countries. Furthermore, a country's current income inequality and governmental redistribution might serve as a reference point for the personal preference for redistribution, since governmental redistribution takes place within national borders. Thus, a rise in national income inequality should increase natives' preference for redistribution, regardless of their educational attainment and the regional relative skill ratio.[23] However, differences in the national income inequality and governmental redistribution policies across European countries are already taken into account by country fixed effects, which absorb both effects in the estimations.

1.6.1 Adjustment of Standard Errors

Since cluster robust standard errors at the country level were used so far, the consistency of the estimation parameters is based on the validity of the asymptotics. However, the number of clusters is small and limited to 20 countries, which could result in downward biased standard errors. If the latter occurs, estimated residuals are systematically biased towards zero, which can cause standard asymptotic tests to over-reject (Cameron and Miller, 2015). In order to reduce the rejection rate and to obtain more accurate cluster-robust inference when there are few clusters, wild cluster bootstrapped t-statistics with asymptotic refinement should be used (Cameron et al., 2008). Since nonlinear models are applied, the score wild bootstrap approach according to Kline and Santos (2012) is used to adjust the cluster-robust standard errors.[24] The procedure of this method is as follows: estimate the nonlinear model only once, generate fitted scores for all sample observations, and perform a wild bootstrap, while perturbing the scores by bootstrap weights at each step. Hereafter, for each bootstrap replication, the perturbed scores are used to build a test statistic. Thus, the resulting distribution of the test statistic can be used for inference. Hereby, the score wild bootstrap creates a set of bootstrap score contributions that mimic the heteroscedastic nature of the true score contributions. The implementation of the score wild bootstrap uses the skewness-correcting bootstrap weights suggested by Webb (2014).[25] The adjustments of the standard errors using score wild bootstrap reinforces previous results (see Table 1.5).[26] Hence, the standard error of the household member and unemployed variable slightly increases.[27] Furthermore, the main effect of the relative skill ratio becomes insignificant after the adjustment. However, the interaction term *skill* × *rsr* remains significant, albeit only weakly. Thus,

[23]Olivera (2015), among others, gives general empirical evidence on the positive association between income inequality and the preference for redistribution.

[24]Cameron and Miller (2011), among others, provide a brief summary of several ways to handle clustering in nonlinear models.

[25]Webb weights are preferred, since Rademacher and Mammen weights only have two mass points (Mammen, 1993). Thus, employing the latter would create spurious precision in estimations with few clusters if some replications are duplicates. Webb weights greatly reduce this problem and improve the reliability of inference by using a uniform six-point bootstrap weight distribution that closely matches Rademacher weights in the first four moments. The six values are: $\pm\sqrt{\frac{3}{2}}, \pm\sqrt{\frac{2}{2}}, \pm\sqrt{\frac{1}{2}}$.

[26]Since each cluster includes many individual observations, cluster-adjusted F-statistics based on Ibragimov and Müller (2010) are additionally employed as a more conservative test for validity of the standard errors. The results of the particular Wald tests and the steps of procedure for the ordered logit model are given in the appendix of this chapter (Esarey and Menger, n.d.).

[27]Reported standard errors are calculated from quasi χ^2-values of the score wild bootstrap. The p-values are based on the Wald test of the particular coefficients and cannot be calculated directly from standard errors.

Table 1.5: Score wild bootstrap adjusted standard errors of the basic ordered logit estimation

age	0.0339	(0.0066)***
age^2	-0.0003	(0.0001)***
female	0.1479	(0.0303)***
life partner	0.0484	(0.0453)
household member	0.0776	(0.0220)**
kids at home	-0.1994	(0.0173)***
(sub-)urban	-0.0278	(0.0499)
employed	*reference*	
unemployed	0.1626	(0.0435)**
not in labor force	0.0792	(0.0270)***
public sector	*reference*	
private sector	-0.0980	(0.0364)**
self-employed	-0.3105	(0.0578)***
other	0.0151	(0.1272)
household income	-0.1218	(0.0134)***
skilled	-0.4285	(0.0810)***
rsr	0.3006	(0.1669)
skilled × rsr	0.3828	(0.2586)*

*Source:*ESS 2010/2011, 2011 Population and Housing Census.
Note: Dependent variable is a native's preference for redistribution. Born samples are employed and raw coefficients of the ordered logit estimation are reported. Country fixed effects are included, but not reported. Standard errors are clustered at the country level and adjusted by score wild bootstrap approach according to Kline and Santos (2012). ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

the positive main effect of the relative skill ratio can be questioned. The results rather suggest that the impacts of immigration through both the labor market and welfare state channel compensate for one another for unskilled natives. The significant interaction term, however, indicates that the conclusions reached for skilled natives thus far can be upheld. Skilled natives' preference for redistribution increases if their regional relative skill ratio rises.

1.6.2 Selective In-Migration and Out-Migration

The strength of the labor market channel and the welfare channel can be assessed, employing the main term and the interaction of the relative skill ratio in the estimations. However, in order to evaluate whether the relative skill ratio affects the preferences for redistribution of natives who are randomly assigned across regions with different relative skill ratios, the particular effect must be measured before natives have sorted themselves into areas according to their educational attainment. Since immigrants' choice of location is based on the regions' labor market conditions, the estimated coefficients of the main and the interaction effect could be biased by selective out-migration or selective in-migration. The main issue is that unskilled natives may leave their regions due to an unskilled immigration impact in order to escape wage pressure on the local labor market. In contrast, skilled natives have an incentive to migrate into regions where an unskilled immigration impact occurs, due to higher skilled wages. Thus, if a region experiences skilled immigration, more skilled natives may leave this region, while unskilled natives would be attracted to it.

As a result of selective in- and out-migration, the estimated coefficients on the main and interaction term of the regional relative skill ratio could be biased towards zero. Thus, estimates can be interpreted as lower bounds on magnitudes. The endogeneity problem can be addressed by using values of the relative skill ratio at higher levels of spatial aggregation as suitable instruments (Dustmann et al., 2011). Here, the key idea is that natives who expect lower wages due to unskilled or skilled immigration will leave the region, but are more likely to migrate to neighboring regions that are relatively close in distance and experience less wage pressure than to regions that are far away. Another reason for restricted mobility outside a given geographical region could be a native's desire to remain in proximity to family and friends. Dustmann and Preston (2001) show that such instruments will reduce the bias induced by the sorting of natives. Since the measure of natives' redistribution preference is an ordered variable, a nonlinear model with a continuous endogenous variable is estimated. In order to specify a common distribution assumption for the error terms of the equations, an ordered probit model is employed:

$$y_i^* = \boldsymbol{x_i'\delta_1} + \pi_{11} \cdot \text{skilled}_i + \pi_{12} \cdot \text{rsr}_{r(i)} + \pi_{13} \cdot \text{skilled}_{r(i)} \cdot \text{rsr}_{r(i)} + u_i \,, \tag{1.29}$$

$$rsr_{r(i)} = \boldsymbol{\overline{x}_r'\delta_2} + \pi_{21} \cdot \overline{\text{skilled}}_r + \pi_{21} \cdot \text{rsr}_{s(i)} + \overline{\text{skilled}}_r \cdot \text{rsr}_{r(i)} + v_i \,, \tag{1.30}$$

where (u, v) have zero mean, a bivariate normal distribution, and are independent of all exogenous variables. To meet these conditions, Equation (1.29), which represents the index model for the redistribution preference, will be estimated by an ordered probit model. Equation (1.30) is a reduced form for $rsr_{r(i)}$, which yields the relative skill ratio at the NUTS level 2 and is endogenous if u and v are correlated. Furthermore, $rsr_{s(i)}$ is the instrumental variable and yields the relative skill ratio at the next higher spatial region, hence the NUTS level 1. Since the dependent variable in (1.30) takes on the same value for all individuals in region r, the contributions from the instrumenting equation should be counted only once per region, according to Dustmann and Preston (2001). Therefore, the regional relative skill ratio is regressed on the regional averages of the individual characteristics within the region.[28] In order to check for endogeneity

[28] In (1.30), $\boldsymbol{\overline{x}_r'}$ does not include the regional averages of country dummies, since this is inappropriate. Thus, countries which only have one NUTS level 1 region, which are Croatia, Czech Republic, Denmark, Finland, Ireland, Norway, Slovak Republic, Slovenia, and Switzerland, can still be considered.

of the relative skill ratio at the NUTS level 2, the control function approach based on Rivers and Vuong (1988) is applied. The potentially endogenous relative skill ratio is regressed on all exogenous variables, including the instrument $rsr_{s(i)}$, and then the residuals $\hat{v}_i$ of the ordinary least squares estimation of Equation (1.30) are added as additional regressors to the main Equation (1.29). Although the relative skill ratio $rsr_{r(i)}$ also appears in the interaction term with the skilled dummy, the interaction term can be treated as exogenous according to Wooldridge (2010), because the main equation in (1.29) is an index model. Furthermore, a simple test for a zero coefficient on the residuals $\hat{v}_i$ can be regarded as a test of exogeneity. Since this test does not fail and takes an χ^2-value of 0.02 (p-value = 0.87), the estimates of Equation (1.29) are unbiased and consistent.

Nevertheless, a comparison of the regular ordered probit results with the IV ordered probit results can be meaningful. First, most of the raw coefficients do not change in their magnitude or their standard errors (see Table 1.6).[29] Second, the main effect of the relative skill ratio is insignificant in the IV probit estimation, whereas the interaction term remains weakly significant. Furthermore, both the main and the interaction term of the relative skill ratio remain relatively similar in magnitude. Overall, skilled natives living in a region which experiences skilled immigration have a higher preference for redistribution than skilled natives living in a region which experiences unskilled immigration or less skilled immigration.

1.6.3 Share of Immigrants and Redistribution Preferences

In general, governmental redistribution aims to reduce income inequality in a country through the tax and transfer system. In addition to a financial self-interest in governmental redistribution, voters have personal views about a minimum or an optimal level of social justice. In particular, these are expressed in terms of a desired or justifiable level of income inequality or poverty. Since most surveys do not provide information on such measures, empirical research concentrates on the determinants of the respondents' sense of justice. Alesina and Glaeser (2004) point out that a respondent's trust, fairness perceptions, and solidarity towards fellow citizens are important drivers in this context. The more solidarity a person has for his or her fellow citizens, the less is, ceteris paribus, the desired level of income inequality, and consequently, the greater the individual preference for redistribution (Alesina and Giuliano, 2009). In turn, immigration always means the influx of new citizens with possibly different cultures and moral concepts, regardless of whether they are skilled or unskilled. Thus, immigration or an increase

[29]Results of an IV ordered probit estimation using the control function approach for a restricted sample are given in Column 1 of Table 1.13 in the appendix of this chapter. For this purpose, only countries with more than one NUTS level 1 region were taken into account in order to predict the residuals at the first stage. However, the resulting outcomes are slightly different.

Table 1.6: Relative skill ratio: Ordered probit and IV ordered probit estimations

	ordered probit		**IV ordered probit**	
age	0.0189	(0.0037)***	0.0189	(0.0037)***
age^2	-0.0002	(0.0000)***	-0.0002	(0.0000)***
female	0.0865	(0.0190)***	0.0864	(0.0189)***
life partner	0.0288	(0.0303)	0.0288	(0.0303)
household member	0.0473	(0.0125)***	0.0474	(0.0125)***
kids at home	-0.1159	(0.0094)***	-0.1160	(0.0094)***
(sub-)urban	-0.0177	(0.0327)	-0.0176	(0.0329)
employed		*reference*		
unemployed	0.0977	(0.0362)***	0.0976	(0.0362)***
not in labor force	0.0484	(0.0169)***	0.0485	(0.0170)***
public sector		*reference*		
private sector	-0.0535	(0.0242)**	-0.0536	(0.0242)**
self-employed	-0.1788	(0.0408)***	-0.1789	(0.0410)***
other	0.0069	(0.0750)	0.0069	(0.0751)
household income	-0.0708	(0.0076)***	-0.0708	(0.0077)***
skilled	-0.2484	(0.0339)***	-0.2482	(0.0341)***
rsr	0.1821	(0.1097)*	0.1891	(0.1222)
skilled × rsr	0.1984	(0.1060)*	0.1956	(0.1057)*

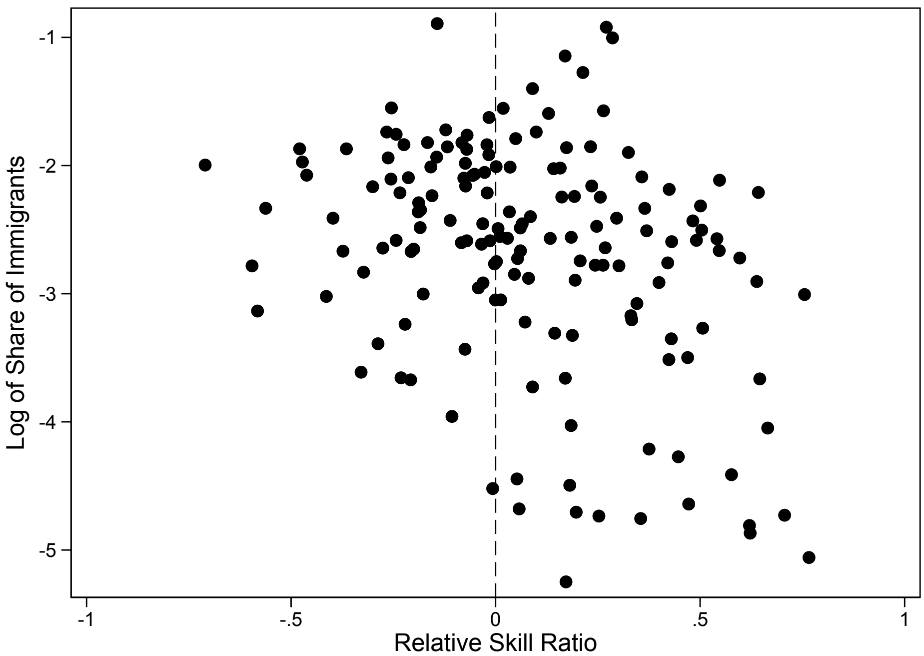
Source: ESS 2010/2011, 2011 Population and Housing Census.
Note: Dependent variable is a native's preference for redistribution. Born samples are employed and raw coefficients of the estimations are reported. Country fixed effects are included, but not reported. Standard errors are in parentheses and clustered at the country level. The relative skill ratio at the NUTS level 1 is used as an instrument for the relative skill ratio at the NUTS level 2. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

in the share of immigrants might fragment the social norms and values of a society. Subsequently, the ethnic and cultural landscape becomes more heterogeneous.

According to the *conflict theory* or *group threat theory*, a rise in ethnic and cultural heterogeneity lowers natives' trust and solidarity towards members of other ethnicities (Stephan et al., 2009). Since the potential for conflict between ethnic groups rises due to increased intergroup contact, natives start to value their own group above the rest. Thus, repeated contact does not reduce stereotypes and prejudices against other ethnicities (Putnam, 2007). Natives strengthen their solidarity with their own peers or in-group members and show more negative attitudes towards out-group members, which can be reflected in the desire for changes in a country's social policy. If there is a possibility to transform the tax and transfer system solely to benefit a single ethnic group, natives would ensure, as they constitute the majority group, that governmental redistribution take place merely in favor of their own group members. The implementation of such a selective redistribution scheme, however, is considered to be impossible in the European countries, since the income tax rate and most types of transfers cannot be discriminatory based on ethnicity. Thus, in regions with a higher share of immigrants, the natives will have a lower preference for redistribution due to a lower solidarity with the population as a whole. Diametrically opposed to conflict theory, the *intergroup contact theory* predicts that a rising share of immigrants would increase the frequency of social contact between natives and members of other ethnic groups, thereby reducing the resentments towards immigrants and increasing the degree of tolerance (Pettigrew, 1998a). Hence, in regions with a high share of immigrants, natives have a higher immigrant solidarity than in regions with a lower share of immigrants. This implies, in contrast to conflict theory, that natives' preference for redistribution must be higher in regions which have a higher proportion of immigrants.[30]

Therefore, the impact of the share of immigrants on a native's preference for redistribution cannot initially be predicted. In particular, consideration must be given to the extent to which the solidarity channel of natives' redistribution preferences, expressed by the regional share of immigrants, is related to the regional relative skill ratio. Using the 2011 Population and Housing Census, there is some evidence for a negative correlation between regions' relative skill ratio and their share of immigrants (see Figure 1.4). Thus, if the estimation does not take the immigrant population share

Figure 1.4: Regional immigrant population share and the relative skill ratio



Source: European Commission (2016), own calculations.

[30]In general, the predictions of the conflict theory and the contact theory apply to all groups in a country. Thus, a higher proportion of natives in the neighborhood would decrease immigrants' solidarity with natives due to the conflict theory, but increase their solidarity due to the intergroup contact theory. Since the focus here is on natives' preferences, explanations are relegated to the majority-building group.

into account, the usual omitted variable bias occurs due to spurious correlation between the two regional variables, i.e. the effect of the relative skill ratio is driven solely by the effect of the immigrant share and is therefore biased. Thus, a higher redistribution preference of natives living in regions which have a higher relative skill ratio might be traced back to the accompanied lower proportion of immigrants living in these regions if the predictions of the conflict theory are met. However, to answer the question of how the share of immigrants affects the preferences for redistribution of natives who are randomly assigned across regions with different immigrant population shares, the effect has to be measured before natives have sorted themselves into areas according to their attitudes towards immigrants. Since a higher share of immigrants can induce the natives whose sense of solidarity with immigrants is the lowest to leave the region, the estimated coefficient of the immigrant population share could be biased towards zero. If such a selective out-migration of natives occurs, the accompanied endogeneity issue can be addressed by using values of the share of immigrants at higher levels of spatial aggregation as suitable instruments. This procedure follows from similar considerations concerning the instrumentation of the relative skill ratio above. Natives who feel less solidarity with immigrants will leave the region, but are more likely to migrate to neighboring regions that are relatively close in distance and have a lower share of immigrants than to regions that are far away.

The estimation is based on the IV approach, which has already been described in detail above, and is now applied to the share of immigrants. The exogeneity test based on the control function approach yields an χ^2-value of 0.73 (p-value = 0.39).[31] Thus, the regular ordered probit estimates are unbiased and consistent. Furthermore, there are only minor differences in the results between the regular ordered probit and the IV ordered probit estimations (see Table 1.7). Both estimations show an insignificant main effect of the relative skill ratio, whereas the interaction effect remains weakly significant. Thus, the relation of the immigrants' and natives' educational composition has a significant impact on the natives' preference for redistribution independently of the regional share of immigrants observed. Interestingly, the coefficient of the immigrant population share is insignificant in both estimations. This suggests that either the number of immigrants within a region has at least no direct impact on natives' support for redistribution or the predicted forces of the two contradictory theories mutually compensate for one another. In turn, both explanations are based on the association between the immigrant population share and a native's solidarity and between a native's solidarity and his or her preference for redistribution. Thus, the absence of a significant effect of the immigrant population share might be due to the

[31] The results of an IV ordered probit estimation using the control function approach for a restricted sample is given in Column 2 of Table 1.13 in the appendix of this chapter. For this purpose, only countries with more than one NUTS level 1 region were taken into account in order to predict the residuals at the first stage. However, the resulting outcomes are slightly different.

Table 1.7: Share of immigrant population: Ordered probit and IV ordered probit estimations

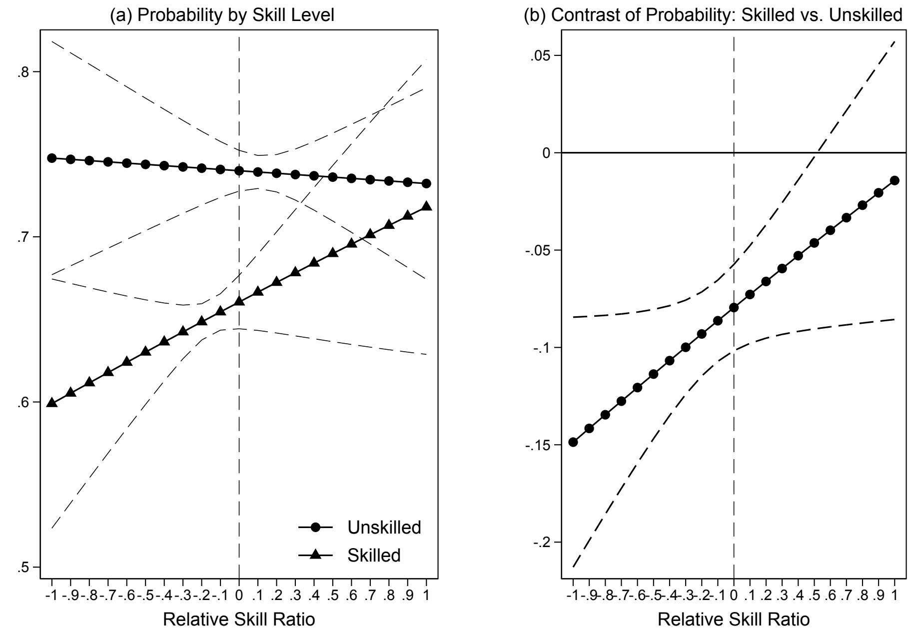
	ordered probit		**IV ordered probit**	
age	0.0184	(0.0036)***	0.0184	(0.0036)***
age^2	-0.0002	(0.0000)***	-0.0002	(0.0000)***
female	0.0867	(0.0187)***	0.0867	(0.0187)***
life partner	0.0261	(0.0317)	0.0263	(0.0317)
household member	0.0469	(0.0122)***	0.0469	(0.0122)***
kids at home	-0.1126	(0.0101)***	-0.1127	(0.0100)***
(sub-)urban	0.0013	(0.0284)	0.0010	(0.0290)
employed		*reference*		
unemployed	0.1008	(0.0359)***	0.1008	(0.0358)***
not in labor force	0.0499	(0.0167)***	0.0498	(0.0165)***
public sector		*reference*		
private sector	-0.0502	(0.0233)**	-0.0503	(0.0232)**
self-employed	-0.1762	(0.0399)***	-0.1761	(0.0403)***
other	0.0070	(0.0750)	0.0070	(0.0750)
household income	-0.0692	(0.0071)***	-0.0693	(0.0071)***
skilled	-0.2474	(0.0347)***	-0.2474	(0.0346)***
rsr	-0.0272	(0.1069)	-0.0256	(0.1079)
skilled × rsr	0.2015	(0.1033)*	0.2014	(0.1034)*
immigrant population share	-0.1370	(0.0903)	-0.1342	(0.0985)

Source: ESS 2010/2011, 2011 Population and Housing Census.
Note: Dependent variable is a native's preference for redistribution. Born samples are employed and raw coefficients of the estimations are reported. Country fixed effects are included, but not reported. Standard errors are in parentheses and clustered at the country level. The migrant population share at the NUTS level 1 is used as an instrument for the migrant population share at the NUTS level 2. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

fact that a native's solidarity, which mediates between the share of immigrants and his or her preference for redistribution, cannot be measured directly.

Taking a closer look at the average marginal effects of the IV ordered probit estimation, previous results regarding the main effect and interaction effect of the relative skill ratio can be reinforced. The skilled and the unskilled natives' redistribution preferences converge if the regional relative skill ratio increases (see Figure 1.5, Panel (a)). Whereas a skilled native living in a region which experiences unskilled immigration shows a lower support for redistribution than an unskilled native living in the same region, this difference gradually declines if the regional relative skill ratio increases. However, once the relative skill ratio exceeds a value of around 0.4, there is, ceteris paribus, no longer a significant difference in the redistribution preference between a skilled and an unskilled native (see Figure 1.5, Panel (b)).

Figure 1.5: Average marginal effect of the regional relative skill ratio for skilled and unskilled natives on the probability of a high preference for redistribution based on IV ordered probit estimation



Source: ESS 2010/2011, 2011 Population and Housing Census.
A high preference for redistribution is defined as the probability of selecting the two top categories "agree" and "strongly agree" of the ordered dependent variable. Thin lines around the predicted values represent the 95 percent confidence intervals.

1.6.4 At-Risk-Of-Poverty Rate and Redistribution Preferences

As already mentioned, income inequality or poverty can also have a direct impact on the preference for redistribution. This is the case if individuals do not have a particular ideal level of income inequality or poverty, but take into account the effects and consequences of a certain level of income inequality or poverty when establishing their redistribution preference. In general, the theoretical and empirical literature posits three explanation which might substantiate the direct influence of income inequality or poverty on an individual's preference for redistribution (Alesina and Giuliano, 2009).

First, high-income earners or skilled persons might have an interest in more governmental redistribution if there are positive externalities in education. Assuming credit market constraints for low-income households, a higher level of inequality implies that more and more people have problems acquiring their optimal level of education. If this occurs, high-income earners might prefer a certain level of redistribution in order to increase the average level of education in their country. If there are positive externalities in education, both the low-income and high-income earners would benefit from a higher average level of education.[32] Second, a rise in income inequality or poverty might

[32] Benabou (1996), among others, offers a good survey about the link between redistribution, externalities

heighten criminal activity in a country.[33]. However, Hicks and Hicks (2014) detect that the visible relative deprivation is crucial to the level of crime in a region, rather than the level of income inequality. In turn, this result confirms the predictions of the *strain theory*, which suggests that perceived inequality makes low-income households feel less committed to social norms and, therefore, come to view crime as more acceptable (Merton, 1938). In either case, high-income earners have an incentive to vote for more redistribution, since lower income inequality or less poverty induces them to spend less on their private security, because their property is generally safe. However, the latter is based on the assumption that it is more beneficial for a high-income earner to achieve a higher level of security through changes in the tax and transfer system than from his or her own security expenditure if income inequality or poverty remain unchanged. Third, high income inequality can provide incentives for low-income earners to increase their working hours in order to receive higher wages and to move up the wage ladder. Moreover, if observed high income inequality is due to higher returns on education and labor market experience, low-income earner might perceive the higher income inequality as an indicator of a high intragenerational upward mobility (Alesina and Angeletos, 2005; Benabou and Tirole, 2006).[34] This reinforces the effect of income inequality and leads to a lower preference for redistribution among low-income earners despite of higher income inequality.

Therefore, the impact of income inequality on natives' preference for redistribution cannot initially be predicted. In particular, the extent to which regional income inequality is related to the regional relative skill ratio must be taken into consideration. Thus, the logarithm of the regional at-risk-of-poverty rate is used as a measure of income inequality or poverty.[35] However, plotting the the regional at-risk-of-poverty rates (European Commission, 2017) against the regional relative skill ratios in 2011 (European Commission, 2016) does not reveal a distinct correlation (see Figure 1.6).[36] Nevertheless, neglecting the at-risk-of-poverty rate in the estimation might generate an omitted variable bias due to partial spurious correlation, i.e the effect of the relative skill ratio on a native's preference for redistribution is driven by the high partial correlation between the relative skill ratio and the at-risk-of-poverty rate. Therefore, renouncing the at-risk-of-poverty rate in the estimations causes the significant effects to be mistakenly attributed to the relative skill ratio. Applying the extended ordered

of education, and imperfect capital markets.

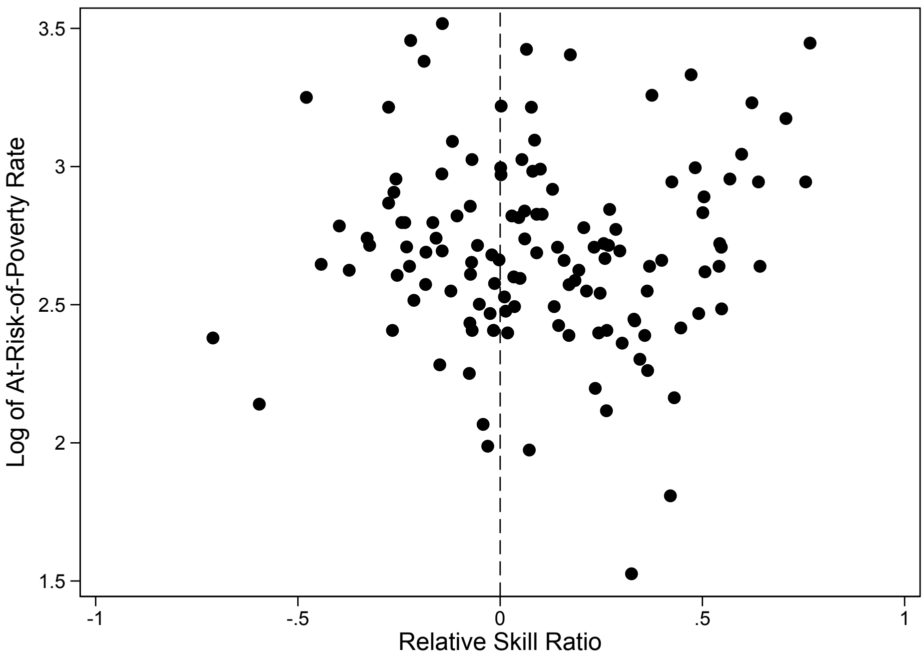
[33]For empirical evidence, see Kelly (2000), Fajnzylber et al. (2002), and Choe (2008), among others

[34]There is a vast collection of literature providing empirical evidence on the *prospects of upward mobility hypothesis* according to Benabou and Ok (2001). See, among others, Alesina and La Ferrara (2005b); Fong (2006); Rainer and Siedler (2008).

[35]The regional at-risk-of-poverty rate represents the percentage of persons with an equivalised disposable income below the risk-of-poverty threshold, which is set at 60 percent of the national median equivalised disposable income, within a region.

[36]Data for Croatia, France, Germany, and the United Kingdom are taken from the national statistics. See Table 1.14 in the appendix of this chapter for references.

Figure 1.6: Regional at-risk-of-poverty rate and the relative skill ratio



Source: European Commission (2017, 2016), and national statistics, own calculations.

probit estimation reinforces the previous results with respect to the main term and the interaction term of the regional relative skill ratio (see Table 1.8). The main effect is still insignificant, but the interaction effect becomes slightly more significant by adding the at-risk-of-poverty rate. In both specifications, the raw coefficients of the interaction term are approximately the same size and also similar in magnitude to previous results. The effect of the interaction term seems to be robust in both its significance and size. However, the at-risk-of-poverty rate is insignificant in both estimations. Since country fixed effects are applied in the estimation and absorb country differences, these results suggest that the within-country variation of the at-risk-of-poverty rate is not high enough to generate significant differences between a country's regions. Whereas the domestic variation of the regional relative skill ratio is relatively high, the domestic variation of the regional at-risk-of-poverty rate is very low (see Figure 1.7 in the appendix of this chapter). Across the European countries, the domestic coefficient of variation for regional relative skill ratio is, on average, 2.08, whilst it is only 0.23 for the at-risk-of-poverty rate. Therefore, the descriptive evidence confirms the suggestions about the within-country variations. Thus, the country fixed effects are sufficient in order to capture differences in the institutional settings and levels of income inequality across the European countries.

Table 1.8: At-risk-of poverty rate: Ordered probit estimations

	(1)		(2)	
age	0.0189	(0.0036)***	0.0186	(0.0035)***
age^2	-0.0002	(0.0000)***	-0.0002	(0.0000)***
female	0.0889	(0.0190)***	0.0882	(0.0186)***
life partner	0.0279	(0.0305)	0.0260	(0.0316)
household member	0.0468	(0.0122)***	0.0465	(0.0119)***
kids at home	-0.1153	(0.0099)***	-0.1131	(0.0103)***
(sub-)urban	-0.0168	(0.0318)	-0.0035	(0.0284)
employed		*reference*		
unemployed	0.0953	(0.0340)***	0.0996	(0.0351)***
not in labor force	0.0467	(0.0169)***	0.0482	(0.0164)***
public sector		*reference*		
private sector	-0.0500	(0.0231)**	-0.0486	(0.0228)**
self-employed	-0.1737	(0.0397)***	-0.1723	(0.0393)***
other	0.0058	(0.0754)	0.0066	(0.0744)
household income	-0.0699	(0.0073)***	-0.0691	(0.0070)***
skilled	-0.2501	(0.0357)***	-0.2497	(0.0362)***
rsr	0.1277	(0.1429)	-0.0499	(0.1378)
skilled × rsr	0.2189	(0.1008)**	0.2210	(0.0998)**
at-risk-of-poverty rate	0.0887	(0.0773)	0.0470	(0.0570)
immigrant population share			-0.1137	(0.0961)

Source: ESS 2010/2011, 2011 Population and Housing Census.
Note: Dependent variable is a native's preference for redistribution. Born samples are employed and raw coefficients of the estimations are reported. Country fixed effects are included, but not reported. Standard errors are in parentheses and clustered at the country level. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

1.7 Conclusion

Immigration has always received much attention among policy makers, economists, and the general public, since the migration of people is accompanied by changes in social landscape and on product and factor markets. In particular, immigrations' effect on wages and the unemployment rate as well as on the tax rate and the level of social benefits have been the concern of some natives and policy makers. Since the gains of immigration are, in general, not equally distributed among natives, there are donors and beneficiaries among them. This might reason the change in a native's attitudes towards particular social policies in order to either compensate for their disadvantages or strengthen their advantages caused by immigration. Thus, this study developed a theoretical framework which enables the distinction of immigration's effect on the labor market and welfare state by the relative skill composition of immigrants compared to natives. Since labor is divided into skilled and unskilled workers, the overall change in a native's net income due to immigration depends on his or her skill type and the relative skill ratio between immigrants and natives. Based on these changes, natives' preference for redistribution can be inferred. If there is unskilled immigration, i.e. immigrants are, on average, less skilled than natives, a skilled native prefers less redistribution, since his or her wage increases due to complementary effects on the labor market and the tax rate increases due to a lower overall average wage. The opposite is true if skilled immigration, i.e. immigrants are, on average, more skilled than natives, occurs. In turn, immigration's effect on unskilled natives' redistribution preference is ambiguous due to the mutually compensating effects of the changes on wages and changes on the tax rate. If there is unskilled immigration, unskilled natives' wages decrease due to substitutive effects on the labor market, which increases their redistribution preference and simultaneously raises the tax rate due to a lower average wage, which lowers their support for redistribution. The opposite occurs if skilled immigration is present.

Using the European Social Survey 2010/2011 and the 2011 Population and Housing Census, the predictions of the theoretical framework with respect to skilled and unskilled natives can be confirmed. On the one hand, skilled natives living in regions which experience more skilled immigration have a higher preference for redistribution than skilled natives living in regions that have less skilled immigration. Thus, if the regional relative skill ratio increases, i.e. the share of skilled immigrants in relation to the share of skilled natives grows, skilled natives' redistribution preference converges to that of the unskilled natives. On the other hand, there is no unambiguous effect of the regional relative skill ratio on unskilled natives. This, in turn, indicates that the mutually compensating effects of immigration on unskilled natives are present at the regional level. In general, if the relative skill ratio increases by 1 percent, a skilled natives' probability of a very high preference for redistribution increases by 5.5 percentage points more than an unskilled native's probability. This significant difference remains robust after adjusting for the standard errors. Furthermore, the results are robust to IV estimation approaches which consider the possibility of selective in- and out-migration at the regional level. Controlling for the regional share of immigrants, the primary results are maintained, even after adjusting for natives' self-selection into regions based on their attitudes towards immigrants. Ultimately, the effect of the relative skill ratio on skilled natives is still significant after controlling for regional income inequality using the at-risk-of-poverty rate. Thus, the predictions of the theoretical framework can generally be confirmed. The skill composition of immigrants matters with respect to natives' preference for redistribution. Since the change in wages due to immigration is not measured directly, the results can be interpreted as natives' perceived changes in wages based on the skill type of immigration. Thus, unskilled natives living in regions which experience more skilled immigration are less concerned about a decline in their wages than unskilled natives living in regions which experience more unskilled immigration. Furthermore, if there is skilled immigration, natives expect a relief of the strain on the tax and transfer system, regardless of whether this occurs. The opposite is true if unskilled immigration is present. The effect of skilled immigration on skilled natives' perception of changes in their net income and preference for redistribution has received less attention in the literature. This study is a first attempt to give some evidence on the validity of the transmission channels for both unskilled and skilled natives. Employing panel data, future research should examine whether a change in the educational composition of immigrants changes unskilled and skilled natives' labor market and welfare state perceptions.

Appendix

Immigration and redistribution preferences in a benefit adjustment model

The net income of a native with skill level j in the benefit adjustment model is defined by

$$I_j = \left(1 - \frac{b}{\overline{w}}\right) w_j + b \,. \tag{1.31}$$

Thus, the effect of a rise in the amount of redistribution on the well-being of a native with skill level j is given by

$$\frac{dI_j}{db} = \frac{\overline{w} - w_j}{\overline{w}} = 1 - \frac{w_j}{\overline{w}} \,. \tag{1.32}$$

Therefore, if a native's wage is less than the average wage of the entire population, more social benefit would increase his or her net income. The opposite is true if a native's wage exceeds the average. Thus, the effect of immigration on a native's preference for redistribution can be expressed by

$$\frac{d}{d\pi}\left(\frac{dI_j}{db}\right) = \frac{\overline{w} w_j \frac{d \ln b}{d\pi} - \overline{w} w_j \frac{d \ln w_j}{d\pi}}{\overline{w}^2} \tag{1.33}$$

Therefore, the benefit adjustment model and the tax adjustment model produce similar results.

Cluster-adjusted *F*-statistics

Ibragimov and Müller (2010) propose the cluster-adjusted t-statistics for hypothesis testing in the presence of clustered data. The following procedure is based on Esarey and Menger (n.d.) and is applied to the ordered logit model. Since a nonlinear model is estimated, F-statistics are used instead of t-statistics:

1. Estimate the pooled model using country fixed effects and save the estimated raw coefficients of the ordered logit model $\hat{\beta}$

2. For each country $g = 1, \ldots, G$, estimate the model based on the observations in the respective country only. Save the estimated raw coefficients of the ordered logit model $\hat{\beta}_g$

3. Calculate the average of the coefficients $\hat{\beta}_g$ and save the average as $\bar{\beta}_G$. Then calculate $\tilde{\beta}_g = \hat{\beta}_g - \bar{\beta}_g$ for any g. Subtracting the grand mean $\bar{\beta}_G$ enables the

consideration of each country as a sample of the distribution of possible clusters centered on the null hypothesis $\beta = 0$.

4. Calculate the standard error of $\bar{\beta}_G$: $\hat{s}_G = \left[\frac{1}{G}\frac{1}{G-1}\sum_{g=1}^{G}\left(\tilde{\beta}_g\right)^2\right]^{\frac{1}{2}}$

5. Calculate the $\hat{\chi}^2$-value: $\hat{\chi}^2_G = \left(\frac{\bar{\beta}_G}{\hat{s}_G}\right)^2$

6. Reject the null hypothesis $\beta = 0$ at level α if and only if $\hat{\chi}^2 > \chi^2_{\alpha,1}$, where $\chi^2_{\alpha,1}$ is the critical χ^2-statistic for a two-tailed F-test at level α with one degree of freedom.

Note that the variance-covariance matrix of the coefficients is recovered in this procedure by $\hat{s}_G$. Thus, standard errors can be calculated on interaction terms as prescribed in Brambor et al. (2006). Furthermore, $\bar{\beta}_G$ and $\hat{\beta}$ will not be equivalent, since the clusters are not all equally sized. Therefore, the 95 percent confidence intervals formed with this procedure will usually not be centered on $\hat{\beta}$.

Table 1.9: Cluster-adjusted F-statistics of basic ordered logit estimation

	coefficient	**χ^2-value**
age	0.0339	23.1960***
age^2	-0.0003	16.8337***
female	0.1479	31.9383***
life partner	0.0484	1.8894
household member	0.0776	9.8794***
kids at home	-0.1994	23.1373***
(sub-)urban	-0.0278	0.0796
employed	*reference*	
unemployed	0.1626	5.3418**
not in labor force	0.0792	7.3923***
public sector	*reference*	
private sector	-0.0980	4.6933**
self-employed	-0.3105	13.0967***
other	0.0151	0.7940
household income	-0.1218	28.4195***
skilled	-0.4285	19.4279***
rsr	0.3006	0.1413
skilled × rsr	0.3828	2.8292*

Source: ESS 2010/2011, 2011 Population and Housing Census.
Note: Dependent variable is a native's preference for redistribution. Born samples are employed and raw coefficients of the ordered logit estimations are reported. Country fixed effects are included, but not reported. Standard errors are in parentheses, clustered at the country level, and adjusted according to Ibragimov and Müller (2010). ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

Table 1.10: Summary statistics of main variables

	average	**standard deviation**
redistribution preference	2.9226	1.0054
age	51.5316	16.5264
female	0.5102	0.4999
life partner	0.6451	0.4785
household member	2.5430	1.3217
kids at home	0.3912	0.4880
(sub-)urban	0.3098	0.4624
employed	0.5464	0.4979
unemployed	0.0685	0.2527
not in labor force	0.3851	0.4866
public sector	0.3614	0.4804
private sector	0.5217	0.4995
self-employed	0.0886	0.2842
other	0.0284	0.1660
household income	5.2689	2.7920
skilled	0.2132	0.4096
relative skill ratio	0.0831	0.3142
Belgium	0.0450	0.2074
Bulgaria	0.0773	0.2670
Croatia	0.0325	0.1774
Czech Republic	0.0608	0.2389
Denmark	0.0470	0.2117
Finland	0.0610	0.2393
France	0.0517	0.2214
Germany	0.0788	0.2694
Greece	0.0474	0.2125
Hungary	0.0442	0.2055
Ireland	0.0513	0.2206
Netherlands	0.0506	0.2192
Norway	0.0480	0.2137
Poland	0.0438	0.2046
Slovak Republic	0.0439	0.2049
Slovenia	0.0315	0.1746
Spain	0.0416	0.1996
Sweden	0.0452	0.2077
Switzerland	0.0344	0.1823
United Kingdom	0.0641	0.2450

Source: ESS 2010/2011, 2011 Population and Housing Census.
Note: Responses of the final born sample, unweighted.

Table 1.11: Ordered logit estimations using the main household income resources

	Without Portugal		**With Portugal**	
age	0.0267	(0.0072)***	0.0262	(0.0071)***
age^2	-0.0002	(0.0001)***	-0.0002	(0.0001)***
female	0.1709	(0.0405)***	0.1716	(0.0396)***
life partner	-0.1352	(0.0502)***	-0.1391	(0.0493)***
household member	0.0165	(0.0159)	0.0186	(0.0155)
kids at home	-0.1444	(0.0233)***	-0.1481	(0.0231)***
(sub-)urban	-0.0561	(0.0670)	-0.0542	(0.0639)
employed		*reference*		
unemployed	0.3745	(0.0752)***	0.3618	(0.0717)***
not in labor force	0.2265	(0.0561)***	0.2272	(0.0556)***
public sector		*reference*		
private sector	-0.0810	(0.0381)**	-0.0763	(0.0376)**
self-employed	-0.1493	(0.0496)***	-0.1396	(0.0481)***
other	0.13	(0.1131)	0.1097	(0.1098)
skilled	-0.6651	(0.0635)***	-0.6704	(0.0628)***
rsr	0.3994	(0.2109)*	0.3074	(0.2092)
skilled × rsr	0.3905	(0.1970)**	0.4146**	(0.1800)
self-employment/capital income		*reference*		
unemployment/social benefits	0.4270	(0.1408)***	0.4344	(0.1377)***
labor income	0.2811	(0.0685)***	0.2827	(0.0674)***
pensions	0.1642	(0.1221)	0.1569	(0.1197)
Obs.	28960		30630	
McFadden R^2	0.049		0.051	
AIC	60624.02		61957.50	
BIC	60781.22		62124.09	
Log Likelihood	-30293.01		-30958.75	

Source: ESS 2010/2011, 2011 Population and Housing Census.
Note: Dependent variable is a native's preference for redistribution. Born samples are employed and raw coefficients of the ordered logit estimations are reported. Country fixed effects are included, but not reported. Standard errors are in parentheses and clustered at the country level. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

Table 1.12: Average marginal effects of basic covariates on the probability of each outcome category

	Born Sample								**Citizen Sample**							
	Outcome 1		*Outcome 2*		*Outcome 3*		*Outcome 4*		*Outcome 1*		*Outcome 2*		*Outcome 3*		*Outcome 4*	
age	-0.0004	(0.0002)*	-0.0002	(0.0001)*	0.0002	(0.0000)***	0.0005	(0.0003)	-0.0003	(0.0003)	-0.0001	(0.0001)	0.0002	(0.0000)***	0.0003	(0.0003)
female	-0.0175	(0.0034)***	-0.0094	(0.0021)***	-0.0010	(0.0002)***	0.0279	(0.0056)***	-0.0172	(0.0031)***	-0.0094	(0.0020)***	-0.0008	(0.0002)***	0.0275	(0.0050)***
life partner	-0.0058	(0.0056)	-0.0031	(0.0029)	-0.0003	(0.0002)	0.0091	(0.0087)	-0.0072	(0.0056)	-0.0039	(0.0030)	-0.0002	(0.0001)*	0.0113	(0.0087)
household member	-0.0092	(0.0026)***	-0.0049	(0.0013)***	-0.0005	(0.0002)***	0.0146	(0.0040)***	-0.0077	(0.0023)***	-0.0042	(0.0011)***	-0.0004	(0.0001)***	0.0123	(0.0035)***
kids at home	0.0238	(0.0023)***	0.0126	(0.0013)***	0.0009	(0.0001)***	-0.0374	(0.0033)***	0.0227	(0.0035)***	0.0123	(0.0015)***	0.0008	(0.0002)***	-0.0358	(0.0050)***
(sub-)urban	0.0033	(0.0065)	0.0018	(0.0034)	0.0002	(0.0003)	-0.0052	(0.0102)	0.0026	(0.0057)	0.0014	(0.0030)	0.0001	(0.0002)	-0.0041	(0.0089)
employed								*reference*								
unemployed	-0.0187	(0.0069)***	-0.0104	(0.0040)***	-0.0020	(0.0015)	0.0311	(0.0123)**	-0.0174	(0.0076)**	-0.0098	(0.0045)**	-0.0015	(0.0014)	0.0287	(0.0134)**
not in labor force	-0.0093	(0.0031)***	-0.0051	(0.0019)***	-0.0005	(0.0003)**	0.0150	(0.0053)***	-0.0112	(0.0031)***	-0.0062	(0.0021)***	-0.0006	(0.0003)**	0.0179	(0.0054)***
public sector								*reference*								
private sector	0.0114	(0.0048)**	0.0062	(0.0025)**	0.0011	(0.0005)**	-0.0187	(0.0078)**	0.0106	(0.0052)**	0.0059	(0.0027)**	0.0009	(0.0006)*	-0.0174	(0.0084)**
self-employed	0.0384	(0.0089)***	0.0195	(0.0041)***	-0.0009	(0.0014)	-0.0570	(0.0118)***	0.0371	(0.0084)***	0.0191	(0.0038)***	-0.0011	(0.0013)	-0.0552	(0.0113)***
other	-0.0017	(0.0150)	-0.0010	(0.0086)	-0.0003	(0.0026)	0.0029	(0.0263)	-0.0001	(0.0137)	-0.0000	(0.0079)	-0.0000	(0.0020)	0.0001	(0.0236)
household income	0.0144	(0.0017)***	0.0077	(0.0007)***	0.0008	(0.0001)***	-0.0229	(0.0024)***	0.0142	(0.0017)***	0.0077	(0.0007)***	0.0007	(0.0001)***	-0.0226	(0.0024)***
no mig. background								*reference*								
mig. background									0.0006	(0.0137)	0.0003	(0.0074)	0.0000	(0.0006)	-0.0010	(0.0217)
mig. experience									0.0024	(0.0062)	0.0013	(0.0033)	0.0001	(0.0002)	-0.0037	(0.0096)

Source: ESS 2010/2011, 2011 Population and Housing Census.
Note: Dependent variable is a native's preference for redistribution. Average marginal effects of country fixed effects, main terms of skilled dummy, and relative skill ratio are not reported. Outcome 1 is "strongly disagree or disagree", Outcome 2 is "neither agree nor disagree", Outcome 3 is "agree", and Outcome 4 is "strongly agree". Standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

Table 1.13: IV ordered probit estimations using the control function approach on a restricted sample

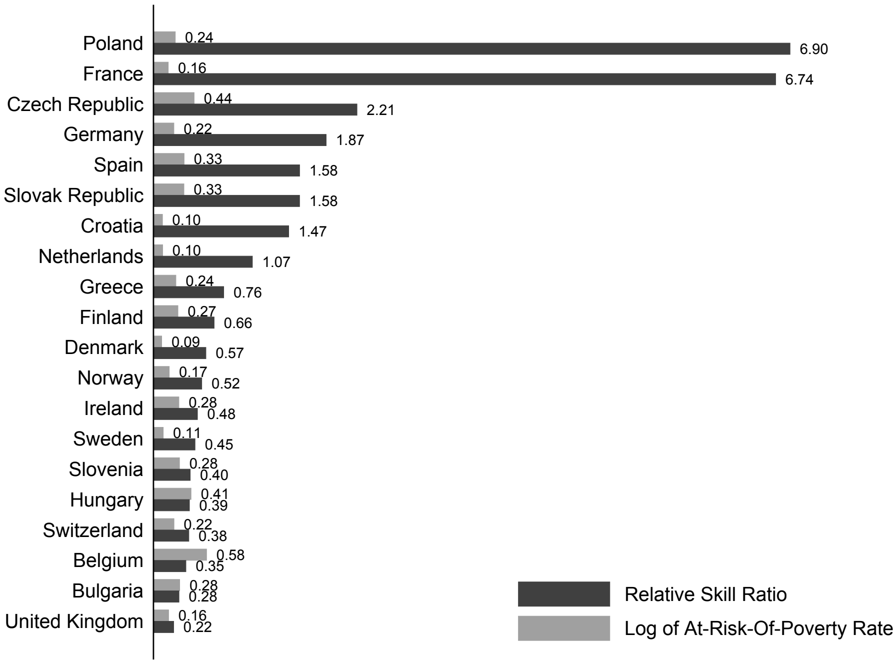
	(1)		(2)	
	relative skill ratio		**share of immigrants**	
age	0.0189	(0.0037)***	0.0184	(0.0036)***
age^2	-0.0002	(0.0000)***	-0.0002	(0.0000)***
female	0.0865	(0.0190)***	0.0867	(0.0187)***
life partner	0.0289	(0.0304)	0.0261	(0.0317)
household member	0.0473	(0.0125)***	0.0469	(0.0122)***
kids at home	-0.1159	(0.0095)***	-0.1126	(0.0100)***
(sub-)urban	-0.0181	(0.0332)	0.0013	(0.0285)
employed		*reference*		
unemployed	0.0978	(0.0362)***	0.1008	(0.0359)***
not in labor force	0.0483	(0.0170)***	0.05	(0.0166)***
public sector		*reference*		
private sector	-0.0535	(0.0242)**	-0.0503	(0.0233)**
self-employed	-0.1788	(0.0407)***	-0.1763	(0.0404)***
other	0.007	(0.0751)	0.0069	(0.0752)
household income	-0.0709	(0.0077)***	-0.0692	(0.0071)***
skilled	-0.2486	(0.0341)***	-0.2475	(0.0347)***
rsr	0.1739	(0.1367)	-0.0284	(0.1066)
skilled × rsr	0.2007	(0.1024)*	0.2018	(0.1034)*
immigrant population share			-0.1384	(0.0949)
$\hat{v}_1$	0.0457	(0.2814)	0.0075	(0.0519)

Source: ESS 2010/2011, 2011 Population and Housing Census.
Note: Dependent variable is a native's preference for redistribution. Born samples are employed and unscaled raw coefficients of the estimations are reported. Scaled coefficients are reported, since scale factors $\sqrt{1+\hat{\pi}_{12}^2 \cdot \hat{\theta}^2}$, where θ represents the unscaled estimated coefficient of $\hat{v}_1$, respond to a value of one in both estimations (Wooldridge, 2010). Thus, scaled and unscaled coefficients do not differ. The relative skill ratio at the NUTS level 1 is used in Column 1 as an instrument for the relative skill ratio at the NUTS level 2 and the share of immigrants at the NUTS level 1 is used in Column 2 as an instrument for the share of immigrants at the NUTS level 2. Therefore, $\hat{v}_1$ refers to the residuals from the first stage regression of the relative skill ratio equation in Column 1 or the share of immigrants equation in Column 2. Excluded from the first stage due to no variation of the relative skill ratio or share of immigrants at NUTS level 1 within the country are Croatia, Czech Republic, Denmark, Finland, Ireland, Norway, Slovak Republic, Slovenia, and Switzerland. Country fixed effects are included, but not reported. Standard errors are in parentheses and clustered at the country level. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

Table 1.14: Sources of data for the regional at-risk-of-poverty rate in 2011

Croatia	**Croatian Bureau of Statistics**, *Census 2011 - At Risk of Poverty Rate.*
France	**Insee**, *Revenus disponibles localisés 2011.*
Germany	**Statistische Ämter des Bundes und der Länder**, *Armut und soziale Ausgrenzung.*
United Kingdom	**Department for Work and Pensions**, *Household Below Average Income Statistics.*

Figure 1.7: Coefficient of variation of the regional relative skill ratio and at-risk-of-poverty rate



Source: European Commission (2017, 2016) and national statistics, own calculations.

2

Attitudes Matter: Ethnic Heterogeneity and Redistribution Preferences

The economic life of the people is accompanied by daily decisions between different alternatives, whereby their primary aim is to increase their own utility or satisfaction. This relates to the demand for particular products as well as deciding how much to invest in human capital. The main focus of an individual is on how a particular decision directly affects his or her own utility. However, once a decision has been made, it affects not only the utility of the decision maker, but also the social environment, since people are social beings and do not live in isolation. In his pioneering work, Becker (1974) reveals that social interactions might entail social preferences, i.e. the individual utility depends on the utility of other persons within the social environment. Thus, voluntary donations can be formally integrated into economic theory. In turn, Freeman (1986), among others, lifts the individual social preferences to the country level and suggests that there must be a minimum level of social capital within a country in order to install a functioning redistribution system. Therefore, an individual's redistribution preference reflects, on the one hand, his or her financial self-interest and, on the other hand, his or her solidarity towards his or her fellow citizens. Therefore, the following chapter investigates how ethnic heterogeneity and interethnic contact affect natives' social capital and their preference for redistribution.

2.1 Introduction

The outbreak of the Syrian civil war in 2011 and the subsequent migration of Syrian, Iraqi, and Afghan refugees via Turkey and the Balkans to Europe has put immigration policy back onto the agenda of policy makers and economists. The *European refugee crisis* reached its peak in 2015 with almost 1.26 million first-time asylum applications, which is the highest amount since the fall of the Iron Curtain. Germany (441900), Hungary (174435), Sweden (156195), Austria (85520), and Italy (83245) had the most first-time asylum applicants in Europe. In 2016, the numbers continued to rise only in Germany and in Italy, whereas the other countries experienced a sharp decline in applications. The majority of first-time asylum seekers came from Syria (28.84 percent), Afghanistan (14.18 percent), Iraq (9.67 percent), Kosovo (5.32 percent), and Albania (5.30 percent) in 2015 (European Commission, 2017). This sudden surge in the extent of foreign-born people in the European host countries brought back hidden anxieties. In particular, voters in Western and Central Europe are concerned about the economic and societal consequences of immigration. In consequence of the refugee crisis, far-right parties were able to mobilize voters in many countries by stigmatizing immigrants as a threat to the economy, cultural values, and national safety. In Sweden, the right-wing populist *Sweden Democrats* doubled their seats in the Parliament in the 2014 elections. The *Freedom Party of Austria* (Austria) and the *Front National* (France) gained votes in the last parliamentary elections in 2012 and in 2013, respectively. Furthermore, in 2015, the *Swiss People's Party* achieved its best election result since the party was founded. In Finland, the *Finns Party* even joined the government coalition in 2015. In Germany, although the *Alternative for Germany* (AFD) emerged as a eurosceptic party in consequence of the Euro crisis, it has been associated with the right-wing populist side of the political spectrum since the outbreak of the refugee crisis. In 2016, AFD entered five state parliaments by obtaining more than 10 percent of the popular vote. In Mecklenburg-Vorpommern and in Saxony-Anhalt, the AFD received even more than 20 percent and took second place in the elections, although the share of immigrants in these federal states is much lower than the shares in West German states (Nordsieck, 2016).

Thus, immigration or ethnic heterogeneity has an influence on natives' concern about the consequences of a change in the composition of the population. Societal fear of changes in everyday life as well as in symbolic values, such as cultural identity or national security, may generate negative attitudes towards immigrants and increase the demand for a more restrictive immigration policy. On the other hand, more interethnic contact due to a higher ethnic diversity could enhance tolerance and solidarity towards immigrants among natives. Tolerance, solidarity, and trust, in turn, are important components of the individual social capital, which affects an individual's attitudes towards the national welfare state and social policy. The empirical literature generally focuses on either the association between ethnic heterogeneity and attitudes towards immigrants or the link between interethnic contact and the demand for redistribution. However, the latter neglects the mediating effect of social capital between ethnic diversity and natives' preference for redistribution. Furthermore, natives' attitudes towards immigrants are part of their social capital and therefore directly influence natives' trust and solidarity towards fellow residents. This study overcomes these shortcomings and brings these two strands of literature together by applying a joint estimation model. Using a bivariate recursive framework, the mediation of natives' solidarity is explicitly taken into account in order to investigate and quantify the underlying mechanism between ethnic diversity and the preference for redistribution. Therefore, the econometric specification proposes that interethnic contact or ethnic heterogeneity influences natives' attitudes towards immigrants, which, in turn, influence natives' preference for redistribution. Furthermore, applying bivariate recursive probit estimations enables the decomposition of the average marginal effects the employed covariates have on the preference for redistribution into a direct and an indirect effect. The direct effect has an immediate impact on the redistribution preference, whereas the indirect effect influences the natives' preference by changing their attitudes towards immigrants. This decomposition is largely unknown in the empirical literature and has so far only been applied to the bivariate recursive binary probit case. Thus, the contribution to the econometric method literature is twofold. To the best of my knowledge, this is the first study that derives and applies the decomposition of marginal effects for a bivariate recursive mixed probit estimation consisting of an ordinal and a binary dependent variable. Second, this study provides a suitable solution for calculating adequate standard errors of the average marginal direct and indirect effects by applying a bootstrap resampling approach.

Using the European Social Survey 2014/2015 allows the inclusion of a wide range of views that natives have about immigrants' influence on the social fabric. The individual data provide adequate information on the socio-economic and demographic characteristics of respondents, as well as plenty of questions concerning immigrants' influence on certain social constructs and their personal relationship with immigrants. Moreover, attitudes towards immigrants are divided into two dimensions, each consisting of three variables. The variables of the first dimension measure a native's real and desired social distance from immigrants in his or her private life and in the workplace. Thus, they map natives' individual apprehension of more social contact with immigrants. In turn, the variables of the second dimension measure natives' perceived threat to symbolic societal values (culture and social life) and tangible goods (national security) of the majority society presented by immigrants. Taking a closer look at the link between ethnic heterogeneity and the two dimensions, the theoretical framework offers two diametrically opposed hypotheses. On the one hand, the intergroup contact theory predicts a positive link, since more interethnic contact may reduce natives' information gaps, prejudices, and stereotypes. On the other hand, the conflict theory predicts that ethnic heterogeneity intensifies the competition between the majority society and other ethnic groups for non-tangible goods, such as the national culture, social life, and social participation. The estimation results show that there is a significantly positive association between the frequency of interethnic contact during everyday life and the variables of the two dimensions. Using the share of immigrants at a higher aggregate level as an instrument for the frequency of interethnic contact in order to control for natives' selective out-migration and reverse causality, the previous results are reproduced. Whereas these findings are valid for all variables of the two dimensions, the effects of natives' attitudes towards immigrants on their preference for redistribution differ. The social distance measures have no significant impact on a native's redistribution preference. However, the perceived threat to the national culture and social life has a significantly negative effect. Thus, natives' concern about the preservation of symbolic norms and values affects the solidarity channel of their redistribution preference. If immigrants are perceived as a threat to the national culture or social life, a native's probability of supporting more redistribution decreases by 6.4 percent or 8.2 percent, respectively. In contrast, if ethnic heterogeneity rises, this probability increases by 0.8 percent. According to the constrict theory, a negative attitude towards immigrants lowers natives' solidarity towards immigrants as well as their same-ethnic peers, too. In order to test this hypothesis, the difference between natives' and immigrants' average incomes (ethnic income gap) at the country level is interacted with natives' perceived outgroup threat in the estimations. In compliance with the constrict theory, the effect of perceived outgroup threat on a native's preference for redistribution should not depend on the national ethnic income gap, whereas the conflict theory predicts that the preference for redistribution of a native who has negative attitudes towards immigrants should diminish more strongly if the ethnic income gap is larger, since immigrants would benefit disproportionally from more governmental redistribution. The empirical results confirm the latter and show that the preference for redistribution of natives with negative attitudes towards immigrants is lower in countries where immigrants earn much less than natives than in countries where the ethnic income gap is smaller.

The rest of the chapter is organized as follows: Section 2.2 provides a literature review and Section 2.3 describes the link between ethnic diversity, attitudes towards immigrants, and a native's preference for redistribution based on the predictions of the intergroup contact theory, conflict theory, constrict theory, and a theoretical model which includes the ethnic income gap. Section 2.4 presents the data sources of the employed variables and Section 2.5 describes the econometric specification. Section 2.6 shows the basic results and empirical extensions using the regional share of immigrants as an instrument to control for selective out-migration and reverse causality. Furthermore, the ethnic income gap is added to the estimations in order to test the predictions of the constrict theory. Finally, Section 2.7 concludes.

2.2 Related Literature

On the one hand, there is a vast body of literature on the impact of immigration or ethnic diversity on the generosity of the welfare state or natives' preference for redistribution. On the other hand, there is also extensive research on the effect of immigration or ethnic diversity on natives' attitudes towards immigrants or immigration. The first strand of literature examines whether there is a direct association between ethnic heterogeneity and governmental redistribution or individuals' support of redistribution.[37] In turn, ethnic heterogeneity is often measured as the share of immigrants or as a fractionalization index. The latter expresses the probability that two persons drawn from a random sample belong to two different ethnic groups. In a cross-country analysis, Alesina et al. (2001) show that an ethnic fractionalization increase of one percentage point lowers government social spending by 7.5 percentage points. However, they found that ethnolinguistic fractionalization had no significant effects. A negative link between the ethnolinguistic fractionalization and government spending on health and education is presented in Kuijs (2000). Furthermore, Soroka et al. (2006) show that there is a negative correlation between the change in the immigrant population ratio and the change in social spending in a country. There is also some empirical evidence at the sub-national level. Thus, Alesina et al. (1999, 2000) show that greater ethnic fractionalization at the regional level is associated with lower spending on public goods in the United States. On the one hand, they attribute this result to the predictions of the conflict theory. On the other hand, a greater ethnic diversity could make the decision-making process for financing public goods more difficult, thus reducing overall provision due to disagreement between ethnic groups. However, Hopkins (2009) shows, using data from communities in Massachusetts and Texas, that it is not the level of ethnic heterogeneity, but rather the change thereof that has a negative impact on the provision of public goods. In Indian regions, Banerjee et al. (2005) determine that a stronger fractionalization in castes and religious heterogeneity lower regional supply of public goods. In contrast, using refugee inflows from non-OECD countries and Turkey as an exogenous shock to Danish administrative regions, Gerdes (2011) finds no significant link between immigrant population share and the size of the public sector.

Regarding individual preference for redistribution, survey respondents in the United States support more redistribution if there is a higher proportion of their same-ethnic peers among social benefit recipients in the neighborhood (Luttmer, 2001). This is true even if the respondent is a high-income earner. Focusing on the black-white gap in the support of redistribution in the United States, Alesina et al. (2001) show that whites who assess blacks as "lazy" prefer less redistribution, whereas whites who have had social contact with blacks at least once support more redistribution. However, the

[37] Stichnoth and Van der Straeten (2013) and Alesina and La Ferrara (2005a), among others, provide an extensive summary of the empirical literature.

authors find no association between blacks' population ratio in the neighborhood and whites' preference for redistribution. Moreover, Lind (2007) finds similar results and shows that a stronger identification of blacks with whites lowers their redistribution preference. For whites, however, a stronger identification with their peers has no significant effect on their support of redistribution. In a cross-country analysis of European countries, Senik et al. (2009) ascertain only a weak association between the perceived share of immigrants and natives' preference for redistribution. A similar result is obtained by Stichnoth (2012) regarding the demand for a more generous unemployment system. As pointed out by Burgoon (2014), the effect of the perceived immigration population ratio may be upwardly biased, since natives who have anti-immigrant attitudes regularly overpredict the ratio in surveys. In contrast to Lee et al. (2006), Gerdes and Wadensjö (2008) find no significant link between the immigrant population share and Danish votes for pro-redistribution parties. For Sweden, Eger (2010) confirms a negative link between immigrant population share and the preference for redistribution. Furthermore, van Oorschot (2008, 2006) shows that the native population in Europe generally sees immigrants as substantially less deserving of social benefits and protections than other vulnerable groups, such as the elderly, disabled, or unemployed.

The second strand of the literature deals with the impact of the immigrant population share or ethnic diversity on natives' attitudes towards immigrants or, more generally, their social capital. However, the empirical literature is divided. Alesina and La Ferrara (2000) show that survey respondents' voluntary commitment is lower in US-American regions with a higher ethnic heterogeneity. Furthermore, Alesina and La Ferrara (2002) ascertain that, generally, trust in fellow citizens is lower in more ethnically diverse US-American cities. This result is also reinforced for ethnically and linguistically diverse communities in Australia (Leigh, 2006b), the population share of persons with a migration background in Sweden (Gustavsson and Jordahl, 2008), and in a cross-country empirical analysis (Leigh, 2006a). Savelkoul et al. (2011) point out that the link between ethnic diversity and natives' social capital is mediated through interethnic social contact. Since a higher ethnic heterogeneity produces the possibility to experience more frequent and profound interethnic social contact, natives' social capital may depend on bad or good experiences and the chance to reduce information gaps about other groups. In a cross-country analysis of European countries, the authors show that greater regional ethnic diversity is associated with natives having more interethnic social contact. The latter, in turn, increases natives' social capital, measured as the frequency of social encounters and aid given, and lowers natives' perceived threat of immigrants (outgroup threats). Moreover, perceived outgroup threats lower natives' informal social capital. In total, a more heterogenous neighborhood raises natives' social capital through more interethnic social contact. However, the empirical literature regarding the impact of ethnic diversity on natives' social capital or anti-immigrant attitudes is divided. On the one hand, there is evidence for the predictions of the *intergroup contact theory*, i.e. a more ethnically diverse neighborhood lowers anti-immigrant attitudes and increases solidarity towards immigrants. On the other hand, there is also evidence for the predictions of the *conflict theory*, which assumes the opposite, i.e. a greater ethnic heterogeneity leads to a rise in anti-immigrant attitudes and a decline in solidarity towards immigrants due to more intense competition between natives and immigrants for tangible and intangible goods. Empirical evidence for a positive triptych between ethnic diversity, interethnic social contact, and natives' pro-immigrant attitudes is affirmed, among others, for Denmark (Schlueter and Scheepers, 2010) and in an earlier cross-country analysis of European countries (Schlueter and Wagner, 2008). In the United States, Dixon (2006) finds similar results regarding the effect of whites' social contact with Hispanics and Asians. Furthermore, more interethnic social contact raises whites' general trust in fellow citizens in Canada (Stolle et al., 2008). Moreover, Laurence (2014) shows that in the United Kingdom, more ethnic diversity only has a negative impact on natives' interethnic attitudes and respect for ethnic minorities if natives have no interethnic social contact at all. In addition, van Oorschot and Uunk (2007) ascertain that, for a selection of European countries, a greater foreign-born population share increases natives' solidarity towards immigrants.

In contrast, there is also some empirical evidence for the conflict theory, i.e. for a positive link between ethnic heterogeneity and anti-immigrant attitudes. Thus, in a cross-country analysis of European countries, Scheepers et al. (2002) determine a positive correlation between a country's share of non-EU citizens and ethnic exclusionism, whereby the latter is measured as an additive index of natives' attitudes towards a more restrictive immigration policy. Despite of that, natives living in urban areas with a much higher concentration of immigrants have more favorable attitudes towards immigrants than natives living in rural areas. Semyonov et al. (2006) convey similar results based on an anti-immigrant index, which measures and totals natives' economic, individual, and societal concerns as wells as their anti-immigration policy opinions. In contrast, Davidov et al. (2008) do not detect any significant effect of the foreign-born population share or the immigrant influx on natives' preference for a more restrictive immigration policy, once controlled for natives' self-transcendence and self-conservation. In turn, Schneider (2008) investigates a hump-shaped relationship between the non-EU share of population and an ethnic threat index, which measures and totals natives' economic, individual, and societal concerns with respect to immigrants. In Germany, Semyonov et al. (2004) evince that there is no significant association between the actual share of foreigners at the regional level and natives' perceived outgroup threats, though natives' perception of the share of foreigners in Germany has a weakly significant impact on perceived outgroup threats. Scheepers et al. (2013) show, using Dutch data, that a greater ethnic diversity in the neighborhood reduces a native's interethnic social contact as well as his or her contact with same-ethnic peers. This, in turn, leads to a decline in natives' overall solidarity towards fellow residents.

2.3 Solidarity and Redistribution Preferences

A governmental redistribution mechanism as well as the welfare state in general follows the distributive logic of closure and the distributive logic of openness (Freeman, 1986). The former describes some kind of aid given by the members of a community according to socially defined concepts of need. The latter reports that the treatment of a person within the welfare state depends on his or her performance in the labor market. Thus, the community or the economy is "a group of people committed to dividing, exchanging, and sharing social goods, first of all among themselves"(Walzer, 1983, p.31). However, this sharing and distributing of social goods depends on some kind of feeling of fellowship. There is a need for solidarity, trust, and fairness between the members of a community or the economy as a whole. A large volume of empirical literature has shown that trust and solidarity are significantly positively related to the support of social policy and redistribution (see Alesina and Glaeser, 2004).

Peoples' solidarity and trust in other residents of their country depend on their socio-economic and demographic characteristics (age, gender, cultural background, etc.), their personal life experiences (discrimination, stroke of fate, etc.), the peculiarities of their immediate environment (income inequality, ethnic heterogeneity, etc.), the intensity and quality of their social contact, and the political institutions (Alesina and La Ferrara, 2002). In general, solidarity and trust can be seen as components of an individual's social capital. Social capital, in turn, can be decomposed into *bonding social capital* and *bridging social capital*. The first summarizes an individual's social contact with persons who resemble him or her in any form. The latter describes social contact with persons who are in some way different from him- or herself (Putnam, 2007). Leigh (2006b) points out that people who have been living in a particular neighborhood for a long time show greater confidence in their fellow citizens than people who recently moved there. This can be attributed to stronger social and cultural integration. Furthermore, (Cohen et al., 2001) demonstrate experimental evidence for the *folk theorem*, i.e. the probability of getting a high-trust equilibrium falls when a high fraction of a test person's partners is changed after each round of the experiment. A test person who was allowed to change the cooperation partner after each round of the experiment kept the partner who was similar in trustworthiness to him- or herself. This, in turn, raises average trust and cooperation within the treatment group.

Applying these results to the ethnic, linguistic, or cultural heterogeneity of a society or a region, it cannot be a priori determined whether the majority group's sense of solidarity with outgroup members increases or decreases due to immigration and a rise in diversity. Finally, the effect depends on majority group members' perceptions of ethnic, linguistic, or cultural outgroups in terms of solidarity and trust. The debate about the effect of heterogeneity on majority group members' attitudes towards subordinate groups polarizes around the *intergroup contact theory* and the *conflict theory*. Whereas the first assumes that more diversity positively influences the intergroup attitudes, the latter predicts that heterogeneity increases the possibility of intergroup conflict and subsequently negative outgroup attitudes. Hereinafter, natives are defined as members of the in-group and immigrants are defined as members of the outgroup, since the analysis is based on the link between natives' attitudes towards immigrants and their redistribution preference.

2.3.1 Intergroup Contact Theory and Conflict Theory

Intergroup contact is defined as 'face-to-face' contact between persons of different groups, whether they be ethnic, cultural, linguistic, or social (Pettigrew and Tropp, 2006).[38] There is no social contact in the case of geographical and non-verbal contact, because there is no information exchanged between members of different groups (Holland et al., 2007; Valentine, 2008). The **intergroup contact theory** assumes that negative attitudes towards members of other groups and towards a group as a whole can be explained by a lack of social contact between the members of both groups. Thus, information gaps about members of other ethnicities can be filled and existing prejudices and stereotypes can be reduced by more contact. However, this requires social contact in the way of social connections, which enables a communicative exchange between the members of different ethnicities (Hewstone, 2009). In the classical explanation of the intergroup contact theory, the positive effect of intergroup contact is tied to four optimal conditions: (i) common goals, (ii) intergroup cooperation, (iii) equal status, and (iv) authority support or sanctions (Allport, 1954; Pettigrew, 1998a). The current literature assumes that positive effects of intergroup contact can also occur under non-optimal conditions (Stein et al., 2000; Pettigrew and Tropp, 2008). By implication, negative experiences of intergroup contact can create negative outgroup attitudes or amplify existing attitudes (Stephan and Stephan, 1985). Furthermore, everyday intergroup contact in schools, at work, and in the neighborhood can lead to a reduction in anti-outgroup attitudes (Dixon and Rosenbaum, 2004; Pettigrew and Tropp, 2006). Aberson and Haag (2007) show that contact can reduce the implicit association between one's own in-group and the concept 'good' as well as the association between outgroups and the concept 'bad'.

Finally, several channels determine how contact with outgroup members lowers prejudices and stereotypes as well as outgroup threats. Here, four processes that change

[38]For a literature review of the intergroup contact theory, see Hewstone and Swart (2011), among others.

majority group members' attitudes can be emphasized: (i) learning about the outgroup, (ii) changing behavior, (iii) generating affective ties, and (iv) in-group revaluation (Pettigrew, 1998a). Thus, contact affects personal attitudes towards outgroup members through the cognitive channel (learning, experiencing, and understanding the outgroup as well as reevaluating the attitude towards one's own group), the behavioral channel (a greater openness to foreign groups and future intergroup contact), and affective channel (generating affective ties and friendships). As a result of the reduction of prejudices and stereotypes, empathy and solidarity towards outgroup members is created and increased (Tausch and Hewstone, 2010). However, to what extent the positive effect of social contact with outgroup members can be generalized remains open. Although the contact triggers a change in attitudes towards certain outgroup members, with whom more or less intense contact is maintained, this does not imply that attitudes are also transferred to outgrup members who are not personally known and with whom no contact is present. Overall, intergroup contact theory predicts that intergroup contact reduces negative anti-outgroup attitudes and may lead to less perceived outgroup threats. Thus, a higher ethnic or cultural heterogeneity in a region or community increases the possibility of social contact between members of different ethnic or cultural groups (Rocha and Espino, 2009). This, in turn, strengthens tolerance, trust, and solidarity between the members of different groups by mitigating the isolation of individual's own group from the others. Thus, the hypothesis is implicitly based on expanding an individual's bridging social capital by a rise in ethnic heterogeneity which, in turn, reduces individual ethnocentrism.

Diametrally opposed to intergroup contact theory, the **conflict theory** or **group threat theory** predicts that the existence of different ethnic, linguistic, and cultural groups leads to a more intense competition between these groups for scarce resources (Blalock, 1967). This competition spurs the perceived fear of shortage for one's own group and the perceived threat to the interests of one's own group. Generally speaking, group members expect negative consequences in some way due to the presence of individuals from dissimilar groups (Stephan and Renfro, 2002; Stephan et al., 2009). Furthermore, the competition for resources can be split into a competition for tangible and non-tangible resources (Stephan and Stephan, 2000). Whereas the participation of different ethnic groups in the labor and housing market is regarded as a tangible resource, the influence on the cultural and religious landscape of a country is considered an intangible resource. Moreover, conflict theory implies that the perceived outgroup threat creates and strengthens in-group members' negative attitudes towards outgroup members, resulting in discrimination and physical conflicts between members of different groups (Pettigrew, 1998b; Scheepers et al., 2002). Therefore, in-group members try to protect or restore the status of their own group by taking negative attitudes towards outsiders (Quillian, 1995). In principle, both components of the conflict theory, perceived threat from outgroups and negative attitudes towards particular outsiders, do not have to be related to each other and can be viewed as stand-alone concepts (Schlueter et al., 2008). Considering ethnic diversity, conflict theory implies that more interethnic contact increases the conflict potential between ethnic groups. Finally, individuals place a stronger distinction between members of their own ethnic group and members of other ethnic groups. There is no reduction of prejudices and stereotypes towards ethnic outgroup members with repeated contact, though these can even be confirmed and strengthened due to personal experiences. In contrast to intergroup contact theory, conflict theory predicts that individuals continue to expand their 'bonding' social capital and are more ethnocentrically engaged (Putnam, 2007).

Both approaches, the intergroup contact theory and the conflict theory, differ in terms of the association between heterogeneity and perceived outgroup threat or anti-immigrant attitudes, but not regarding the link between these attitudes and the solidarity or trust in immigrants. Actually, natives' heightened perception of threat or anti-immigrant attitudes lower their solidarity with immigrants. Less solidarity, in turn, decreases the natives' preference for redistribution, since a part of governmental redistribution also benefits immigrants. The opposite holds for natives who feel more solidarity with immigrants. In general, if there is the possibility to transform the tax and transfer system solely to the benefit of a single ethnic group, natives exhibiting anti-immigrant attitudes could enforce that governmental redistribution takes place merely in favor of their own ethnic group. The implementation of such a selective redistribution scheme, however, is not possible in the European countries, since the income tax rate and most types of social benefits cannot be discriminatory based on ethnicity. Thus, natives who have a stronger perception of outgroup threat and anti-immigrant attitudes will have a lower preference for redistribution.

2.3.2 Constrict Theory

In principle, conflict theory and contact theory are opposed to one another, but both approaches implicitly assume that individual in-group trust or solidarity and outgroup trust or solidarity are negatively correlated. Conflict theory predicts that a raising heterogeneity enhances in-group members' isolation from outgroup members, but encourages commitment to the interest of the in-group at the same time. In contrast, intergroup contact theory presumes that more intergroup social contact due to higher heterogeneity lowers exclusive self-identification with the in-group and triggers stronger solidarity with outgroup members. Therefore, both theories suppose that there is a negative correlation between an individual's bridging social capital and his or her bonding social capital, i.e. if you have many friends from your in-group, you should only have few friends from the outgroup and vice versa (Putnam, 2007). This logical relationship, however, excludes the possibility that individuals may use both more bonding and more bridging social capital at once. The **constrict theory** takes this possibility into account and assumes that more diversity not only reduces trust and solidarity towards outgroup members, but also lowers trust and solidarity towards in-group members. There are some potential mechanisms which may explain such a corollary.

First, the *divergent social networks mechanism* posits that heterogeneity divides society members' networks along group boundaries, making the intra-civic sharing of information, common norms and rules more difficult (Habyarimana et al., 2007). Furthermore, penalizing violations of informal rules, norms, and values is more difficult within a piecemeal society. This, in turn, reduces the willingness of both in-group and outgroup members to follow common civic norms. As a result, in-group members' trust and solidarity towards both their own group as well as outgroup members decline, since mutual dependence within groups has shrunk due to smaller networks.

Second, the *divergent norm mechanism* states that a higher heterogeneity is accompanied by a higher diversity of norms, values, and traditions. This, in turn, impedes communication between members of different groups, especially in the case of linguistic heterogeneity (Leigh, 2006b; Desmet et al., 2009). Misunderstandings, misinterpretations, and conflicts between groups are more frequent; hence individuals gradually withdraw from social life. In this case, a lack of contact with in-group members as well as outgroup members may lower trust and solidarity towards both groups.

Third, the *divergent preferences mechanism* takes into account the preference of groups to stand out from other groups. Here, a person's self-esteem is partly obtained from group identity and depends on how much the in-group can differentiate itself from other groups (Brown, 2000). This identity-creating feature can, however, differ greatly across a society's groups. A stronger identification could encourage in-group members to participate more intensively in social activities and civic projects. Since such engagement could also benefit outgroup members as heterogeneity increases, in-group members may reduce their social activities and as a result weaken social alliance with in-group peers and outgroup members (Alesina and La Ferrara, 2002).

Fourth, the *divergent in-group preferences mechanism* assumes that more diversity reveals or even amplifies the variance of norms, values, and traditions within a group (Wong, 2010; Williamson, 2015). In this case, the presence of heterogeneity already prompts the in-group members to redefine former commonalities of their own group and delineations from other groups. During this process, divergent perceptions and attitudes of in-group members regarding group- and self-definition could occur or could be strengthened. In turn, a rise in divergent positions within groups could lower in-group members' attachment to their peers. Thus, an increasing heterogeneity acts as an exogenous shock to the definition and self-image of the in-group, without the need for interaction between in-group members and outgroup members. The question of dealing with a higher heterogeneity and its impact on the in-group identity is sufficient to divide in-group members among themselves and, in the end, reduce in-group members' trust and solidarity towards their peers.

The constrict theory predicts that higher heterogeneity and more social contact with members of other ethnic, linguistic, or cultural groups can increase outgroup threats and reduce solidarity with outgroup members. Moreover, in-group members' solidarity with their peers also diminishes as a result of the above-mentioned mechanisms. Thus, in general, diversity reduces the average solidarity of in-group members, which implies less overall support of redistribution among in-group members.

Table 2.1: Theoretical effects of natives' attitudes towards immigrants on redistribution preferences

Intergroup Contact Theory	**Conflict Theory**	**Constrict Theory**
Higher ethnic heterogeneity or more social contact leads to ...		
lower outgroup threats	higher outgroup threats	higher outgroup threats
↓	↓	↓
higher solidarity with outgroup	lower solidarity with outgroup	lower solidarity with outgroup
lower solidarity with in-group	higher solidarity with in-group	lower solidarity with in-group
↓	↓	↓
higher support of redistribution	lower support of redistribution	lower support of redistribution

Comparing these three theories with respect to their effects on natives' redistribution preferences, it becomes clear that only the intergroup contact theory predicts a higher support of redistribution due to a rise in heterogeneity or more social contact with immigrants (see Table 2.1). In contrast, the other approaches predict a decrease in natives' redistribution preference. Apart from that, however, they differ in the change of natives' solidarity towards in-group members.

2.3.3 Ethnic Income Gap, Solidarity and Preference for Redistribution

Based on the theories presented so far, a native's solidarity negatively correlates with his or her support of redistribution. However, if the predictions of the constrict theory are confirmed in reality, it is no longer possible to distinguish whether this lower preference is solely driven by a lower solidarity with immigrants or can be attributed to natives' overall lower feeling of solidarity, induced by a simultaneous decline in natives' solidarity towards their ethnic peers. Hereinafter, same-ethnic solidarity is combined with the average income gap between natives and immigrants in order to draw some conclusions regarding all three theories. Assume a unit mass infinite population of consumers. The pre-tax income of a native i is defined by w_i. The population has the size n and can be divided into two subpopulations, the natives with size n_b and the immigrants with size n_f. The average pre-tax income of the population is expressed by

$$\overline{w} = (1-\gamma)\overline{w}_f + \gamma\overline{w}_b, \tag{2.1}$$

where $\gamma = \frac{n_b}{n}$ yields the proportion of natives in the population and $\overline{w}_b$ and $\overline{w}_f$ are the average pre-tax income of natives and immigrants, respectively. The governmental redistribution works through a linear tax and transfer system with a uniform tax rate $\tau \in (0,1)$ and a lump-sum social benefit b. The tax rate is assumed to be exogenous and does not affect the labor supply decisions of an individual. The post-tax income of native i is expressed by

$$I_i = (1-\tau)w_i + \tau\overline{w}, \tag{2.2}$$

In addition to the financial self-interest aspect of governmental redistribution, natives have individual views about the minimum or an optimal level of social justice. In particular, these are expressed in terms of a desired or justifiable level of income inequality or an average resident's standard of living. Therefore, a native's overall utility is the combination of private utility, expressed through his or her net income, and utility from the well-being of an average resident. The extent to which the social interest drives a native's preference for redistribution depends on his or her general solidarity with fellow residents. This is captured by the 'altruism' parameter $\phi_i \in (0,1)$. Notwithstanding, the natives' benevolence towards their same-ethnic peers and the immigrants could differ. Thus, the total utility of a native is a convex combination of private utility and the weighted sum of fairness perceptions regarding both subpopulations.

$$u_i = (1-\phi_i)I_i + \phi_i\left[\alpha_i\bar{I}_b + (1-\alpha_i)\bar{I}_f\right], \tag{2.3}$$

where $\alpha_i \in (0,1)$ is a relative weighting parameter of the natives', $\bar{I}_b$, and immigrants', $\bar{I}_f$, average post-tax income. Thus, the parameter measures the relative importance between the natives' average well-being and immigrants' average well-being for a native. Higher values for α_i indicate that a native's solidarity is more pronounced for his or her own ethnic group than for the immigrant group. This formulation is in line with intergroup contact and conflict theories. Combining the former equations results in the indirect utility $V_i(\alpha_i, \tau)$, expressed by

$$V_i = (1-\phi_i)\Big[(1-\tau)\,w_i + \tau\overline{w}\Big] + \phi_i\Big\{\alpha_i\Big[(1-\tau)\overline{w}_b + \tau\overline{w}\Big] + (1-\alpha_i)\Big[(1-\tau)\overline{w}_f + \tau\overline{w}\Big]\Big\} \tag{2.4}$$

Differentiating the indirect utility by the tax rate yields

$$\frac{dV_i}{d\tau} = (1-\phi_i)(\overline{w}-w_i) + \phi_i\Big[\alpha_i(\overline{w}-\overline{w}_b) + (1-\alpha_i)(\overline{w}-\overline{w}_f)\Big] \tag{2.5}$$

The effect of same-ethnic solidarity on a native's redistribution preference can be computed by

$$\frac{d}{d\alpha_i}\left(\frac{dV_i}{d\tau}\right) = \phi_i(\overline{w}_f - \overline{w}_b) \tag{2.6}$$

Since ϕ_i can only take positive values, the sign of the differential depends on the difference between natives' and immigrants' average income. Based on the term in Equation (2.6), two additional conclusions regarding the link between natives' same-ethnic solidarity and their preference for redistribution can be drawn. First, a native's higher in-group solidarity changes his or her preference for redistribution depending on the average income gap between natives and immigrants. If immigrants' pre-tax income is, on average, lower than natives', the term in (2.6) becomes negative. Natives who are more supportive to their same-ethnic peers will consequently support less redistribution, since immigrants are, on average, recipients of the tax and transfer system and benefit from it disproportionately. In contrast, the term in (2.6) becomes negative if the opposite occurs. In this case, natives prefer more redistribution, since natives are, on average, recipients of the tax and transfer system and benefit from it disproportionately. These effects should be smaller in magnitude, the less solidarity natives feel with their own ethnic group. Second, if the constrict theory applies, instead of the intergroup contact or conflict theories, a greater heterogeneity should reduce both the solidarity towards immigrants and towards natives. In total, solidarity towards the average resident declines and natives will support less redistribution. Therefore, the effect of natives' solidarity on their redistribution preference should no longer depend on the average income gap between natives and immigrants. Since natives' solidarity towards same-ethnic peers and immigrants diminishes, there is no ethnic group which is favored by natives.

2.4 Data and Variables

The analyses of the association between natives' attitudes towards immigrants and their redistribution preference is twofold. First, the effect of more social contact with immigrants - due to higher ethnic heterogeneity - on natives' attitudes towards immigrants is examined. Second, the effect of these attitudes on natives' preference for redistribution is assessed. Since individual data are required for investigation, the seventh wave of the European Social Survey is used. This cross-country survey covers 21 countries (20 European countries and Israel) as the ultimate sampling unit and contains persons aged 15 and above residing within private households (European Social Survey, 2015). It provides detailed information on respondents' socio-economic and demographic background, their attitudes towards immigrants, both on a personal as well as on a general level, and their attitudes towards several sociopolitical issues. The respondents are also asked to what extent they agree or disagree with the following statement:*"The government should take measures to reduce differences in income levels"*. Respondents can choose between five ordered categories: "strongly agree", "agree", "neither agree nor disagree", "disagree", and "strongly disagree". In the following empirical examination, the answers to this question are defined as the measure of a respondent's preference for redistribution.[39] Overall, there is a high demand for redistribution in the European countries. Almost 71 percent of the respondents chose the top categories "agree" and "strongly agree" (see Table 2.2). However, the European

Table 2.2: Preference for redistribution based on the responses to the question: *"The government should take measures to reduce differences in income levels"* (in percent)

Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
3.07	11.60	14.08	41.37	29.88

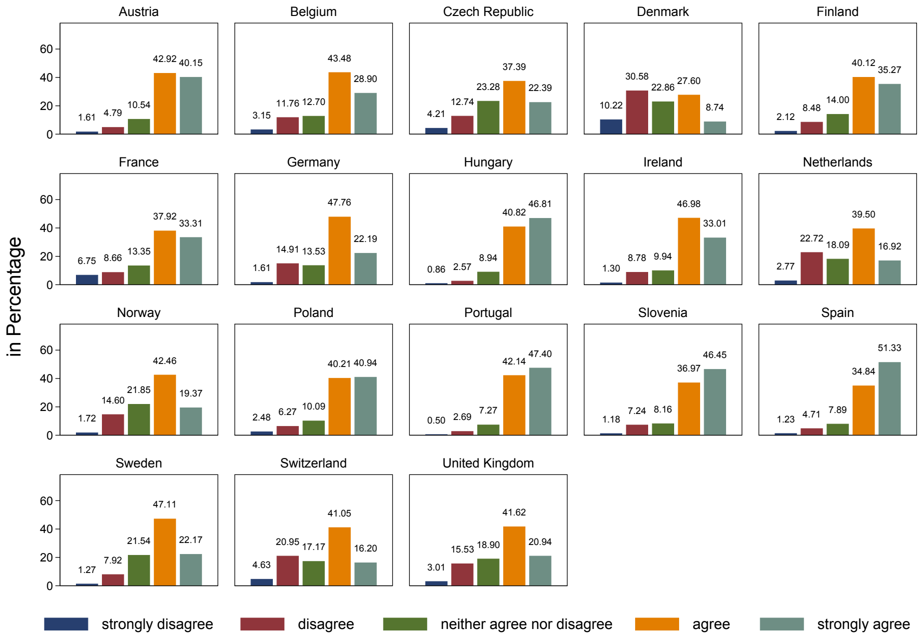
Notes: Calculation based on responses of the final born sample, weighted with design and population weights.

countries differ relatively strongly in the distribution of redistribution preferences (see Figure 2.1). While in Spain, the population share with the highest demand for redistribution is 51.33 percent, the Netherlands and Switzerland show values of around 16 percent. In particular, the post-communist countries have a very high preference for redistribution as well as two Mediterranean countries, Portugal and Spain. Both Spain and Portugal have experienced a sharp rise in the unemployment rate and income inequality in the aftermath of the financial crisis and during the ensuing euro crisis. The unemployment rate almost tripled in Spain between 2007 and 2013, whereby it almost doubled in Portugal during the same period (European Commission, 2017). Furthermore, between 2007 and 2014, the market income inequality, measured by the Gini coefficient, increased in Spain from about 50 percent to 55 percent and in Portugal from 46 percent to almost 52 percent (Solt, 2016). In line with Meltzer and Richard (1981), a rise in gross income inequality favors the demand for redistribution among citizens, because a larger proportion of the population would benefit from a higher governmental redistribution due to a larger income gap between the median voter and the mean voter. In addition, the European Social Survey 2014/2015 has a battery of questions about attitudes towards immigrants and immigration. From this pool, six questions are selected to map two dimensions of attitudes towards immigrants.[40] The first dimension defines the individual relationship of respondents to immigrants. Three

[39] In the empirical literature, this question has emerged as an appropriate measure for the individual preference for redistribution (see among others Burgoon, 2014; Corneo and Grüner, 2000, 2002; Finseraas, 2008; Senik et al., 2009).

[40] The wording of these questions is given in Table 2.10 in the appendix of this chapter.

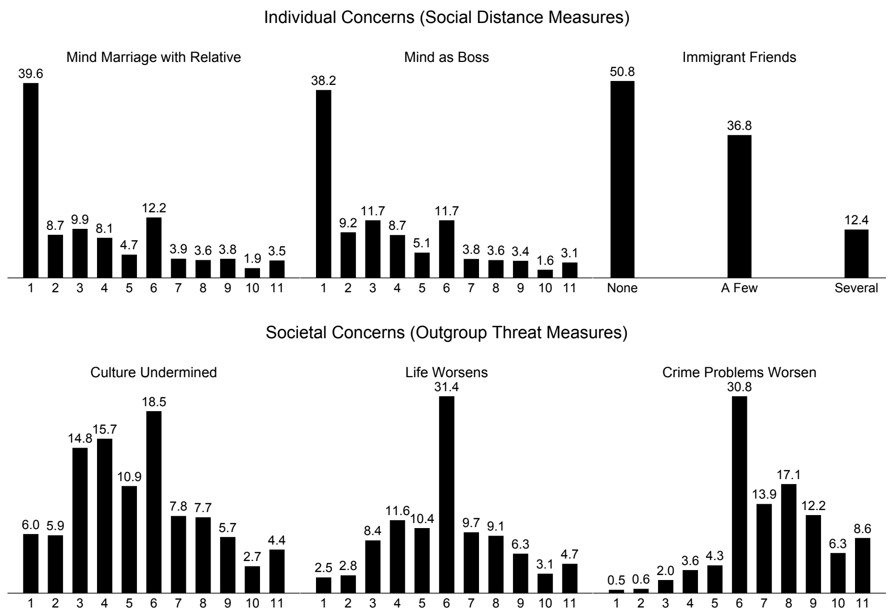
Figure 2.1: Distribution of preferences for redistribution across European countries



Notes: Responses of the final born sample weighted with country-specific design weights.

questions were picked that cover respondents' individual concern about and social distance from immigrants. The variables *Mind Marriage with Relative* and *Mind as Boss* express the personal dislike or affection of respondents for potential social contact with immigrants in their private or professional life. Thus, both variables cover specific parts of everyday life, which are associated with different types of social contact. Whereas the design and the intensity of social contact during working time may be strongly determined by exogenous factors, respondents determine the nature and frequency of their social contact in their free time independently. Therefore, individuals may evaluate changes in their social contact during working time and changes during free time differently. Undesirable social contact during working time would be accepted before unwanted social contact in respondents' free time, i.e. if a respondent does not want to establish social contact with immigrants, he or she would rather accept more social contact in the workplace than during his or her free time. Interestingly, however, the assessment of potential changes in social contact with immigrants during working time and during free time differs only slightly (see Figure 2.2). Almost 40 percent of respondents do not mind the marriage of a close relative to an immigrant and also do not mind an immigrant as a supervisor or boss. Furthermore, there are no severe deviations in the other values of both variables. Apparently, respondents treat changes in social contact in their professional life and their private life equally. A similar picture emerges for the third variable of the first dimension. Just over half of the respondents do not have a friend who is an immigrant. In contrast to previous questions, this variable

Figure 2.2: Overall distribution of social distance and outgroup threats



Notes: Responses of the final born sample, weighted with design and population weights. 11-point-scale variables are coded from (1) "absolute positive attitude" to (11) "absolute negative attitude". Therefore, rising values represent stronger anti-immigrant or negative outgroup attitudes.

measures the present social distance of a respondent to immigrants. For the empirical analysis, all three questions are recoded to binary variables. Based on the empirical distribution of the original questions, *Mind Marriage with Relative* and *Mind as Boss* are encoded with 1 if the original values are between 2 and 11 and otherwise encoded with 0. The variable *Immigrant Friends* is expressed by the value 0 if "a few" or "several" are present and otherwise by the value 1.

The second questionnaire covers natives' anxiety that immigrants endanger the provision of public goods and social constructs, such as national identity and national traditions. The selected questions measure the expected or perceived affect of immigrants' presence on tangible (crime or security) and intangible (culture and social life) goods. The empirical distribution of respondents' societal concern and outgroup threats is in sharp contrast to the social distance measures. For all three questions, the variation of values is very pronounced. The variable *Crime Problems Worsen* has a relatively small proportion of respondents in the first five values and about 58.1 percent of respondents assume a worsening of the security situation in the country due to immigrants. In turn, 55.7 percent assess immigrants' impact on social life positively, whereby 31.5 percent of respondents do not expect or perceive a strong change in social life from the presence of immigrants. Furthermore, only 28.3 percent of respondents believe that immigrants undermine the culture or the cultural life of the country. For empirical evaluation, all three questions are recoded to binary variables. The focus here is to pool those respondents who have a strongly positive attitude towards immigrants regarding the aforementioned societal concepts within a group. Thus, the three binary variables take the value 0 if the original questions have values between 1 and 3 and the value 1 for remaining values of the original questions, respectively.

There are two reasons for abstaining from a division of ordered variables at the center of the scale. First, the assignment of an individual with an indifferent value, i.e. who chose the middle answer to the question, to one of the two groups of a binary variable is arbitrary, but may change the empirical results to a great extent. Second, focusing on a few values on the positive margin of the variables allows for contrasting respondents who have strongly positive attitudes with respondents who have latent negative or strongly negative attitudes. Therefore, the results of the empirical evaluation are to be interpreted in light of this coding scheme. A significant effect of one of these variables means that the effect may certainly be driven by strongly negative attitudes, but at the same time it is not compensated by latent negative values and it could even be strengthened.

Additionally, attitudes towards immigrants depend on the experience of social contact in everyday life. This can either strengthen or moderate individual and societal threats. In order to measure the frequency of social contact which is not due to friendships with immigrants, the following question of the European Social Survey is suitable:*"How often do you have any contact with people of a different race or ethnic group [...], when your are out and about?"* Since the question relates to contact in everyday life, i.e. interactions in public transport, in public places, and in the neighborhood, higher values point to a higher immigrant density in the immediate neighborhood of the respondent and thus to a higher ethnic heterogeneity. The proportion of respondents with no contact to immigrants during their everyday lives is very low, at 12.96 percent (see Table 2.3). Over half of the respondents have contact with immigrants at least once a week. Comparing the number of immigrant friends and the frequency of social contact with immigrants, there is an early indication that social contact does not per se convert to bridging social capital among respondents.

Table 2.3: Social contact with immigrants based on the question:
"How often do you have any contact with people of a different race or ethnic group...?"
(in percent)

Never	Less than once a month	Once a month	Several times a month	Once a week	Several times a week	Everyday
12.96	11.37	7.38	14.71	8.17	20.01	25.40

Notes: Calculation based on responses of the final born sample, weighted with design and population weights.

Since socio-economic and demographic characteristics are important determinants of the redistribution preference, social distance from immigrants, and natives' perceived outgroup threats, a basic set of exogenous variables is prepared. This includes the respondent's age, gender, education years, marital status, labor force status, household size, household income, political orientation, size of the place of residence, presence of kids, and current or previous type of employment. A respondent's labor force status is summarized by the categories "employed", "unemployed", and "not in labor force", whereby the latter includes "sick", "disabled", "stay-at-home", and "retired".[41] The size of the place of residence is expressed by the binary variable *urban*, where "big city" and "suburb of big city" have the value 1 and "town/small city", "country/village" and "farm/home in countryside" have the value 0. The marital status is summarized in the binary variable *married*, where married respondents and respondents in a civil union take the value 1 and separated, divorced, widowed, and never-married respondents take the value 0. *Political orientation* is a measure of ideological self-assessment on an 11-point-scale, where 1 is "extreme right" and 11 is "extreme left". In addition, the type of employment indicates whether the respondent works or worked in the "public sector", "private sector", was "self-employed" or "other". Individual data on Estonia are excluded from the analysis, because there is no information on respondents' household income. Since the share of immigrants at the NUTS level 2 is used to instrument social contact in the upcoming empirical examination, Israel and Lithuania are excluded from the analysis, respectively due to missing regional data and due to a lack of variation at the regional level. In order to prevent distortions of the estimations by an insufficient number of observations within NUTS level 2 regions, regions with less than 30 valid observations are not taken into account. In total, the final sample includes 18 European countries and the immigrant population share for 154 regions.[42] As the purpose of the study is to measure the effect of attitudes towards immigrants and ethnic heterogeneity on a native's preference for redistribution, all respondents with a place of birth outside the country of data collection were dropped from the original sample.

2.5 Econometric Specification

Based on the introduced theories about the formation of attitudes towards immigrants, there is a link between these attitudes and a native's preference for redistribution through the solidarity channel. On the other hand, there is an association between social contact with immigrants or ethnic heterogeneity and natives' social distance from immigrants or their perceived outgroup threat. Thus, the logical chain goes from social distance over attitudes towards immigrants to natives' support of redistribution. In such a framework, there are two dependent variables, the attitudes and redistribution preference, whereby the first is at the same time an endogenous covariate of the latter.

[41] Respondents who are currently in education are not taken into account, as most of them are not entitled to vote.

[42] The summary statistics of the basic covariates are presented in Table 2.9 in the appendix of this chapter.

In total, this calls for a recursive bivariate model. Since both outcome variables are of categorical nature, the following recursive bivariate probit model is applied

$$\begin{aligned}
y_1^* &= \boldsymbol{x}_1'\boldsymbol{\beta}_1 + \gamma \cdot y_2 + \epsilon_1\,, && y_1 = m \quad \text{if} \quad \kappa_{m-1} \le y_1^* < \kappa_m \quad \text{for} \quad m = 1,\dots,4\,,\\
y_2^* &= \boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta \cdot \psi + \epsilon_2\,, && y_2 = 1 \quad \text{if} \quad y_2^* > 0, 0 \quad \text{otherwise}\,,
\end{aligned} \tag{2.7}$$
$$\left(\begin{array}{c} \epsilon_1 \\ \epsilon_2 \end{array} \middle| \boldsymbol{x}_1, \boldsymbol{x}_2, \psi \right) \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right],$$

where the errors ϵ_1 and ϵ_2 are jointly normally distributed and may correlate, which is mirrored in the significance of the coefficient of correlation ρ. Furthermore, y_1^* and y_2^* are the latent endogenous variables of the model, which are observed only as their categorical realizations y_1 and y_2. The first outcome variable y_1 measures a native's preference for redistribution, is ordinal, and originally has five categories. Since only 3.07 percent of the final sample "strongly disagree", the last two categories, "strongly disagree" and "disagree", are collapsed (see Table 2.2). As ordered probit regressions are based on the *proportional odds assumption*, they can be compared to a series of binary probit regressions. However, estimating a binary response model, where only 3.07 percent of observations have the value 1 is not recommended (Hamilton, 1992). Thus, a native's preference for redistribution has four categories and the underlying latent y_1^* can be divided using the thresholds (or cutoff points) κ_1 to κ_3, which were estimated together with the coefficients of the model. Further, it is assumed that $\kappa_0 = -\infty$ and $\kappa_4 = \infty$. Hence, the observed response categories are tied to the latent variable by the measurement model

$$y_i = \begin{cases} 1 \quad (\text{“strongly disagree” or “disagree}), & \text{if} \quad -\infty \le y_i^* < \kappa_1 \\ 2 \quad (\text{“neither agree nor disagree”}), & \text{if} \quad \kappa_1 \le y_i^* < \kappa_2 \\ 3 \quad (\text{“agree”}), & \text{if} \quad \kappa_2 \le y_i^* < \kappa_3 \\ 4 \quad (\text{“strongly agree”}), & \text{if} \quad \kappa_3 \le y_i^* < \infty \end{cases}$$

The second outcome variable y_2 represents a native's attitude towards immigrants and is binary. Since attitudes towards immigrants are covered by two dimensions, each with three variables, a total of six different outcome variables is used. Interestingly, the dependent variable y_2^* can be carried as observed explanatory variable y_2 into the equation for y_1 with no special attention to its endogeneity (see Maddala, 1983, for derivation). In contrast to the linear recursive model, the recursive probit model does not require an exclusion restriction for identification, i.e. all exogenous covariates may appear in both equations if there is sufficient variation in the data (Wilde, 2000).[43] This condition is secured by adding the frequency of interethnic contact, denoted as ψ, to

[43]Greene (1998, p. 292) mentions that this property "seem[s] not to be widely known" in the discussion of two-step probit models.

the right-hand side of the second outcome equation, since aforementioned sociological theories predict an association between interethnic contact during everyday life and a native's attitudes towards immigrants (see Table 2.3). Additionally, $\boldsymbol{x}_1$ and $\boldsymbol{x}_2$ are matrices of individual socio-economic and demographic control variables, including the basic set of covariates described above, whereby $\boldsymbol{x}_1 = \boldsymbol{x}_2$ holds. Furthermore, the model includes a full set of country dummies to capture country-specific effects, whereby the intercept in $\boldsymbol{x}_1$ (or $\boldsymbol{x}_2$) varies across countries. These are required, since both unobservable and observable measures, e.g. the current level of income inequality and governmental redistribution, may have an effect on both outcome variables. Through these intercepts, it is possible to net out the impact of country-level variables which are assumed to be homogenous across fellow natives. The fixed effect estimation of an ordered response model may give rise to the incidental parameter problem (Chamberlain, 1984). The maximum likelihood estimator of the incidental parameters (fixed effects) is consistent as long as $T \to \infty$, for given N (assuming that there are T observations for each individual unit $i = 1, \ldots, N$). However, the estimator is inconsistent for given T, as $N \to \infty$. Since country fixed effects are included, the parsed panel is very long. N is small and T is high, as there are many observations within each country. Given these properties of the data, the incidental parameter problem is not an issue for estimation results. Finally, design and population weights are applied, since observations are pooled and all parameters are constrained to be constant across countries.

2.5.1 Direct and Indirect Effects

Although the raw estimation results of a probit model can be interpreted with regard to the parameters' sign and significance, they do not have a direct economic interpretation, i.e. the magnitude of the effects in comparison to each other. Thus, marginal effects of the covariates have to be calculated in order to assess the importance and magnitude of the effects on the respective outcome variable. Since the first outcome variable y_1 is ordinal, in principle, the marginal effects can be calculated for each category separately. For a better and more catchy interpretation of the estimation results, however, the marginal effects on a high preference for redistribution are calculated. In turn, a high preference for redistribution is defined as the probability of selecting one of the two top categories, "agree" and "strongly agree", of the ordered dependent variable. Thus, the bivariate recursive model can be expressed in probabilities as follows:

$$\begin{aligned}
&\Pr(y_2 = 1|\boldsymbol{x}_2) = \Phi(\boldsymbol{x}_2'\boldsymbol{\beta}_2)\,, \\
&\Pr(y_1 \geq 3, y_2|\boldsymbol{x}_1, \boldsymbol{x}_2) = \Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 + \gamma y_2\,,\ q_{i2}(\boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi)\,,\ q_{i2}\rho)\right)\,,
\end{aligned} \tag{2.8}$$

where $q_{i2} = 2y_{i2} - 1$ takes the value +1 if a native has a negative attitude towards immigrants and otherwise the value −1. Hereinafter, $\phi(\cdot)$ and $\Phi(\cdot)$ respectively indicate the univariate standard normal density and the cumulative density function, whereas $\phi_2(\cdot)$ and $\Phi_2(\cdot)$ respectively specify the bivariate normal density and cumulative density function.[44] The primary interest, as in the present study, is the extent of the marginal effects of $\boldsymbol{x}_1$ (or $\boldsymbol{x}_2$) and y_2 on y_1. Since some exogenous variables, $\boldsymbol{x}_1$ (or $\boldsymbol{x}_2$), occur in both outcome equations and interethnic contact, ψ, occurs only in the second outcome equation, the channels through which these exogenous variables affect y_1 differ. Whereas a change in $\boldsymbol{x}_1$ directly affects y_1 (direct effect), a change in $\boldsymbol{x}_2$ indirectly influences y_1 via a change in the endogenous variable y_2 (indirect effect). Natives' years of education, for example, appear in both outcome equations. Thus, years of education have an effect on the probability of a high preference for redistribution directly through the first outcome equation. Concurrently, they affect natives' attitudes towards immigrants, whereby this effect is, in turn, transmitted back to the preference for redistribution. Therefore, it is possible to quantify the indirect effect of an exogenous variable, which appears only in the second outcome equation, on a native's support for redistribution. In particular, this is of interest regarding the indirect marginal effect of interethnic contact on a native's support of redistribution. Finally, the probability of a high preference for redistribution can be expressed by[45]

$$\begin{aligned}
&\Pr(y_1 \geq 3, y_2 | \boldsymbol{x}_1, \boldsymbol{x}_2, \psi) \\
&= \Pr(y_2 = 1 | \boldsymbol{x}_2, \psi) \cdot \Pr(y_1 \geq 3, y_2 = 1 | \boldsymbol{x}_1, \boldsymbol{x}_2, \psi) \\
&\quad + \Pr(y_2 = 0 | \boldsymbol{x}_2, \psi) \cdot \Pr(y_1 \geq 3, y_2 = 0 | \boldsymbol{x}_1, \boldsymbol{x}_2, \psi) \\
&= \Phi(\boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi) \cdot \frac{\Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 + \gamma \,,\, \boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi \,,\, \rho\right)}{\Phi(\boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi)} \\
&\quad + \Phi(-\boldsymbol{x}_2'\boldsymbol{\beta}_2 - \delta\psi) \cdot \frac{\Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 \,,\, -\boldsymbol{x}_2'\boldsymbol{\beta}_2 - \delta\psi \,,\, -\rho\right)}{\Phi(-\boldsymbol{x}_2'\boldsymbol{\beta}_2 - \delta\psi)} \\
&= \Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 + \gamma \,,\, \boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi \,,\, \rho\right) + \Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 \,,\, -\boldsymbol{x}_2'\boldsymbol{\beta}_2 - \delta\psi \,,\, -\rho\right). \qquad (2.9)
\end{aligned}$$

[44] The bivariate normal cumulative density function is

$$\Pr(X_1 < x_1, X_2 < x_2) = \int_{-\infty}^{x_2}\int_{-\infty}^{x_1} \phi_2(w_1, w_2, \rho)\, dw_1\, dw_2$$

and the bivariate normal density is

$$\phi_2(x_1, x_2, \rho) = \frac{\exp\left[-\frac{1}{2}\left(x_1^2 + x_2^2 - 2\rho x_1 x_2\right)/\left(1-\rho^2\right)\right]}{2\pi\sqrt{1-\rho^2}} \qquad \text{(Greene and Hensher, 2010).}$$

[45] Greene and Hensher (2010) show this for the recursive bivariate binary case, where both endogenous variables are binary. Due to the proportional odds assumption, their implementation can easily be transferred to the ordinal or mixed case.

The first and second term in (2.9) represent the direct and the indirect effect, respectively. Thus, the first indicates which part of the proportion of natives who have a high preference for redistribution in the data is due to the direct effects and the latter correspondingly shows the part which is attributable to indirect effects.

2.5.2 Marginal Effects

The marginal effects are obtained by taking the derivatives of (2.9) with respect to $\boldsymbol{x}_1$, $\boldsymbol{x}_2$, ψ, and y_2.[46] In the calculation of the marginal effects on a high preference for redistribution, a distinction is made between three cases: (i) the marginal effect of a continuous exogenous variable, (ii) the marginal effect of a categorical or binary exogenous variable, and (iii) the marginal effect of the endogenous explanatory variable y_2. The direct marginal effect of a continuous variable x_{1k} is its derivative with respect to $\boldsymbol{x}_1$:[47]

$$\begin{aligned}\frac{\partial \Pr(y_1 \geq 3, y_2 | \boldsymbol{x}_1, \boldsymbol{x}_2, \psi)}{\partial x_{1k}} =& \left[\phi(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 + \gamma) \cdot \Phi\left(\frac{\boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi - \rho(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 + \gamma)}{\sqrt{1-\rho^2}}\right)\right.\\ &\left. + \phi(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1) \cdot \Phi\left(\frac{-\boldsymbol{x}_2'\boldsymbol{\beta}_2 - \delta\psi + \rho(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1)}{\sqrt{1-\rho^2}}\right)\right] \cdot \beta_{1k}\end{aligned} \tag{2.10}$$

The sign of the direct marginal effect is equal to the sign of the coefficient β_{1k}, since the term in the square brackets is positive. In turn, the indirect effect of a continuous variable x_{2k} and ψ is its derivative with respect to $\boldsymbol{x}_1$ and ψ, respectively:

$$\begin{aligned}\frac{\partial \Pr(y_1 \geq 3, y_2 | \boldsymbol{x}_1, \boldsymbol{x}_2, \psi)}{\partial x_{1k}} =& \phi(\boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi) \cdot \left[\Phi\left(\frac{-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 + \gamma - \rho(\boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi)}{\sqrt{1-\rho^2}}\right)\right.\\ &\left. - \Phi\left(\frac{-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 - \rho(\boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi)}{\sqrt{1-\rho^2}}\right)\right] \cdot \beta_{2k}\end{aligned} \tag{2.11}$$

The sign of the indirect marginal effect depends on the sign of β_{2k} and γ. If $\gamma > 0$ holds, the term in the square brackets is positive and the marginal effect takes the same sign as β_{2k}. However, if $\gamma < 0$ applies, the term in the square brackets is negative and the marginal effect takes the opposite of the sign of β_{2k}. Since the ψ appears only in the second outcome equation, the frequency of interethnic contact only has an indirect marginal effect on natives' preference for redistribution. Thus, in Equation (2.11), the

[46] More precisely, the average marginal effects are estimated by computing the respective derivatives for each observation, totaling these values and taking the mean. For notational simplicity, the summation is suppressed.

[47] The derivations of the bivariate normal cumulative distribution function are based on the implications of the recursive bivariate binary case in Greene (1998) and Greene and Hensher (2010) and were transferred to the ordinal or mixed case.

β_{2k} for ψ has to be replaced with the respective coefficient δ from the second outcome equation.

For a discrete exogenous variable x_l, the direct marginal effect can be obtained by taking the difference in the probabilities of a high preference for redistribution:

$$\begin{aligned}
&\Pr(y_1 \geq 3, y_2|\boldsymbol{x}_1, \boldsymbol{x}_2, \psi, x_{1l} = 1) - \Pr(y_1 \geq 3, y_2|\boldsymbol{x}_1, \boldsymbol{x}_2, \psi, x_{1l} = 0) \\
&= \left[\Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 + \gamma\,,\, \boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi\,,\, \rho\right) + \Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1\,,\, -\boldsymbol{x}_2'\boldsymbol{\beta}_2 - \delta\psi\,,\, -\rho\right)\right]\Bigg|_{x_{1l}=1} \\
&- \left[\Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 + \gamma\,,\, \boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi\,,\, \rho\right) + \Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1\,,\, -\boldsymbol{x}_2'\boldsymbol{\beta}_2 - \delta\psi\,,\, -\rho\right)\right]\Bigg|_{x_{1l}=0}
\end{aligned} \tag{2.12}$$

The indirect marginal effect is calculated in a similar manner:

$$\begin{aligned}
&\Pr(y_1 \geq 3, y_2|\boldsymbol{x}_1, \boldsymbol{x}_2, \psi, x_{2l} = 1) - \Pr(y_1 \geq 3, y_2|\boldsymbol{x}_1, \boldsymbol{x}_2, \psi, x_{2l} = 0) \\
&= \left[\Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 + \gamma\,,\, \boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi\,,\, \rho\right) + \Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1\,,\, -\boldsymbol{x}_2'\boldsymbol{\beta}_2 - \delta\psi\,,\, -\rho\right)\right]\Bigg|_{x_{2l}=1} \\
&- \left[\Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 + \gamma\,,\, \boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi\,,\, \rho\right) + \Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1\,,\, -\boldsymbol{x}_2'\boldsymbol{\beta}_2 - \delta\psi\,,\, -\rho\right)\right]\Bigg|_{x_{2l}=0}
\end{aligned} \tag{2.13}$$

Since the endogenous explanatory variable y_2 is binary, the direct marginal effect on y_1 is calculated as follows:

$$\begin{aligned}
&\Pr(y_1 \geq 3, y_2 = 1|\boldsymbol{x}_1, \boldsymbol{x}_2, \psi) - \Pr(y_1 \geq 3, y_2 = 0|\boldsymbol{x}_1, \boldsymbol{x}_2, \psi) \\
&= \frac{\Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1 + \gamma\,,\, \boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi\,,\, \rho\right)}{\Phi(\boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta\psi)} - \frac{\Phi_2\left(-\kappa_2 + \boldsymbol{x}_1'\boldsymbol{\beta}_1\,,\, -\boldsymbol{x}_2'\boldsymbol{\beta}_2 - \delta\psi\,,\, -\rho\right)}{\Phi(-\boldsymbol{x}_2'\boldsymbol{\beta}_2 - \delta\psi)}
\end{aligned} \tag{2.14}$$

2.6 Empirical Results

The theoretical considerations predict that there is a link between interethnic contact and natives' attitudes towards immigrants as well as an association between natives' sociotropic concern due to the presence of immigrants and their preference for redistribution. In turn, natives' attitudes can be divided into two dimensions: social distance measures and perceived outgroup threat measures. The first quantifies to what extent natives avoid or want to avoid social interactions with immigrants in their leisure time and at their workplace. The latter measures the magnitude of natives' symbolic threats or threats to tangible goods presented by immigrants. Thus, a bivariate recursive probit model can be applied and estimated by full information maximum likelihood, whereby

Table 2.4: Bivariate probit estimations of natives' preference for redistribution and social distance measures

	(1)		(2)		(3)	
	preference for redistribution	*mind marriage with relative*	*preference for redistribution*	*mind immigrant as boss*	*preference for redistribution*	*immigrant friends*
age	0.019	0.015	0.019	0.015	0.018	0.005
	(0.005)***	(0.006)***	(0.005)***	(0.006)***	(0.005)***	(0.006)
age^2	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(0.000)***	(0.000)	(0.000)***	(0.000)	(0.000)***	(0.000)
female	0.042	-0.003	0.043	0.048	0.041	0.102
	(0.025)*	(0.029)	(0.025)*	(0.029)	(0.025)*	(0.030)***
married	-0.023	0.081	-0.027	0.022	-0.029	0.120
	(0.031)	(0.035)**	(0.030)	(0.035)	(0.031)	(0.035)***
kids at home	-0.022	0.027	-0.023	0.008	-0.022	-0.033
	(0.035)	(0.043)	(0.035)	(0.043)	(0.036)	(0.044)
household member	0.019	0.001	0.019	0.005	0.019	0.013
	(0.015)	(0.020)	(0.015)	(0.019)	(0.015)	(0.020)
(sub-)urban	-0.014	-0.072	-0.011	-0.096	-0.006	-0.185
	(0.028)	(0.032)**	(0.027)	(0.031)***	(0.029)	(0.032)***
political orientation	0.109	-0.092	0.112	-0.071	0.114	-0.023
	(0.009)***	(0.007)***	(0.007)***	(0.007)***	(0.006)***	(0.007)***
education years	-0.018	-0.026	-0.017	-0.023	-0.016	-0.032
	(0.004)***	(0.004)***	(0.004)***	(0.004)***	(0.004)***	(0.004)***
public sector			*reference*			
private sector	-0.072	0.074	-0.074	0.085	-0.077	0.051
	(0.029)**	(0.033)**	(0.029)***	(0.033)**	(0.028)***	(0.034)
self-employed	-0.157	-0.012	-0.158	-0.004	-0.158	-0.106
	(0.045)***	(0.053)	(0.046)***	(0.054)	(0.046)***	(0.052)**
other	-0.095	0.004	-0.096	-0.020	-0.096	0.086
	(0.074)	(0.094)	(0.074)	(0.094)	(0.075)	(0.097)
employed			*reference*			
unemployed	0.070	0.023	0.068	-0.015	0.069	-0.250
	(0.064)	(0.070)	(0.064)	(0.070)	(0.065)	(0.071)***
not in labor force	-0.006	0.007	-0.007	0.019	-0.008	-0.054
	(0.035)	(0.043)	(0.035)	(0.042)	(0.035)	(0.043)
household income	-0.072	-0.005	-0.072	-0.008	-0.071	-0.016
	(0.006)***	(0.007)	(0.006)***	(0.007)	(0.006)***	(0.007)**
mind marriage with relative	**-0.129**					
	(0.191)					
mind immigrant as boss			**-0.051**			
			(0.141)			
immigrant friends					**0.025**	
					(0.109)	
interethnic contact		*-0.083*		*-0.090*		*-0.181*
		*(0.008)****		*(0.008)****		*(0.008)****
atanh $\hat{\rho}$	0.0685		0.0384		0.0031	
	(0.1175)		(0.0854)		(0.0688)	
Obs.	18915		18915		18915	
AIC	71,851.28		71,817.33		70,790.65	
BIC	72,392.77		72,358.82		71,332.14	
Log Likelihood	-35856.64		-35839.66		-35326.32	

Notes: The born sample is employed and raw coefficients of the estimations are reported. In maximum likelihood estimation, ρ is not directly estimated, but atanh $\rho = 0.5 \cdot \ln((1+\rho)/(1-\rho))$ applies. *Political orientation* is a measure of ideological self-assessment on an 11-point-scale, where 1 is "extreme right" and 11 is "extreme left". Country fixed effects are included, but not reported. Standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

a native's perceptions are carried as observed in the right-hand side of the first outcome equation (Roodman, 2011). The estimation results show that more interethnic contact during everyday life leads to more positive attitudes towards immigrants among natives (see Table 2.4). This holds for all employed social distance measures. More years of education as well as a stronger leftist political conviction reduce the probability of social distance to immigrants. On the one hand, education generates a liberalization effect through the reduction of prejudices and stereotypes (Hainmueller and Hiscox, 2007; Hello et al., 2002). On the other hand, more highly educated people are usually better informed about foreign cultures, countries, and traditions. Therefore, they may develop sympathy for immigrants more quickly. Furthermore, living in a suburban or urban area decreases a native's probability of anti-immigrant attitudes. The effects of the remaining covariates are mixed. Married natives oppose a relative's marriage to an immigrant more strongly and show a higher probability of having no immigrant friends than unmarried natives. However, married and unmarried natives do not significantly differ in their rejection of an immigrant as a supervisor. Taking a closer look at the determinants of a native's preference for redistribution, the common effects can be confirmed. Earning a higher income diminishes the support of redistribution, as higher income lowers a native's social benefits and increases his or her taxes (Meltzer and Richard, 1981). According to the *prospects of upward mobility hypothesis*, more highly educated individuals prefer less redistribution, since they expect future increases in their income (Benabou and Ok, 2001). Moreover, private sector employees and self-employed persons prefer less redistribution than public sector employees, since public employment directly benefits from a large government. The elderly who benefit from health and pension spending are also more supportive of redistribution. Interestingly, none of the social distance measures have a significant impact on a native's redistribution preference. Thus, natives' social distance or desire to avoid social relationships with immigrants has no influence on their support of redistribution, neither through the solidarity nor through the conflict channel.

However, this picture changes once the perceived outgroup threat dimension is considered (see Table 2.5). The basic set of covariates takes the same signs as above and the frequency of interethnic contact is again negatively associated with natives' anti-immigrant attitudes. Apart from the variable *crime problems worsen*, the remaining outgroup threat measures, *culture undermined* and *social life worsens*, have a significantly negative impact on a native's redistribution preference. This result emphasizes that natives' support of redistribution is rather driven by symbolic concern about the nation or the society as a whole than by social distance to immigrants. On the one hand, the estimations confirm the predictions of intergroup contact theory, since more interethnic contact diminishes natives' negative attitudes towards immigrants, prejudices, and stereotypes. Furthermore, this implies that a rise in ethnic diversity in a native's imme-

Table 2.5: Bivariate probit estimations of natives' preference for redistribution and out-group threat measures

	(1)		(2)		(3)	
	preference for redistribution	*culture undermined*	*preference for redistribution*	*social life worsens*	*preference for redistribution*	*crime problems worsen*
age	0.014	-0.009	0.014	-0.012	0.016	-0.029
	(0.005)***	(0.006)	(0.005)***	(0.007)*	(0.005)***	(0.011)***
age^2	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(0.000)**	(0.000)	(0.000)**	(0.000)	(0.000)***	(0.000)***
female	0.053	0.036	0.063	0.113	0.046	0.112
	(0.024)**	(0.031)	(0.024)**	(0.036)***	(0.024)*	(0.054)**
married	-0.017	0.002	-0.017	0.009	-0.020	-0.041
	(0.030)	(0.037)	(0.030)	(0.042)	(0.030)	(0.068)
kids at home	-0.009	0.066	-0.014	0.049	-0.019	0.186
	(0.036)	(0.046)	(0.035)	(0.051)	(0.036)	(0.089)**
household member	0.015	-0.007	0.019	0.009	0.016	0.001
	(0.016)	(0.020)	(0.015)	(0.022)	(0.015)	(0.035)
(sub-)urban	-0.048	-0.106	-0.048	-0.135	-0.018	-0.050
	(0.027)*	(0.033)***	(0.026)*	(0.037)***	(0.026)	(0.062)
political orientation	0.090	-0.110	0.094	-0.112	0.115	0.012
	(0.010)***	(0.008)***	(0.007)***	(0.009)***	(0.006)***	(0.013)
education years	-0.029	-0.062	-0.023	-0.039	-0.017	0.017
	(0.005)***	(0.005)***	(0.004)***	(0.005)***	(0.004)***	(0.010)
public sector			*reference*			
private sector	-0.035	0.146	-0.038	0.161	-0.068	0.095
	(0.030)	(0.035)***	(0.028)	(0.040)***	(0.028)**	(0.060)
self-employed	-0.166	-0.015	-0.174	-0.052	-0.173	-0.039
	(0.045)***	(0.056)	(0.045)***	(0.063)	(0.046)***	(0.095)
other	-0.089	-0.056	-0.080	-0.041	-0.082	0.203
	(0.076)	(0.094)	(0.075)	(0.107)	(0.076)	(0.159)
employed			*reference*			
unemployed	0.077	-0.005	0.077	0.018	0.077	0.061
	(0.064)	(0.072)	(0.064)	(0.089)	(0.064)	(0.144)
not in labor force	0.009	0.050	0.005	0.052	-0.007	-0.226
	(0.035)	(0.048)	(0.035)	(0.053)	(0.035)	(0.085)***
household income	-0.075	-0.036	-0.074	-0.033	-0.070	0.006
	(0.006)***	(0.007)***	(0.005)***	(0.009)***	(0.005)***	(0.012)
culture undermined	**-0.646**					
	(0.160)***					
social life worsens			**-0.775**			
			(0.115)***			
crime problems worsen					**-0.056**	
					(0.208)	
interethnic contact		*-0.068*		*-0.050*		*-0.031*
		*(0.009)****		*(0.010)****		*(0.016)***
atanh $\hat{\rho}$	0.3765		0.4416		0.0435	
	(0.1083)***		(0.0734)***		(0.0777)	
Obs.	19405		19405		19405	
AIC	67,142.48		61,255.76		52,244.65	
BIC	67,701.48		61,814.76		52,803.65	
Log Likelihood	-33500.24		-30556.88		-26051.32	

Notes: The born sample is employed and raw coefficients of the estimations are reported. In maximum likelihood estimation, ρ is not directly estimated, but atanh $\rho = 0.5 \cdot \ln((1+\rho)/(1-\rho))$ applies. *Political orientation* is a measure of ideological self-assessment on an 11-point-scale, where 1 is "extreme right" and 11 is "extreme left". Country fixed effects are included, but not reported. Standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

diate neighborhood has a positive influence on his or her attitudes towards immigrants. In order to examine a curvilinear link between interethnic contact and outgroup threats perceived by natives, a squared interethnic contact term is added to all estimations. However, the results strongly reject a curvilinear relationship.[48] On the other hand, the predictions of the conflict theory are also confirmed, since natives' concern of intensified competition for intangible goods and resources, such as national culture and social life, decrease their solidarity and simultaneously their preference for redistribution. Therefore, it is not natives' social distance from immigrants or their desire to avoid social contact with immigrants in their private life and in the workplace that resonate with their sociopolitical claims. However, natives' perceived threat to their in-group norms and values by the presence of immigrants has a significantly negative impact on their support of redistribution.

2.6.1 Indirect and Direct Effects

The bivariate recursive probit estimation allows for the division of a predictor's marginal effect into a direct and an indirect effect. The direct effect measures the impact of a covariate on a native's preference for redistribution via a direct association, whereby the indirect effect specifies the influence of a covariate on a native's support of redistribution through a change in his or her attitudes towards immigrants. In turn, the sum of both effects yields the overall effect of any predictor. Thus, such a decomposition enables the assessment of the indirect impact of interethnic contact on natives' redistribution preference. The estimates show that a rise in interethnic contact increases the probability of a high redistribution preference by 0.8 percent (see Table 2.6). At first glance, this effect may challenge the previous results of the empirical literature, but it does not exclude a negative effect of ethnic heterogeneity at the country level. Whereas the association between ethnic diversity and the redistribution preference implies an unambiguous channel at the country level, the indirect effect of interethnic contact is merely transmitted through a change in a native's attitudes towards immigrants. In turn, the frequency of interethnic contact in everyday life depends on the share of immigrants in the immediate neighborhood. If immigrants are geographically unequally distributed across the country and the immigrant population is concentrated in a few agglomerations, most natives do not experience any interethnic contact. Thus, a country with less ethnic diversity may show, ceteris paribus, a higher average redistribution preference among natives than a country with more ethnic diversity if the immigrant population is geographically more unevenly distributed across the latter

[48] Since the frequency of interethnic contact is ordinal scaled, the estimations are repeated, taking the ordinal structure of the predictor into account. However, the results do not differ from a treatment as a continuous predictor. A native's probability of expressing negative attitudes towards immigrants diminishes ascending in the categories of the predictor. Results are presented for social distance and outgroup threat measures in Table 2.11 in the appendix of this chapter.

Table 2.6: Decomposition of the average marginal effects on natives' preference for redistribution

	Culture undermined			**Social Life Worsens**		
	direct effect	*indirect effect*	*total effect*	*direct effect*	*indirect effect*	*total effect*
age	0.004	0.001	0.005	0.004	0.001	0.005
	(0.002)***	(0.000)	(0.002)***	(0.002)***	(0.000)	(0.002)***
female	0.016	-0.002	0.014	0.019	-0.006	0.014
	(0.008)**	(0.002)	(0.007)*	(0.008)**	(0.002)***	(0.007)*
married	-0.005	-0.000	-0.006	-0.006	-0.000	-0.006
	(0.010)	(0.002)	(0.009)	(0.010)	(0.002)	(0.009)
kids at home	-0.002	-0.004	-0.006	-0.004	-0.002	-0.007
	(0.010)	(0.003)	(0.010)	(0.010)	(0.003)	(0.010)
household member	0.005	0.000	0.005	0.006	-0.000	0.005
	(0.005)	(0.001)	(0.005)	(0.005)	(0.001)	(0.005)
(sub-)urban	-0.015	0.006	-0.009	-0.015	0.007	-0.008
	(0.009)*	(0.002)***	(0.008)	(0.009)*	(0.002)***	(0.008)
political orientation	0.028	0.006	0.035	0.029	0.005	0.035
	(0.003)***	(0.002)***	(0.002)***	(0.002)***	(0.001)***	(0.002)***
education years	-0.009	0.004	-0.006	-0.007	0.002	-0.005
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.000)***	(0.001)***
public sector			*reference*			
private sector	-0.011	-0.009	-0.020	-0.012	-0.008	-0.020
	(0.009)	(0.003)***	(0.008)**	(0.009)	(0.002)***	(0.008)**
self-employed	-0.054	0.001	-0.053	-0.056	0.003	-0.053
	(0.015)***	(0.003)	(0.015)***	(0.015)***	(0.004)	(0.015)***
other	-0.029	0.004	-0.025	-0.026	0.002	-0.023
	(0.021)	(0.007)	(0.021)	(0.021)	(0.006)	(0.021)
employed			*reference*			
unemployed	0.024	0.000	0.024	0.024	-0.001	0.023
	(0.020)	(0.004)	(0.019)	(0.019)	(0.004)	(0.019)
not in labor force	0.003	-0.003	0.000	0.002	-0.003	-0.001
	(0.012)	(0.003)	(0.012)	(0.012)	(0.003)	(0.011)
household income	-0.024	0.002	-0.022	-0.023	0.002	-0.022
	(0.002)***	(0.001)***	(0.002)***	(0.002)***	(0.000)***	(0.002)***
culture undermined	**-0.064**					
	(0.038)*					
social life worsens				**-0.082**		
				(0.030)***		
interethnic contact		*0.004*			*0.002*	
		*(0.001)****			*(0.001)****	
Obs.		19385			19385	
Prob. (direct)		0.499 (0.009)***			0.589 (0.006)***	
Prob. (indirect)		0.200 (0.006)***			0.110 (0.004)***	
Prob. (total)		0.699 (0.004)***			0.699 (0.004)***	

Notes: The born sample is employed. *Political orientation* is a measure of ideological self-assessment on an 11-point-scale, where 1 is "extreme right" and 11 is "extreme left". Country fixed effects are included, but not reported. Bootstrapped standard errors with 100 replications are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

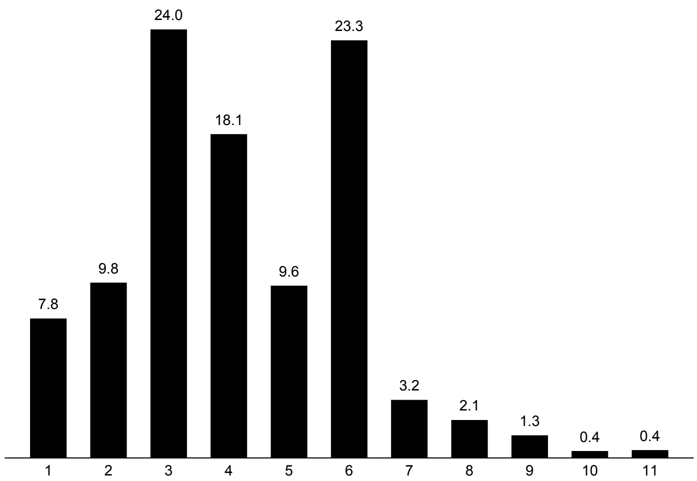
than the former.

Another special feature of the decomposition is that the separation of the overall effect uncovers whether the direct and indirect effects compensate for one another for some covariates. With regards to the cultural threat measure, another year of education reduces natives' probability of a high redistribution preference by 0.9 percent (direct effect), though at the same time, the probability increases by 0.4 percent due to a lower probability of perceived cultural threat (indirect effect). In all, the total average marginal effect is -0.6. In regard to the household income, the negative direct effect overcompensates for the positive indirect effect as well. In turn, employees or former employees of the private sector show a lower probability, both indirectly and directly, of a high support for redistribution than their counterparts in the public sector. However, the negative association is driven much more by the indirect effect, i.e. through the change of perceived outgroup threats. In contrast, both effects of political orientation operate in the same direction and strengthen each other. Examining perceived cultural threat (threat to social life), a stronger leftist political conviction along the ideological scale directly increases a native's preference for redistribution by 2.8 (2.9) percent and additionally by 0.6 (0.5) percent through its negative impact on a native's perceived cultural threat (threat to social life). Ultimately, the average marginal effects of both outgroup threat measures on a native's support of redistribution are significant. Natives' concern about the national cultural landscape reduces their support by 6.4 percent and natives' anxiety of a deterioration of social life due to immigrants lowers their support by 8.2 percent. Overall, almost 70 percent of the surveyed natives show a high preference for redistribution. According to the decompositions, 71.5 to 84.1 percent of this proportion can be explained by direct effects, whereby 15.9 to 28.5 percent results from the indirect effect of the perceived outgroup threat channel.

2.6.2 Interethnic Contact and Bad Experience with Interethnic Contact

Additionally, the investigated association so far implies that the experience of interethnic contact in everyday life is mainly positive. However, if a native has a lot of interethnic contact in his or her neighborhood and the majority of this contact is assessed as a bad experience, he or she is more likely to take negative attitudes towards immigrants. The European Social Survey 2014/2015 offers a possibility to examine the association between the frequency of interethnic contact and the natives' evaluation of the quality of contact. For this purpose, the following question is used as a measure of bad contact experience:"*Thinking about this contact, in general how bad or good is it?*". Respondents can choose between eleven ordered categories, where the lowest category represents an extremely good experience and the highest category expresses an extremely bad experience. Only few natives have bad experiences in everyday interethnic contact (see Figure 2.3). The top five categories total just 7.4 percent. Thus, most natives who have interethnic contact no less than once a month assess their contact as predominantly positive. Since bad experience with interethnic contact is the dependent variable, it is recoded to a binary variable for two reasons. First, employing the original dependent variable calls for an ordered probit estimation which is based on the proportional odds assumption and can be compared to a series of binary probit regressions. However, esti-

Figure 2.3: Overall distribution of bad experiences with interethnic contact



Notes: Responses of the final born sample, weighted with design and population weights. 11-point-scale variables are coded from (1) "extremely good experience" to (11) "extremely bad experience". Therefore, decreasing values represent better experience with interethnic contact.

mating binary regressions where less than 4 percent of the observations have the value one, such as the top five categories, is not recommended (Hamilton, 1992). Second, the focus of the analysis is to pool the respondents who have very positive experiences with interethnic contact. Thus, the quality of contact is recoded as a binary variable which takes the value zero if the original values are between 1 and 3, and otherwise the value 1. Therefore, using the basic set of covariates and the frequency of interethnic contact as predictors, a binary probit estimation is applied. The average marginal effects show that more interethnic contact significantly lowers the probability of bad experiences by 3.12 percent.[49] Thus, more interethnic contact or more ethnic heterogeneity leads, on average, to more positive experiences with interethnic contact. Hence, the predictions of the intergroup contact theory are valid.

2.6.3 Selective Out-Migration

Previous results show that interethnic contact is positively related to all attitudinal measures of both dimensions. Although natives' social distance from immigrants does not affect their preference for redistribution, two out of the three perceived outgroup threat measures have a significant impact. However, in order to detect the effect of interethnic contact on anti-immigrant attitudes of natives who are randomly assigned across regions with different immigrant population shares, the effect of interethnic contact must be measured before natives have sorted themselves into an area according

[49] Average marginal effects of all covariates are in Table 2.12 in the appendix of this chapter. Furthermore, instrumenting interethnic contact with the log of the immigrant population share in order to control for a bias due to selective out-migration or reverse causality (see next subsection) yields similar results.

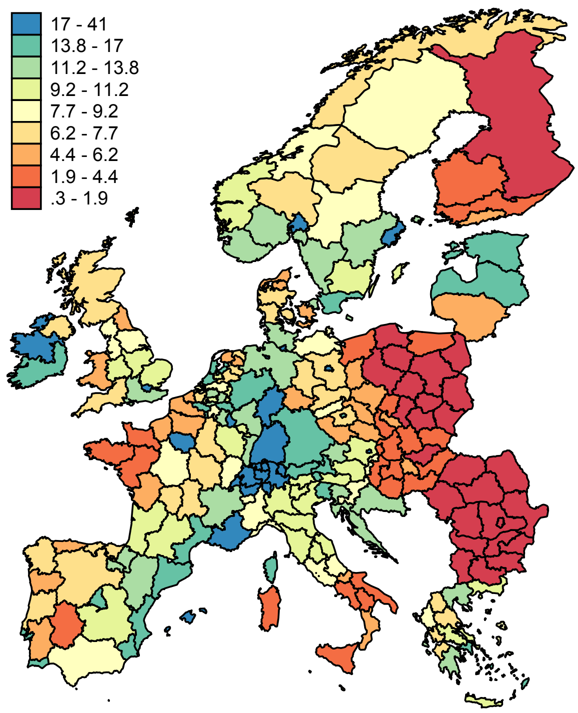
to their attitudes towards immigrants. Since immigrants' choice of residence is not random and mostly based on the location decision of previous generations of immigrants from the same country and on the labor market condition in a region, the estimated effects of interethnic contact could be biased by selective out-migration of natives (Card and DiNardo, 2000). The main issue is that the effect of interethnic contact on outgroup threats might be biased by natives' self-selection. Natives who have negative outgroup attitudes actively avoid interaction and contact with immigrants during everyday life and may leave their neighborhoods due to an inflow of immigrants in order to escape interethnic contact. In contrast, natives who have positive outgroup attitudes actively seek contact with immigrants and may stay in their neighborhood. In conclusion, there is reverse causality if the frequency of interethnic contact is determined by natives' attitudes towards immigrants.[50] The endogeneity problem can be addressed by using values of interethnic contact at higher levels of spatial aggregation as suitable instruments (Dustmann et al., 2011). Since interethnic contact in the neighborhood depends on the presence of immigrants, the actual ethnic heterogeneity at a higher level of spatial aggregation is a valid instrument. For this purpose, the share of immigrants at the NUTS level 2, which is calculated based on the 2011 Population and Housing Census, is used (European Commission, 2016).[51] The immigrant population shares vary widely across European countries as well as across NUTS level 2 regions within countries (see Figure 2.4). The region with the highest share is Brussels (70 percent) in Belgium and the region with the lowest share is Sud-Vest Oltenia (0.3 percent) in Romania. Additionally, the United Kingdom shows the largest variation of the immigrant population share across the NUTS level 2 regions, whereas Croatia has the smallest variation. Furthermore, the countries of the former Eastern bloc have relatively low immigrant ratios compared to the Western European countries. The two Baltic states, Latvia and Estonia, are an exception. This is due to the high proportion of ethnic Russians who were settled there in the Soviet era. Aside from that, the immigrant population share is generally higher in urban agglomerations than in rural regions of the European countries. Overall, the variation of the immigrant population shares across NUTS level 2 regions is sufficient to use them as an instrument for natives' interethnic contact in everyday life.

Here, the key idea is that natives who have negative outgroup attitudes will leave their neighborhood due to an increase in the number of immigrants, though they are more likely to migrate to areas that are relatively close in distance and have less immigrants, e.g. from cities to rural areas nearby, than to regions that are far away. Another reason for a restricted mobility out of a given geographical region could be the

[50] In most empirical studies, reverse causality is less pronounced (Powers and Ellison, 1995; Pettigrew and Tropp, 2006).

[51] For the estimations, the log of immigrant population share is used to reduce the effect of outlier values. The results are similar when the immigrant population share is used instead.

Figure 2.4: Immigrant population shares across European NUTS level 1/2 regions



Notes: For Germany and the United Kingdom, the NUTS level 1 regions are mapped. For all other countries, the NUTS level 2 regions are presented.

desire to remain in proximity to family, friends, and workplace. Dustmann and Preston (2001) show that such instruments reduce the bias induced by natives' self-sorting. Since the measure of interethnic contact is ordinal, the instrumenting equation is added as a latent variable model to the bivariate recursive probit model:

$$y_1^* = \boldsymbol{x}_1'\boldsymbol{\beta}_1 + \gamma \cdot y_2 + \epsilon_1\,, \qquad y_1 = m \quad \text{if} \quad \kappa_{m-1} \le y_1^* < \kappa_m \quad \text{for} \quad m = 1,\dots,4\,, \tag{2.15}$$

$$y_2^* = \boldsymbol{x}_2'\boldsymbol{\beta}_2 + \delta \cdot \psi + \epsilon_2\,, \qquad y_2 = 1 \quad \text{if} \quad y_2^* > 0, 0 \quad \text{otherwise}\,, \tag{2.16}$$

$$\psi^* = \boldsymbol{x}_3'\boldsymbol{\beta}_3 + \theta \cdot \text{impop} + \epsilon_3\,, \qquad \psi = r \quad \text{if} \quad \kappa_{r-1} \le \psi^* < \kappa_r \quad \text{for} \quad r = 1,\dots,7\,, \tag{2.17}$$

$$\left(\begin{matrix}\epsilon_1\\ \epsilon_2\\ \epsilon_3\end{matrix}\,\middle|\, \boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3, \text{impop}\right) \sim N\left[\begin{pmatrix}0\\0\\0\end{pmatrix}, \begin{pmatrix}1 & \rho_{12} & \rho_{13}\\ \rho_{12} & 1 & \rho_{23}\\ \rho_{13} & \rho_{23} & 1\end{pmatrix}\right],$$

where the errors ϵ_1, ϵ_2 and ϵ_3 are jointly normally distributed and may correlate, which is mirrored in the significance of the coefficients of correlation ρ_{12} , ρ_{13} and ρ_{23}. Furthermore, y_1^* and y_2^* are the latent endogenous variables of natives' preference for redistribution and perceived outgroup threats, respectively, whereas ψ^* is the latent endogenous variable of natives' interethnic contact. As in the bivariate recursive case, the dependent variable ψ^* can be carried as observed ψ into the equation of y_2^* with no special attention to its endogeneity. Moreover, the right-hand side of the third equation contains the full set of basic covariates, whereby $\boldsymbol{x}_1 = \boldsymbol{x}_2 = \boldsymbol{x}_3$ holds, and the immigrant population share at the NUTS level 2 (*impop*). In order to receive consistent and efficient estimates, full information maximum likelihood is applied. Since the full observed recursive probit model contains the simultaneous estimation of three equations, a modification of the Geweke-Hajivassiliou-Keane algorithm is implemented to compute higher-dimensional cumulative normal distributions (Geweke, 1989; Hajivassiliou and McFadden, 1998; Keane, 1994).[52] The obtained results are similar in magnitude and significance to the estimated parameters of the pure bivariate recursive probit estimations (see Table 2.7). This can be traced to the fact that the correlation coefficients (ρ_{23}) are insignificant for all three outgroup threat measures, thus ruling out the possibility of endogeneity due to selective out-migration. Since there is no significant correlation (ρ_{13}) between the instrumenting equation and the first outcome equation, the decomposition of the marginal effects can be done independently of the instrumenting equation and differs only slightly in the magnitude of the direct and indirect effects from the results thus far.

[52] See Roodman (2011) for a detailed explanation about the advantages and disadvantages of the modified Geweke-Hajivassiliou-Keane algorithm.

Table 2.7: Bivariate probit estimations of natives' preference for redistribution and outgroup threats controlling for selective out-migration

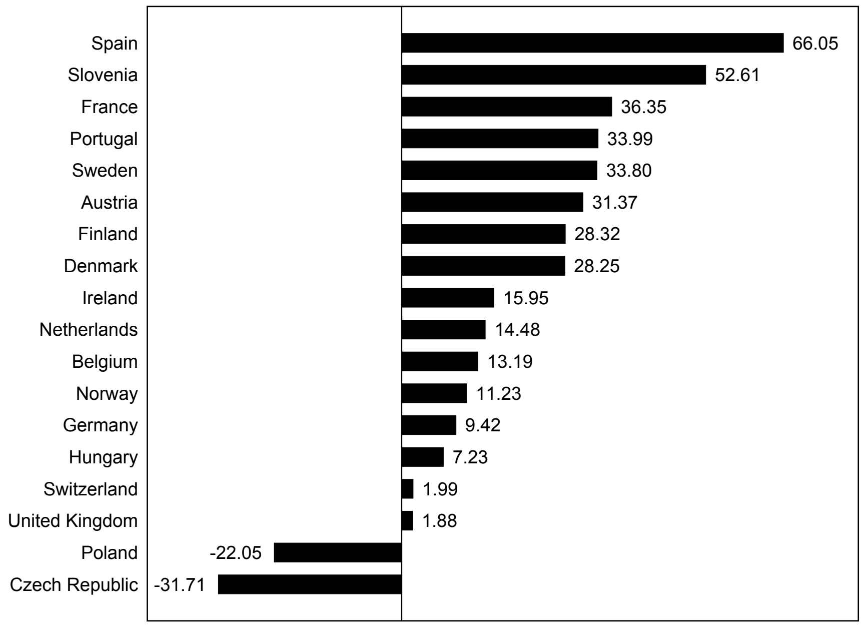
	Preference for Redistribution		Outgroup Threat		Interethnic Contact	
outgroup threat: culture undermined						
culture undermined	**-0.726**	**(0.163)*****				
interethnic contact			-0.078	(0.034)**		
immigrant population share					0.471	(0.030)***
atanh $\hat{\rho}_{12}$			0.431	(0.116)***		
atanh $\hat{\rho}_{23}$			0.017	(0.064)		
atanh $\hat{\rho}_{13}$			-0.018	(0.014)		
outgroup threat: social life worsens						
social life worsens	**-0.774**	**(0.117)*****				
interethnic contact			-0.083	(0.035)**		
immigrant population share					0.474	(0.030)***
atanh $\hat{\rho}_{12}$			0.440	(0.075)***		
atanh $\hat{\rho}_{23}$			0.063	(0.679)		
atanh $\hat{\rho}_{13}$			-0.005	(0.013)		
outgroup threat: crime problems worsen						
crime problems worsen	**-0.081**	**(0.212)**				
interethnic contact			0.029	(0.054)		
immigrant population share					0.472	(0.030)***
atanh $\hat{\rho}_{12}$			-0.032	(0.079)		
atanh $\hat{\rho}_{23}$			-0.119	(0.102)		
atanh $\hat{\rho}_{13}$			0.008	(0.013)		

Notes: The Born sample is employed and raw coefficients of the estimations are reported. In maximum likelihood estimation, ρ is not directly estimated, but atanh $\rho = 0.5 \cdot \ln((1+\rho)/(1-\rho))$ applies. Country fixed effects and basic set of covariates are included at every stage of estimation, but not reported. Standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

2.6.4 Ethnic Income Gap and Natives' Preference for Redistribution

Based on the results thus far, it has been shown that merely natives' perception of symbolic threats presented by immigrants have a direct negative influence on their support of redistribution. This could be attributed to the predictions of the conflict theory if a more intense competition for intangible goods, such as culture or social life, between the majority group and the ethnic minorities increases natives' solidarity towards their same-ethnic peers, but diminishes their solidarity towards outgroup members. In contrast, the constrict theory predicts that natives who have stronger anti-immigrant attitudes lower their solidarity towards both immigrants and same-ethnic fellows at the same time. One way to check the validity of this hypothesis is to investigate whether the effect of outgroup threats on natives' redistribution preference depends on the ethnic income gap. The ethnic income gap measures the difference in the average income of natives and immigrants at the country level. Thus, a positive ethnic income gap indicates that immigrants earn less than natives, whereas a negative ethnic income gap expresses that immigrants earn even more than natives. Hence, a decreased ethnic income gap represents a relative rise in immigrants' average standard of living in comparison to natives. According to the conflict theory, natives who take a negative attitude towards immigrants and live in countries with a greater ethnic income gap should lower their redistribution preference more than natives with similar circumstances who live in countries with a lower or even negative ethnic income gap. If the ethnic income gap increases, natives anticipate that immigrants benefit disproportionally from the governmental redistribution, since an immigrant's probability to be a net social benefit recipient increases. Among the European countries, there is some variation in the ethnic income gaps (see Figure 2.5).[53]

Figure 2.5: Ethnic income gap across European countries



Notes: Natives' and immigrants' average incomes are in purchasing power parity. The ethnic income gap is measures in percentage of immigrants' average income. For Switzerland and Hungary, data refer to 2013 and 2011, respectively. For all other countries, ethnic income gap is measured in 2014.

Spain shows the greatest ethnic income gap. Immigrants earn, on average, 66 percent less than an average native worker there. In turn, the Czech Republic and Poland are at the lower end of the ranking. There, immigrants' average income exceeds natives' average income by 22 to 32 percent. Thus, less governmental redistribution would disproportionally benefit the immigrants' net income in these countries. Since country fixed effects already capture both observable and unobservable country effects in the recursive probit models, additional country-level variables cannot be considered in the estimations. However, country-specific variables can be integrated into interaction terms with individual variables without taking the main effect into account. Thus,

[53]Ethnic income gaps are calculated using the average income of natives and immigrants in purchasing power parity to control for different cost of living and price levels across European countries. For the estimations, the log of the ratio between natives' and immigrants' average income is used to reduce the effect of outlier values. The results are similar when the ethnic income gap is used instead.

this empirical strategy fulfills the purpose of the analysis, since the major interest lies in determining whether the effect of natives' outgroup threat on their redistribution preference changes dependent on the extent of the national ethnic income gap. Therefore, an interaction term between the perceived outgroup threat and the ethnic income gap is added to the first outcome equation. Since there is no indication of selective out-migration, a bivariate recursive probit model is used without the instrumenting equation.[54] Taking a closer look at the raw coefficient estimates, the main terms of both outgroup threat measures, cultural threat and social life threat, are negatively significant and in their magnitude similar to previous results (see Table 2.8).

Table 2.8: Bivariate probit estimations of natives' preference for redistribution and outgroup threats taking the ethnic income gap into account

	Preference for Redistribution		**Outgroup Threat**	
outgroup threat: culture undermined				
culture undermined	-0.557	(0.170)***		
culture undermined x **ethnic income gap**	**-0.168**	**(0.146)**		
interethnic contact			-0.070	(0.009)***
ougroup threat: social life worsens				
social life worsens	-0.658	(0.126)***		
social life worsens x **ethnic income gap**	**-0.509**	**(0.189)*** **		
interethnic contact			-0.052	(0.010)***

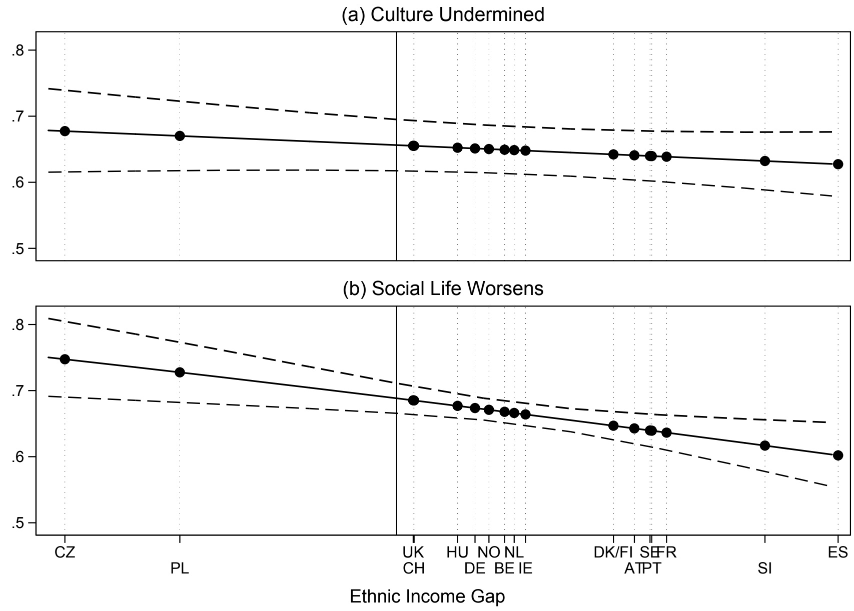
Notes: The born sample is employed and the raw coefficients of the estimations are reported. Country fixed effects and basic set of covariates are included at every stage of the estimations, but not reported. Standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

Using the threat to social life in the estimation, the interaction term between natives' outgroup threat and the ethnic income gap has a significantly negative impact on natives' preference for redistribution. Thus, a rise in the ethnic income gap strengthens the negative effect of natives' perceived threat to social life on their support of redistribution. Once a native perceives immigrants as a threat to social life, his or her preference for redistribution generally diminishes through the main effect of the perceived outgroup threat and decreases more strongly if the ethnic income gap rises. Thus, the effect of negative attitudes towards immigrants on natives' preference for redistribution is higher in countries that have a wide ethnic income gap than in countries that have a narrow ethnic income gap. Whereas a higher ethnic income gap entails that immigrants would benefit disproportionally from more governmental redistribution, the opposite is true for a negative ethnic income gap. Thus, a native's probability of a high preference for redistribution is, on average, 60.2 percent in Spain if he or she assesses immigrants as a threat to social life (see Figure 2.6).[55]

[54]Repeating the estimations using the full recursive probit model maintains similar results.

[55]Since the ethnic income gap is solely included within an interaction term and outgroup threat measures are binary, the latter are treated as continuous variables for the calculation of the probabilities. However, this procedure merely results in a small bias of the estimates.

Figure 2.6: Probability of a high preference for redistribution as a function of the ethnic income gap



Notes: The vertical solid line detects the zero value for the ethnic income gap, e.g. natives and immigrants earn, on average, the same income. Dashed lines show the 95 percent confidence boundaries. For Switzerland and Hungary, data refer to 2013 and 2011, respectively. For all other countries, ethnic income gap is from 2014. ES = Spain , SI = Slovenia , FR = France , PT = Portugal , SE = Sweden , AT = Austria , DK = Denmark , FI = Finland , IE = Ireland , NL = Netherlands , BE = Belgium , NO = Norway , DE = Germany , HU = Hungary , CH = Switzerland , UK = United Kingdom , PL = Poland , CZ = Czech Republic.

In contrast, a similar native who lives in Poland shows, on average, a probability of around 72.8 percent, since immigrants earn more than Poles, on average. However, the effect of perceived cultural threat on natives' support of redistribution subject to the ethnic income gap varies only slightly across the European countries. The values are between 62.7 and 67.7 percent, which points out that there is no significant difference in the probabilities of natives who perceive immigrants as a cultural threat depending on varying ethnic income gaps. In general, the results provide an illustrative test to what extent the conflict theory or the constrict theory occurs in reality. According to the constrict theory, the effects of the outgroup threat measures on natives' redistribution preference should not differ across various values of the ethnic income gap, since stronger outgroup threats should be associated with diminished solidarity towards both immigrants and same-ethnic peers. This is true for natives' perceived cultural threat, but not for natives' perceived threat to social life. Thus, the results do not provide clear evidence for the constrict theory, but rather evidence - although limited to one outgroup threat measure - for the conflict theory. Therefore, natives' negative attitudes towards immigrants may have opposing effects on the solidarity towards their same-ethnic peers and outgroup members, such as immigrants.

2.7 Conclusion

Immigration and ethnic heterogeneity are important in shaping national economic and social policies. They change the social environment of a country and may challenge essential societal values, such as trust and solidarity. In the literature, there are two notable theories which predict diametrically opposed effects of ethnic heterogeneity on societal values. Whereas the conflict theory predicts that ethnic heterogeneity erodes the basis for general solidarity and encourages natives to focus more strongly on their own ethnic group (ethnocentrism), the intergroup contact theory expects that ethnic heterogeneity reduce information gaps, prejudices, and stereotypes and also generate a higher solidarity towards foreign-born people. The empirical results confirm this hypothesis and show that more interethnic contact in everyday life is positively related to a native's attitudes towards immigrants. Thus, prejudices and stereotypes can be reduced through more social togetherness and the personal experience of ethnic heterogeneity. This applies to both natives' social distance from immigrants and natives' perceived threat to the norms and values of the majority society due to immigrants. In turn, an open-minded and tolerant attitude promotes natives' solidarity. Since solidarity towards fellow residents is an important driver of the individual preference for redistribution, there is a causal connection between interethnic contact via natives' attitudes towards immigrants and natives' preference for redistribution. In order to implement this connection, bivariate recursive probit estimations are applied. The results show that the social distance measures are not reflected in natives' demand for redistribution; however, natives' perceived threats to societal values due to immigrants have a significantly negative impact. If immigrants are perceived as a threat to the national culture and social life, a native's probability of a high preference for redistribution decreases by 6.4 percent and 8.2 percent, respectively. In contrast, if ethnic heterogeneity rises, this probability increases by 0.8 percent. These findings are maintained even after controlling for the possibility of natives' selective out-migration. Whether this reduction can be attributed to a selective decline in natives' solidarity towards immigrants or a decline in natives' solidarity towards all residents of the country remains open at first. Hence, adding the ethnic income gap to the estimations enables the testing of the constrict theory, which predicts that natives lower their solidarity towards both immigrants and same-ethnic peers once they take negative attitudes towards immigrants. Thus, the magnitude of the effect of perceived outgroup threats should not depend on the ethnic income gap. In contrast, the derived Meltzer and Richard (1981) model predicts that the negative effect of perceived outgroup threats should be stronger if immigrants benefit disproportionally from governmental redistribution. The results show that the predictions of the constrict theory are not valid. Natives who take negative attitudes towards immigrants show, ceteris paribus, a lower preference for redistribution if immigrants earn much less than natives in their respective country.

Appendix

Table 2.9: Summary statistics of basic covariates

	average	**standard deviation**
age	52.421	16.700
female	0.508	0.500
married	0.551	0.497
kids at home	0.367	0.482
household member	2.487	1.292
(sub-)urban	0.294	0.455
political orientation	5.939	2.182
education years	13.116	4.041
public sector	0.330	0.470
private sector	0.555	0.497
self-employed	0.092	0.289
other	0.022	0.148
employed	0.570	0.495
unemployed	0.051	0.221
not in labor force	0.378	0.485
household income	5.533	2.752
interethnic contact	4.515	2.100
Austria	0.049	0.216
Belgium	0.054	0.226
Czech Republic	0.055	0.228
Denmark	0.049	0.217
Finland	0.076	0.265
France	0.063	0.244
Germany	0.099	0.298
Hungary	0.048	0.214
Ireland	0.064	0.245
Netherlands	0.066	0.248
Norway	0.048	0.214
Poland	0.044	0.205
Portugal	0.038	0.191
Slovenia	0.035	0.184
Spain	0.045	0.207
Sweden	0.058	0.234
Switzerland	0.038	0.191
United Kingdom	0.071	0.257

Source: ESS 2014/2015. *Notes:* Responses of the final born sample, unweighted.

Table 2.10: Survey questions about attitudes towards immigrants

Attitudinal Dimensions	**Variable**	**Survey Question**	**Range of Responses**
Individual Concern (Social Distance)	Mind Marriage with Relative	Would you mind or not mind if someone like this (different race or ethnic group) married a close relative of yours ?	1: not mind at all 11: mind a lot
	Mind as Boss	Would you mind or not mind if someone like this (different race or ethnic group) was appointed as your boss ?	1: not mind at all 11: mind a lot
	Immigrant Friends	Do you have any close friends of a different race or ethnic group ?	1: no, none at all 2: yes, a few ; 3: yes, several
Societal Concern (Outgroup Threat)	Culture Undermined	Is cultural life generally undermined or enriched by people coming to live here from other countries ?	1: cultural life enriched 11: cultural life undermined
	Social Life Worsens	Is this country made a worse or better place to live by people coming to live here from other countries ?	1: better place to live 11: worse place to live
	Crime Problems Worsen	Are crime problems made worse or better by people coming to live here from other countries ?	1: crime problems made better 11: crime problems made worse

Notes: Questions about attitudes towards immigrants are based on original scaling of the European Social Survey, but ordering is partially reversed.

Table 2.11: Bivariate recursive probit estimations based on ordinal treatment of interethnic contact

	Social Distance Measures						**Outgroup Threat Measures**					
	preference for redistribution	*mind marriage with relative*	*preference for redistribution*	*mind immigrant as boss*	*preference for redistribution*	*immigrant friends*	*preference for redistribution*	*culture undermined*	*preference for redistribution*	*social life worsens*	*preference for redistribution*	*crime problems worsen*
mind marriage with relative	-0.177 (0.206)											
mind immigrant as boss			-0.109 (0.149)									
immigrant friends					0.063 (0.102)							
culture undermined							-0.686 (0.149)***					
social life worsens									-0.783 (0.114)***			
crime problems worsen											-0.106 (0.216)	
no contact at all						*reference*						
contact less than once a month		-0.186 (0.064)***		-0.083 (0.064)		-0.932 (0.076)***		-0.113 (0.071)		-0.005 (0.082)		-0.104 (0.126)
contact once a month		-0.165 (0.073)**		-0.036 (0.072)		-1.157 (0.083)***		-0.098 (0.081)		-0.090 (0.091)		-0.121 (0.134)
contact several times a month		-0.346 (0.061)***		-0.229 (0.061)***		-1.353 (0.075)***		-0.278 (0.068)***		-0.150 (0.075)**		-0.150 (0.124)
contact once a week		-0.270 (0.072)***		-0.156 (0.070)**		-1.345 (0.081)***		-0.186 (0.078)**		-0.180 (0.088)**		-0.039 (0.142)
contact several times a week		-0.436 (0.062)***		-0.378 (0.061)***		-1.447 (0.073)***		-0.308 (0.069)***		-0.195 (0.074)***		-0.120 (0.125)
everyday contact		-0.564 (0.061)***		-0.531 (0.060)***		-1.657 (0.074)***		-0.450 (0.070)***		-0.296 (0.074)***		-0.268 (0.125)**
atanh $\hat{\rho}$	0.098 (0.128)		0.075 (0.091)		-0.022 (0.065)		0.405 (0.103)***		0.447 (0.074)***		-0.021 (0.081)	
Obs.	18915		18915		18915		19405		19405		19405	
AIC	71,835.17		71,788.00		70,416.08		67,128.44		61,261.89		52,245.62	
BIC	72,415.90		72,368.73		70,996.81		67,726.81		61,860.26		52,843.99	
Log Likelihood	-35843.59		-35820.00		-35134.04		-33488.22		-30554.95		-26046.81	

Notes: The born sample is employed and raw coefficients of the estimations are reported. In maximum likelihood estimation, ρ is not directly estimated, but atanh $\rho = 0.5 \cdot \ln((1+\rho)/(1-\rho))$ applies. Country fixed effects and basic set of covariates are included at every stage of estimations, but not reported. Standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

Table 2.12: Binary probit estimation of bad experience with interethnic contact on the frequency of interethnic contact

age	-0.001	(0.000)**
female	-0.006	(0.011)
married	-0.016	(0.014)
kids at home	0.023	(0.017)
household member	-0.007	(0.008)
(sub-)urban	0.018	(0.012)
political orientation	-0.017	(0.003)***
education years	-0.009	(0.002)***
public sector	*reference*	
private sector	0.019	(0.013)
self-employed	-0.023	(0.021)
other	0.084	(0.035)***
employed	*reference*	
unemployed	0.009	(0.027)
not in labor force	0.017	(0.016)
household income	-0.008	(0.003)***
interethnic contact	**-0.031**	**(0.003)***

Notes: The born sample is employed and the average marginal effects of the estimation are reported. *Political orientation* is a measure of ideological self-assessment on an 11-point-scale, where 1 is "extreme right" and 11 is "extreme left". Country fixed effects are included, but not reported. Standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

3 Intergenerational Income Mobility in Germany and the United States

So far, it has been shown that the individual preference for redistribution consist of a financial self-interest component as well as a social component. Since the latter requires interdependent utilities, its fulfillment can be tied to the type of redistribution. In principle, governmental redistribution takes place within a country through in-kind and in-cash transfers. As already pointed out by Daly and Giertz (1972), the two types of transfers are based on the positive externalities in consumption and the utility of the other members of society, respectively. If the interdependency between contributors and recipients of the redistribution system is tied to a recipient's consumption of a particular good, contributors will prefer in-kind transfers more. However, in-cash transfers are sufficient if contributors' utility merely depends on the net income of recipients. In particular, the latter is decisive for the amount of a country's social subsistence, which commonly depends on the number of children in poor households. Thus, the contributors aim to improve the well-being of the poor and to support the human capital investments of poor families in their children, whereby the latter is supposed to ensure that children from poor households can leave poverty in the long run. This, in turn, begs an interesting question: how strongly are the incomes of parents and their children correlated with one another? Therefore, the following chapter examines intergenerational income mobility in Germany and the United States and substantiates the need for reforms in order to create more equality of opportunity in the education system, especially in Germany.[56]

[56]This chapter is based on joint work with Sarah Sauerhammer that appeared as Coban and Sauerhammer (2016).

3.1 Introduction

The rise in income inequality in many industrialized countries over the last three decades has brought the distribution of income back onto the agenda of policy makers and economic researchers. In the United States and Germany, the inequality of market incomes increased from around 44 to 51 Gini points between 1980 and 2010 (Solt, 2016). Thus, both countries experienced a similar growth in income inequality, despite strongly different institutional arrangements and regulations. Since the annual income inequality is merely an aggregated measure of the distribution of financial resources at a given time, a change in values does not imply that individuals' income positions are stationary. In contrast, citizens might still experience drastic movements among the income distribution over time. Closely related to the long-term development of income inequality is the intergenerational income mobility, which measures the ascents and descents of children relative to their parents' rank in the income distribution. Thus, this element examines the question of whether and to what extent children's income in their adulthood is determined by their family background. Put more simply: Do poor children become poor adults and vice versa?

In the empirical literature, intergenerational income mobility is commonly estimated by the *intergenerational income elasticity*, where a value of, e.g., 0.5 means that 50 percent of parents' income advantage or disadvantage is passed on to their children. Thus, if the parents' income is 10 percent higher than the average income in their generation, the expected income of their children is 5 percent higher than the average income in their own generation. Therefore, higher values for the intergenerational income elasticity imply a higher persistence of income positions across generations and thus a lower level of intergenerational income mobility. However, high intergenerational income persistence cannot generally be interpreted as a lack of equal opportunity. Instead, if children from high-income households have, on average, a stronger preference for human capital investment than children from low-income households, a higher intergenerational income elasticity occurs due to the distribution of preferences, which may or may not be inherited. The latter may be caused by the transfer of talents, abilities, or occupational choices within the family. However, within market economies, intergenerational inequalities that are driven solely by individual preferences and independent choices are mainly accepted (Roemer, 2004). In contrast, high intergenerational income persistence is indicative of a lack of equal opportunity if it is exogenously influenced by institutional conditions, credit market constraints for low-income households, or other social factors. In this case, intergenerational income persistence is economically inefficient because the talents and abilities of poor children remain unused.

A comparison of the existing literature on intergenerational income mobility shows that there are considerable differences across countries (Solon, 1999; Björklund and

Jäntti, 2009; Black and Devereux, 2011). Hence, the consensus estimate for the intergenerational income elasticity in the United States lies between 0.4 and 0.5 (Corak, 2006). Thus, in the international comparison, the United States is located towards the top of the ranking of intergenerational income persistence and has a rather lower level of intergenerational income mobility. Furthermore, France and Italy have similarly high values of 0.4 and 0.5 with respect to the intergenerational income elasticity, respectively (Lefranc and Trannoy, 2005; Mocetti, 2007; Piraino, 2007). In contrast, the Scandinavian countries exhibit very low elasticities between 0.2 and 0.3 (Nilsen et al., 2008; Hussain et al., 2009; Pekkarinen et al., 2009; Björklund et al., 2012). Germany is generally classified between the United States and the Scandinavian countries. The estimates obtained are of the order of approximately 0.2 to 0.3 (Vogel, 2006; Eisenhauer and Pfeiffer, 2008; Schnitzlein, 2009).

This study conducts a direct comparison of the structure and extent of intergenerational income mobility in Germany and the United States. Consistent with existing results, the intergenerational income elasticity is found to be higher in the United States than in Germany. When comparing intergenerational rank mobility, however, the results for the two countries are relatively similar. In terms of intergenerational income share mobility, greater differences exist between Germany and the United States. With each higher percentile, the income share mobility of the sons in Germany drops by a higher amount when compared to their fathers than in the United States. For both countries, the results of the quantile regressions provide no evidence of non-linearities. The final decomposition of intergenerational income inequality shows both greater income mobility and stronger progressive income growth for Germany than exists in the United States. Section 3.2 subsequently describes the data used and addresses some measurement issues in the approximation of lifetime income data. Section 3.3 gives some descriptive evidence on the income inequality in the parents' and children's generation. Various mobility measures are provided and estimated in Section 3.4. Finally, Section 3.5 includes several economic policy recommendations to increase intergenerational income mobility and is followed by a brief summary in Section 3.6.

3.2 Data and Measurement Issues

In order to be able to examine intergenerational income mobility empirically, suitable individual data are required for at least two generations. Long-term panel surveys of households that already capture information for children while they are still living in their parents' homes and continue into the older adult years are suitable for this purpose (Corak, 2006). For a country comparison, it is also necessary that the individual data used are reliable and highly comparable. Here, the survey design, the survey method, and the survey period are of importance. Thus, the Socio-economic Panel (SOEP) and the Panel Study of Income Dynamics (PSID) are utilized for Germany and for the United States, respectively. Both records collect information on all adult persons of a household and survey them repeatedly in the subsequent years. Thus, children who leave their parents' homes and establish their own households can continue to be covered over time. Both household surveys are part of the Cross-National Equivalent File (CNEF) project (Frick et al., 2007). This project offers a harmonized individual data set of the underlying national household surveys. In particular, it provides a reliable data basis for international comparisons of income, tax, and transfers. The individual annual income in the CNEF includes wages and salaries from both paid employment and self-employment as well as bonus payments, income from overtime, and profit sharing (Grabka, 2014; Lillard, 2013).

3.2.1 Measurement Error and Life-Cycle Bias

In order to measure lifetime income, all of a respondent's income data over the entire working life would be required.[57] However, with a long survey period, the number of people who continue to participate in the survey is reduced. This so-called panel mortality can correlate with particular socio-economic and demographic characteristics of the persons, such as the educational attainment, resulting in a relatively homogeneous longitudinal sample (Fitzgerald et al., 1998). In turn, if the properties of the selection are correlated with the individual income, the estimation parameters might substantially downward biased due to the so-called *panel attrition bias* (Solon, 1989, 1992).

Thus, lifetime incomes are approximated by means of annual income observations. However, these income data consist of a permanent as well as a transitory component (Solon, 1989, 1992; Zimmerman, 1992). The latter causes lifetime income to be determined with measurement errors. Thus, if parental income is approximated by income data from only one particular point in time, the classical errors-in-variables problem occurs (Wooldridge, 2010). This leads to a systematic downward bias of the estimated intergenerational income elasticity (*attenuation bias*). Solon (1992) proposes to utilize the average of five valid annual income estimates for the parental generation in order to reduce the variance of the fluctuating component. This procedure does not completely eliminate the bias, but can significantly reduce it.[58] Since the direction of the bias is known, an estimate of the intergenerational income elasticity can be interpreted as a lower bound for the true estimation parameter. In contrast, in the approximation of the children's lifetime income, measurement errors only lead to higher standard errors.

In addition, Haider and Solon (2006) point out that the approximation of child

[57]The lifetime income of a person generally includes both labor and capital income. Since in surveys the collection of information in capital income is associated with problems, here the concept of income refers to the labor income of a person

[58]The derivation of the attenuation bias as well as its magnitude are presented in the appendix of this chapter.

lifetime income depends on the chosen stage of life and propose to use the income information at the middle of a person's working age. Since individual income during the working life takes a hump-shaped function, the income at the beginning of the working life is lower, which underestimates the lifetime income of a person. Furthermore, differences in income between high- and low-skilled workers are smaller at the beginning of their working lives and increase over time. Thus, if incomes at the beginning of the working life are taken into account, the intergenerational income elasticity might be underestimated (*life-cycle bias*). This circumstance is verified by Böhlmark and Lindquist (2006) for Sweden and Brenner (2010) for Germany. For the United States, Haider and Solon (2006) show that for sons the age range between mid-30s and mid-40s produces a good approximation of the lifetime incomes. Schnitzlein (2016) uses the income of sons between 35 and 42 years of age for Germany.

3.2.2 Sample Definition

The selected samples from the SOEP and the PSID are defined congruently in order to ensure reliable comparability of the results. The analysis is based on data from the years 1984-2013. The individual annual labor income is used. The SOEP sample does not include imputed income data.[59] All income statements are deflated to 2010.[60] In order to be able to compare the results with the existing literature, annual real incomes of less than 1200 Euro or 1200 US dollar are not included in the estimates. To prevent a bias due to wage developments in East Germany after reunification, the analysis for Germany is limited to the persons who lived in West Germany in 1989 (Schnitzlein, 2009).

The generation of the parents is restricted to the income observations of the fathers and the generation of the children to the income observations of the sons.[61] Fathers' incomes are drawn from the period 1984 to 1993, from which at least five valid income observations must be available. The lifetime income of the fathers is approximated by the formation of the average of the annual incomes. Only income observations from the age of 30 to 55 years are considered. Thus, the fathers belong to the birth cohorts of the period from 1933 to 1958. The incomes of the sons are drawn from the years 2003-2013, during which time period at least one valid income observation must be available. Again, the lifetime income of the sons is approximated by the formation of

[59]Missing income statements are estimated in the SOEP with the help of personal and household characteristics as well as past income data (Frick et al., 2012). The CNEF-PSID features no imputed income data.

[60]For the SOEP, the Consumer Price Index and, for the PSID, the Consumer Price Index of All Urban Consumers and All Items based on the recommendation of Grieger et al. (2009) are utilized.

[61]This limitation is due to the divergent labor market participation of women in both countries, which can lead to a bias of differences in intergenerational income elasticity. While in the United States female labor market participation was at 52.6 percent in the 1980s and at 54.3 percent in the 2000s on average, Germany features values of 43.7 percent and 47.6 percent, respectively (World Bank, 2016).

the average of the annual incomes. Only incomes from the age of 35 to 42 years are taken into account. Thus, the sons belong to the birth cohorts of the period from 1961 to 1978, which do not overlap with the cohorts of their fathers. A total of 361 father-son pairs are thus recorded in the SOEP and 617 father-son pairs in the PSID (see Table 3.1). On average, the sons earn more than their fathers in both countries. In Germany

Table 3.1: The sons' and the fathers' income and age

	Father		**Son**		
	Mean	Std.Dev.	Mean	Std.Dev.	
SOEP					
Income	40391.86	19455.34	46779.53	27541.14	
Age	46.74	4.57	38.16	1.80	
Father-Son Pairs					*361*
PSID					
Income	63938.29	59018.93	66989.02	69295.17	
Age	43.74	5.45	37.86	1.87	
Father-Son Pairs					*617*

Source: SOEP (1984-2013), PSID (1984-2013)

the income of the sons is 15.8 percent higher, while in the United States it is only 4.8 percent higher than the income of the fathers. The average age of the fathers is mid-40s in both countries, older than that of the sons, whose average age is late 30s. The younger age of the sons also determines the higher variance in incomes.

3.3 Descriptive Evidence

Since the purpose of studying the intergenerational income mobility is to investigate the income position of sons within their own income distribution depending on their fathers' income, a natural starting point is the examination of the income inequality of both generations. Comparing the Gini coefficients of the fathers' generation with that of the sons' generation in Germany and the United States, it can be observed that they have increased in both countries over time (see Table 3.2). Whereas income inequality

Table 3.2: Income inequality of the fathers' and the sons' generation

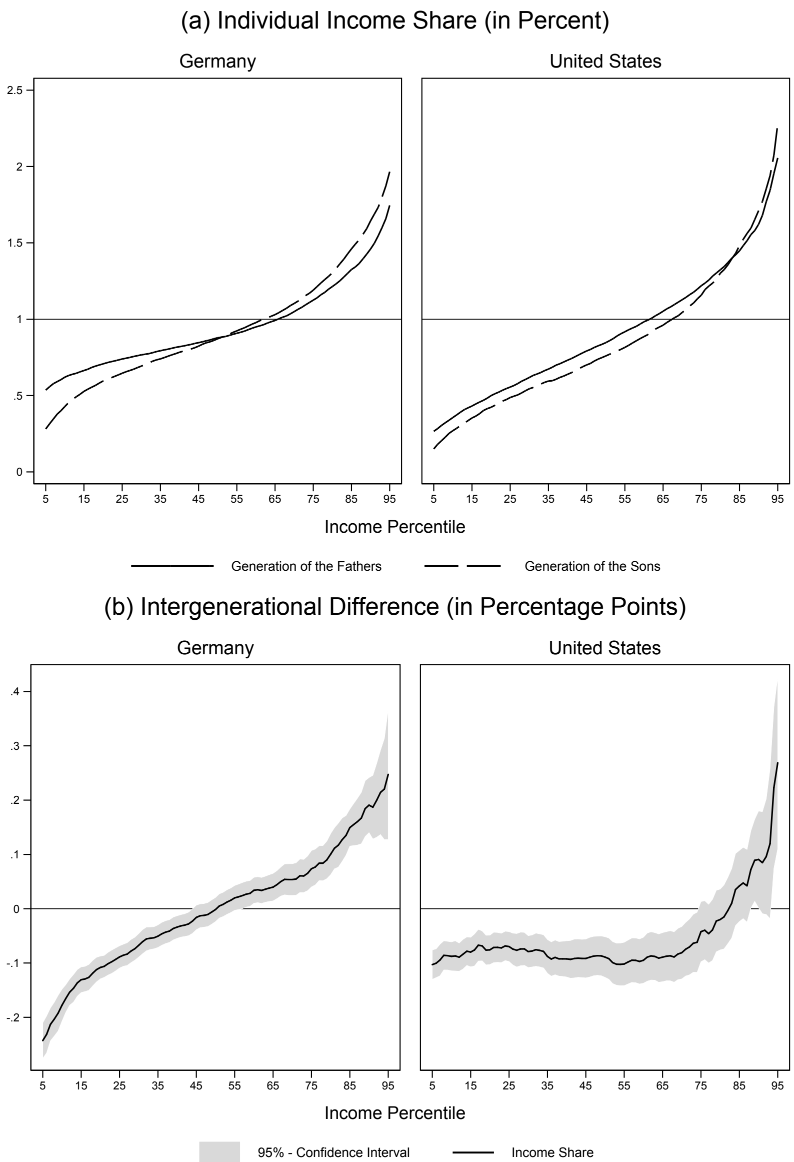
	Fathers' Generation (1984-1993)	**Sons' Generation (2003-2013)**
Germany	21.58	29.44
United States	33.48	41.32

Source: SOEP (1984-2013), PSID (1984-2013)
Notes: Income inequality is measured by the Gini coefficient and is based on unweighted data. A comparison with weighted values showed that the effects of panel mortality and selection bias are minor. The demarcations from Section 3.2 were applied, but were not limited to father-son pairs.

in the United States increased by 23.42 percent, income inequality in Germany rose by 36.42 percent.

There were both losers and winners as a result of this development along the income distribution (see Figure 3.1). The quantile curves for both countries (panel (a)) show the

Figure 3.1: Income share curves of the fathers' and the sons' generation



Source: SOEP (1984-2013), PSID (1984-2013)
Notes: Confidence intervals have been estimates using paired bootstrap resampling with 1000 replications.

share of the total income covered by the respective percentile of the income distribution. Percentiles with values greater than one claim a disproportionately higher share of the total income for themselves. The quantile curve assumes a slightly s-shaped run in Germany, while the United States exhibit a strongly convex curve. In Germany, fathers from the 65th percentile and sons from the 62nd percentile possess a disproportionate share of total income. In the United States, fathers from the 61st percentile and sons from the 67th percentile receive a disproportionate share of the total income. Thus, the two countries do not differ much with regard to the proportionality limit. However, the empirical picture changes when considering the top percentile. The top 1 percent of income earners in Germany receive 3.8 percent (fathers) and 4.4 percent (sons) of the total income, while in the United States these values are found to be 6.1 percent (fathers) and 9.1 percent (sons).[62] The quantile curves of the two generations intersect at the 51st percentile in Germany and at the 83rd percentile in the United States.

The rising income inequality means that in Germany, just over half of the individuals from the sons' generation are poorer compared to those from the fathers' generation, and in the United States, this share even reaches four-fifths of the sons' generation (panel (b)). Measured in percentage points, the lower percentiles of the sons' generation must accept greater losses in Germany than in the United States. The percentile with the greatest loss in Germany loses 62.76 percent in comparison to the percentile of the fathers' generation, while the maximum loss in the United States is 43.23 percent. Thus, on the one hand, the drop at the lower end of the income distribution in Germany is stronger than in the United States. On the other hand, the share of losers in the total population in the United States is greater than in Germany.

Moreover, the logarithmized incomes of the fathers and sons exhibit a positive correlation (see Figure 3.2). The slope of the line of best fit from the bivariate ordinary least squares (OLS) regression is higher for the United States than for Germany. However, it also becomes clear that the income data points in both countries are heavily scattered around the regression line. In order to examine the simple linear relationship more closely, a bivariate Nadaraya-Watson estimation is employed and illustrated.[63] Both countries show deviations compared to the OLS estimation, but the 95 percent confidence intervals include the OLS regression line over nearly the entire distribution of paternal income. From the bivariate evidence, therefore, it cannot be concluded that the intergenerational income elasticity changes significantly along the income distribution of the fathers.

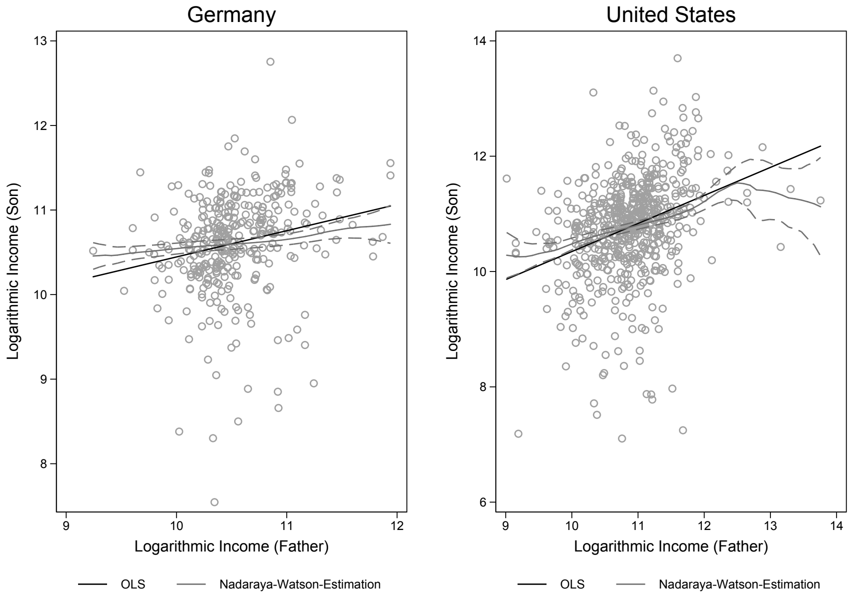
3.4 Empirical Results

There are different ways to measure and to estimate the intergenerational income mobility. On the one hand, the mobility can be expressed in terms of the correlation

[62]The analysis of the top incomes in the SOEP and the PSID should be treated with caution, since high-income earners are systematically less likely to provide information about their income. The values can thus be biased downwards and are to be regarded as a lower limit for the true parameter.

[63]The Nadaraya-Watson-Estimation is a non-parametric estimation method in order to determine the correlation between two variables by means of the conditional kernel density functions. Furthermore, linearity in parameters is postulated to estimate the intergenerational income elasticity. However, estimation moves a fixed window along the conditional density function of the dependent variables.

Figure 3.2: Intergenerational income correlation



Source: SOEP (1984-2013), PSID (1984-2013)
Notes: The Nadaraya-Watson estimation uses the Epanechnikov kernel with bandwidth based on a rule of thumb according to Silverman (1986). Dashed lines represent the 95 percent confidence intervals of the Nadaraya-Watson estimations. OLS: Ordinary Least Squares estimation.

in absolute incomes between the generations. On the other hand, it can be examined how strongly the relative incomes or the income positions of the fathers and the sons are associated with one another. Both measures and estimations are closely linked, but focus different aspects of the intergenerational income mobility. In the following, a detailed analysis of the intergenerational income mobility with the breakdown of the various measures and with respect to non-linearities among the income distribution is given.

3.4.1 Intergenerational Income Elasticity

The relationship between parents' lifetime income and their children's lifetime income is based on the model of the family according to Becker and Tomes (1979, 1986). The starting point is a family which maximizes its utility over two generations, dividing its disposable income between consumption and investments in the human capital of its children. Solon (2004) simplifies this approach in order to rationalize the intergenerational income elasticity usually estimated in empirical studies by

$$y_i^c = \beta_0 + \beta_1 y_i^p + \epsilon_i^c \,, \tag{3.1}$$

where y_i^c and y_i^p represent the logarithmic lifetime income of the son and his father for each family i, respectively.[64] The intercept β_0 yields the average lifetime income in the generation of the son, and the slope β_1 is the intergenerational income elasticity. As the incomes are logarithmized, the slope parameter gives the average percentage increase in the son's lifetime income if his father's lifetime income increases by 1 percent. Thus, the income of the son is independent of his father's income and takes the average value of his generation if β_1 equals zero. The higher the value of β_1, the stronger the link between the lifetime income of a father and his son is, and consequently, the lower the intergenerational income mobility. Furthermore, β_1 can be interpreted as the correlation between the lifetime incomes of the two generations if the variance of the fathers' and sons' lifetime incomes is approximately equal (Solon, 2004; Angrist and Pischke, 2009):

$$\beta_1 = \frac{\mathrm{Cov}\left(y_i^c, y_i^p\right)}{\mathrm{Var}\left(y_i^p\right)} = \frac{\mathrm{Cov}\left(y_i^c\right)}{\sqrt{\mathrm{Var}\left(y_i^p\right)}\sqrt{\mathrm{Var}\left(y_i^c\right)}} = \rho_{y^p y^c} \,, \tag{3.2}$$

$$\beta_0 = \mathrm{E}\left(y_i^c\right) - \beta_1 \mathrm{E}\left(y_i^p\right) = \mu_y\left(1-\beta_1\right) = \mu_y\left(1-\rho_{y^p y^c}\right) \,, \tag{3.3}$$

where $\rho_{y^p y^c}$ yields the intergenerational income correlation and $\mu_y = \mathrm{E}(y_i^c) = \mathrm{E}(y_i^p)$ gives the average lifetime income in both generations. Thus, the conditional expectation function can be expressed by

$$\mathrm{E}\left(y_i^c \middle| y_i^p\right) = \mu_y\left(1-\rho_{y^p y^c}\right) + \rho_{y^p y^c} y_i^p \,, \tag{3.4}$$

whereby the son's lifetime income equals, given his father's lifetime income, the weighted average of his father's lifetime income and the average lifetime in the generation of the son. In turn, this implies that sons of rich families will not be as rich as their fathers and vice versa.[65] In the empirical research, the sons' and fathers' income data are usually measured at different times of life and the number of valid observations varies between respondents. In order to control for both aspects, the vector $\boldsymbol{x_i}$ which includes polynomials of the sons' and father's average age and the number of valid observations of the son is added to the estimation (Schnitzlein, 2016):

$$y_i^c = \beta_0 + \beta_1 y_i^p + \boldsymbol{\gamma x_i'} + \epsilon_i^c \tag{3.5}$$

If the samples of the two countries are limited to the observed father-son pairs, the simple intergenerational income elasticity can be determined using bivariate OLS estimations. For Germany, a value of 0.310 is obtained, while in the United States, the value is 0.486 (see Table 3.3). According to this, 31 percent and 49 percent of the

[64] Since the present study is limited to father-son pairs, the term 'child' or 'kid' always refers to sons and the term 'parent' refers to fathers.

[65] Galton (1886) already discovered this peculiarity in his study on the intergenerational correlation of the body size and described it as a *regression towards mediocrity in hereditary stature*.

Table 3.3: OLS estimation of intergenerational income elasticity

	Germany				United States			
Father's Log. Income	0.310	(0.081)***	0.316	(0.079)***	0.486	(0.068)***	0.455	(0.069)***
Son's Age			0.263	(1.253)			-1.392	(1.201)
Sons's Age^2			-0.003	(0.016)			0.019	(0.016)
Father's Age			-0.022	(0.121)			0.022	(0.099)
Father's Age^2			0.000	(0.001)			0.000	(0.001)
Son's Obs.			0.028	(0.027)			0.146	(0.054)***
Obs.	361		361		617		617	
R^2	0.044		0.071		0.104		0.139	

Source: SOEP (1984-2013), PSID (1984-2013)
Notes: Estimates for the SOEP are based on non-imputed data. The intergenerational income elasticities are determined for an annual lower income limit of 1200 Euro/US-Dollar. Standard errors are clustered at family level and calculated using paired bootstrapped resampling with 1000 replications. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

father's income advantage or disadvantage is passed on to the son in Germany and the United States, respectively. Taking into account the polynomials of the average age of the fathers and the sons, as well as the number of valid observations for the sons, the estimates for the intergenerational income elasticity change only slightly.[66] Therefore, we can assume that the selected age limits are correctly selected. The intergenerational income elasticity is thus higher in the United States than in Germany.[67]

The above estimates include observations with earned incomes of at least 1200 Euro/US dollar per year. Because such a low income is not sufficient for the survival of a single individual in either country without additional income sources or social transfers, the estimates are repeated for income floors of 6000 Euro/US dollar and 12000 Euro/US dollar per year (see Table 3.4).[68] For Germany, the estimates were conducted both with and without imputed income data. The two countries show different developments

[66] Considering birth cohorts of fathers and sons, the intergenerational income elasticity changes to 0.340 in Germany and 0.453 in the United States (see Table 3.8 in the appendix of this chapter). A reduction of the sample to fathers born after World War II yields a value of 0.332 for Germany and a value of 0.510 for the United States (see Table 3.9 in the appendix of this chapter). Thus, depending on the selected sample the results vary slightly, but the United States consistently exhibit a higher intergenerational income elasticity.

[67] There could be distortions in the estimates of the intergenerational income elasticity despite of the consideration of fathers' and sons' age in the estimations if sons and fathers have, in general, divergent age-income profiles (Fertig, 2003). However, the bootstrapped Hausman-tests show for Germany (χ^2 = 0.097) and the United States (χ^2 = 2.05) that the estimates of the intergenerational income elasticity based on the age-adjusted lifetime incomes that were separately estimated for the fathers and the sons are not significantly different from the estimates of the intergenerational income elasticity based on the age-adjusted lifetime incomes that were jointly estimated for the fathers and the sons. The procedure to detect distortions in the estimates due to different age-income profiles is given in the appendix of this chapter.

[68] Estimations including periods of unemployment do still exhibit significant differences in the intergenerational income elasticity in Germany and the United States after adjusting for influential observations according to Belsley et al. (1980). The estimation results are given in Table 3.10 in the appendix of this chapter.

Table 3.4: Intergenerational income elasticity for different lower income limits

	United States	**Germany** *Without imputed Income Data*	*With imputed Income Data*
	Panel A: Income > 1200 Euro / 1200 US-Dollar		
IGE	0.455	0.316	0.294
	(0.069)***	(0.079)***	(0.077)***
Obs.	617	361	401
R^2	0.139	0.071	0.074
	Panel B: Income > 6000 Euro / 6000 US-Dollar		
IGE	0.450	0.323	0.345
	(0.061)***	(0.073)***	(0.069)***
Obs.	599	355	396
R^2	0.169	0.101	0.122
	Panel C: Income > 12000 Euro / 12000 US-Dollar		
IGE	0.415	0.357	0.363
	(0.061)***	(0.069)***	(0.071)***
Obs.	570	344	385
R^2	0.156	0.128	0.146

Source: SOEP (1984-2013), PSID (1984-2013)
Notes: Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1000 replications. Other control variables include: polynomials for the father's age and the son's age, and the number of valid observations of the son. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent. IGE: Intergenerational income elasticity.

of intergenerational income elasticity. While the intergenerational income elasticity in the United States decreases with a rising lower income limit, the corresponding value increases in Germany for both non-imputed and imputed income data. In the United States, the estimated value drops from 0.455 to 0.415. In Germany, the value increases from 0.316 to 0.357 without imputed incomes and from 0.294 to 0.363 with imputed incomes. Thus, the gap between the United States and Germany is shortened by an increase in the income limit, even though the United States exhibit stronger intergenerational income elasticities across all lower income limits. Since an increasingly larger piece is cut off at the left-hand side of the income distribution with an increasing lower income limit, the estimates provide initial evidence that the intergenerational income elasticity may differ along the income distribution.

3.4.2 Rank Mobility and Income Share Mobility

The intergenerational income elasticity measures the absolute income movements between two generations and thus provides a comprehensive measure for income mobility. However, it is not possible to make statements on the precise upward or downward mobility of the sons in comparison with their fathers. Transition matrices illustrate how strongly the income position of the son depends on the income position of his father. More specifically, each value indicates the probability of a son to reach a certain quantile within his own income distribution, depending on his own father's quantile affiliation. If both generations are divided into quintiles, all the cells in a completely mobile society should assume a value of 0.2.[69] The income position of the son is then independent of the income position of his father. In a completely immobile society, on the other hand, the main diagonal assumes a value of one with a value of zero being assigned to all remaining cells. In this case, the income position of the son can be perfectly predicted from the quintile affiliation of the father. The sons occupy the exact positions of their fathers along the income distribution.

Along the main diagonals, Germany and the United States differ more strongly from one another only in the lowest quintile (see Table 3.5).[70] In the United States, the probability of a son whose father is located in the lowest quintile remaining in that quintile is 37.12 percent, whereas in Germany the probability is 30.71 percent. In the United States, it is thus more difficult for sons from the lowest quintile to leave this income position. However, the upward mobility of sons from the higher quintiles is more pronounced in the United States. Consequently, the downward mobility of the sons from the upper quintiles in the United States is slightly lower. Overall, intergenerational persistence is higher at the upper and lower end of the income distribution in the United States than in Germany, although the differences between the two countries are not very pronounced.

Although estimated transition matrices measure the movements between broad income groups, they cannot illustrate movements of the sons within a certain quintile. The intergenerational rank mobility

$$IRM_i^c = \psi_i^c - \psi_i^p$$

provides another way to determine upward and downward mobility in more detail and measures the absolute change in a son's income rank ψ_i^c compared to his father's income rank ψ_i^p (Bratberg et al., 2017). A further advantage of this measure is its robustness to measurement issues, since the ranking of incomes eliminates outliers at both ends of the income distribution (Nybom and Stuhler, 2015). Combining the intergenerational rank mobility and the long-term development of income inequality enables a more detailed comparison of the intergenerational mobility across countries. Hence, some

[69]Since income quantiles are an ordinal variable, the transition probabilities of the sons are estimated using ordered logistic regressions (Schnitzlein, 2009; Fertig, 2003). Subsequently, the estimated transition probabilities are averaged over the entire sample.

[70]Full estimation results of the ordered logistic regressions are given in Table 3.11 in the appendix of this chapter

Table 3.5: Estimation of transition probability matrices

Germany

Income Quintile (Father)	**Income Quintile (Son)** 1	2	3	4	5
1	**30.71**	23.11	20.53	15.59	10.06
2	28.35	**22.65**	21.12	16.73	11.16
3	16.89	18.03	**22.15**	23.18	19.75
4	13.74	15.91	21.44	**25.02**	23.90
5	8.42	11.23	18.15	27.06	**35.13**

United States

Income Quintile (Father)	**Income Quintile (Son)** 1	2	3	4	5
1	**37.12**	22.63	18.76	13.09	8.40
2	24.32	**20.41**	21.80	19.00	14.48
3	15.72	16.30	**21.61**	23.78	22.59
4	12.09	13.73	20.28	**25.57**	28.32
5	8.32	10.39	17.46	26.45	**37.39**

Source: SOEP (1984-2013), PSID (1984-2013)
Note: The tables include the estimated average probabilities from the ordinal logistic regressions of the income position of the sons, conditioned to the income position of their fathers. The income positions of fathers and sons are based on the unweighted income distribution of their respective generation. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1000 replications. Other control variables include: polynomials for the father's and son's age and the number of valid observations for the son.

countries might show similar values of their intergenerational income elasticity, but differ strongly in their long-term annual income inequality. The intergenerational rank mobility takes both patterns into account, since a higher annual income inequality hampers an income earner's likelihood to move among the income distribution due to the larger income intervals of particular ranks.

Intergenerational income share mobility (ISM), in turn, is a hybrid measure that reflects both the absolute and the relative mobility of sons. For this purpose, the absolute incomes of sons and fathers are scaled to the average income of their own generations. The difference forms the hybrid measure

$$ISM_i^c = \frac{y_i^c}{\mathrm{E}(y^c)} - \frac{y_i^p}{\mathrm{E}(y^p)}$$

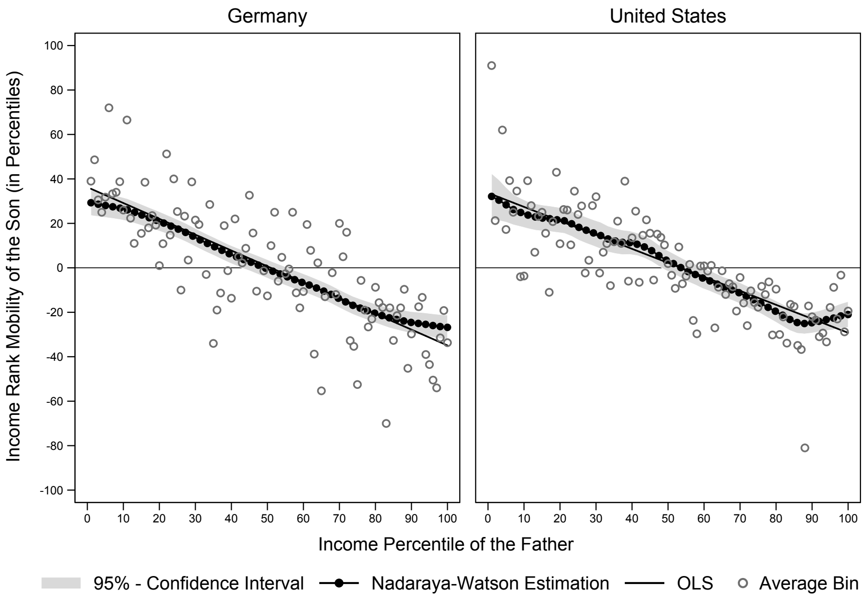
and is equal to the change of the share of a family in the total income, where $\mathrm{E}(y^g)$, $g = c, p$, is the expected or average lifetime income of sons and fathers, respectively. Thus, the intergenerational income share mobility is suitable for measuring family-income changes between multiple generations. The estimation of intergenerational rank mobility and intergenerational income share mobility is carried out with the aid of non-parametric mobility curves with the respective OLS estimator being used as a benchmark (Aaberge and Mogstad, 2014):

$$IRM^c(\psi^p) = \mathrm{E}\left(\psi_i^c - \psi_i^p \mid \psi_i^p = j, \boldsymbol{x_i}\right) \qquad \forall j = 1, 2, \ldots, 100 \tag{3.6}$$

$$ISM^c(\psi^p) = \mathrm{E}\left(\frac{y_i^c}{\mathrm{E}(y^c)} - \frac{y_i^p}{\mathrm{E}(y^p)} \,\middle|\, \psi_i^p = j, \boldsymbol{x_i}\right) \qquad \forall j = 1, 2, \ldots, 100\,. \tag{3.7}$$

The intergenerational mobility curves provide information on how the mobility of sons varies along the income distribution of the fathers (Bhattacharya and Mazumder, 2011; Chetty et al., 2014; Mazumder, 2014).[71] The intergenerational rank mobility curve measures how many percentiles the son ascends or descends dependent on the income position of his father (see Figure 3.3).[72] The intergenerational mobility curves

Figure 3.3: Mobility curves of income rank mobility



Source: SOEP (1984-2013), PSID (1984-2013)
Notes: The Nadaraya-Watson estimation uses Epanechnikov kernel with bandwidth based on a rule of thumb according to Silverman (1986). The gray shaded areas indicate the 95 percent confidence intervals of the Nadaraya-Watson estimations. OLS: Ordinary Least Squares estimation.

[71] A commonly applied alternative to the intergenerational rank mobility curve is the estimation of the intergenerational rank-rank association or rank persistence (Chetty et al., 2014; Dahl and DeLeire, 2008)

$$\psi_i^c = \beta_0 + \beta_1 \psi_i^p + \epsilon_i^c\,,$$

where β_1 yields the extent of ranks the son, on average, move up or down if his father's rank increases by one rank.

[72] According to Chetty et al. (2014), the rank persistence stabilizes at the age of 30. Mazumder (2014) shows that by the age of 40, the rank persistence in the PSID no longer exhibits downward bias. Thus, by limiting the sample, both requirements are met.

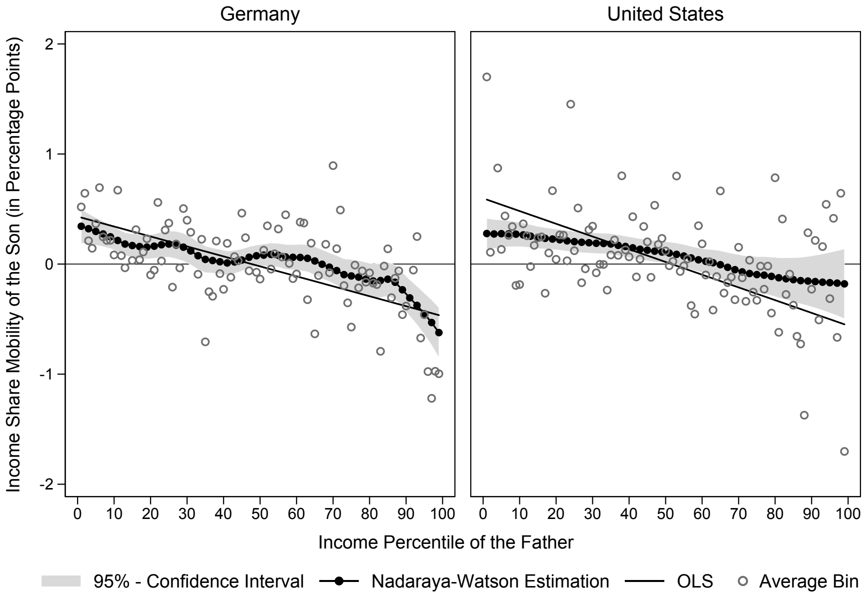
show a negative slope. According to this, the son's upward mobility decreases with the father's increasing income position. The OLS estimates of the income rank mobility are -0.708 for Germany and -0.648 for the United States.[73] Thus, if the father's income position increases by one percentile, this leads to a reduction of the son's absolute rank mobility by 0.708 percentiles in Germany and 0.648 percentiles in the United States. Sons whose fathers rank in the lowest five percentiles ascend on average by 32-35 percentiles in Germany and by 31-33 percentiles in the United States. Sons whose fathers rank in the highest five percentiles descend on average by 31-34 percentiles in Germany and by 26-29 percentiles in the United States. Thus, upward and downward mobility of the sons at the ends of the paternal income distribution exhibit similarly high values in Germany. In the United States, the downward mobility at the upper end of the paternal income distribution is lower than the upward mobility at the lower end. Therefore, also regarding intergenerational rank mobility, Germany is more mobile than the United States. Significant downward mobility is observed in Germany from the 55th percentile and in the United States from the 57th percentile of the parental income distribution. Comparing the OLS estimates with the Nadaraya-Watson estimation, it can be concluded for both countries that there is no evidence of non-linearities in the development of rank mobility along the income distribution of the fathers.

The intergenerational income share mobility measures the change in a family's share of the total income of the society over two generations. The corresponding intergenerational mobility curve indicates the change dependent on the income position of the father (see Figure 3.4). The incomes of the sons who have the same father were averaged to ensure an intergenerational family comparison. As the father's income percentile increases, the income share mobility of the son decreases. Although the effect of the paternal income percentile is significant, the OLS estimator is relatively small. If the father's income position rises by one percentile, this results in a reduction of the son's income share mobility by 0.9 percentage points in Germany and 1.2 percentage points in the United State.[74] Thus, the United States are more mobile regarding intergenerational income share mobility than Germany. The income share of the sons whose fathers rank in the lowest five percentiles increases by 39-42 percentage points in Germany and by 54-59 percentage points in the United States. The income share of the sons whose fathers rank in the top five income percentiles is 42-47 percentage points lower in Germany and 50-56 percentage points lower in the United States compared to their fathers. Thus, the sons at the upper end of the paternal income distribution in Germany lose more income shares than the sons at the lower end of the income distribution gain. In the United States, this is reversed.

In comparison to intergenerational rank mobility, the intergenerational income

[73] Full estimation results are given in Table 3.12 in the appendix of this chapter.
[74] Full estimation results are given in Table 3.13 in the appendix of this chapter.

Figure 3.4: Mobility curves of income share mobility



Source: SOEP (1984-2013), PSID (1984-2013)
Notes: The Nadaraya-Watson estimation uses Epanechnikov kernel with bandwidth based on a rule of thumb according to Silverman (1986). The gray shaded areas indicate the 95 percent confidence intervals of the Nadaraya-Watson estimations. OLS: Ordinary Least Squares estimation.

share mobility tends to exhibit non-linearities in both countries. For Germany, the Nadaraya-Watson estimator deviates significantly from the OLS estimator between the 60th and 85th percentile. In particular, the sons from the highest decile of the paternal income distribution experience an abrupt reduction in income share mobility. The empirical picture of the United States suggests that the OLS estimator overestimates intergenerational income share mobility due to outliers at the two endings of the fathers' income distribution. The Nadaraya-Watson estimator smooths these outliers and provides evidence that the intergenerational income share mobility in the United States is on average only 0.5 and is therefore below the German value. Thus, the United States preserve the distribution of total income to the families over two generations more strongly than Germany does.

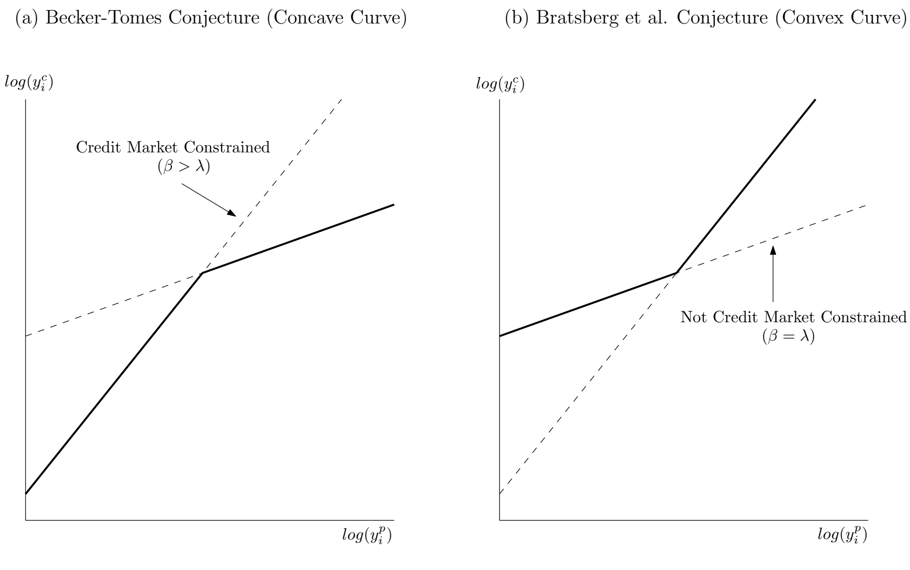
3.4.3 Non-Linearities in Intergenerational Income Elasticity

Thus far it has been postulated that the relationship between the father's income and that of the son is linear, i.e. the intergenerational income elasticity is constant along the entire income distribution of the sons. If, however, non-linearities exist, the influence of paternal income on the economic success of the sons changes along the income distribution. Becker and Tomes (1986) already pointed out that the intergenerational income elasticity can take a concave shape when poor fathers experience credit market constraints that do not apply for rich fathers. The intergenerational income elasticity will then be less pronounced for more affluent families, since the intergenerational income mobility of sons from rich families depends solely on the non-monetary transfer within the family and poorer families invest less than optimal in the human capital of their children (Grawe and Mulligan, 2002). A convex run of the intergenerational income elasticity can be observed if education policy and institutions of the country are designed in such a way as to ensure a basic level of human capital for all sons, regardless of their fathers' level of income. Beyond the socially guaranteed level, credit market constraints remain in place, such that the total amount of human capital investment in the son is again dependent on paternal income (Bratsberg et al., 2007). Consequently, the intergenerational income elasticity among poor families will be lower than among rich families.[75] The equilibrium intergenerational income elasticity

$$\beta = \frac{\lambda + r\theta}{1 + \lambda r\theta} \qquad , \lambda < 1 \, , \tag{3.8}$$

enables the presentation of both cases, where λ is the share of father's human capital which is passed to the son independent of the paternal income. Furthermore, θ and r yield the marginal utility and return of the paternal human capital investment in the child, respectively.[76] Using different values of the equilibrium parameters enables the illustration of the concave and convex case (see Figure 3.5). In the special case

Figure 3.5: Nonlinear intergenerational income elasticity functions



Source: According to Bratsberg et al. (2007), own illustration.

of a meritocratic education system or perfect capital markets, the intergenerational income elasticity equals to the non-monetary, intra-family transfer of human capital ($\beta = \lambda$), since the sons' human capital is independent of their parents' investment

[75]This situation can be accounted for by the fact that the optimal human capital investment of the fathers grows with the increasing talent of the sons (Han and Mulligan, 2001; Grawe and Mulligan, 2002).
[76]In contrast to Solon (2004), public human capital investments are not considered in the equilibrium.

($\theta = 0$). Once the sons' human capital and the parental investment correlates ($\theta > 0$), the intergenerational income elasticity will be higher ($\beta > \lambda$). Thus, the concave case occurs, when poor fathers experience credit market constraints ($\beta > \lambda$) that do not apply for rich fathers ($\beta = \lambda$). In contrast, the intergenerational income elasticity takes a convex function, when credit market constraints are merely binding for rich fathers ($\beta > \lambda$) but not binding for poor parents due to the public education system ($\beta = \lambda$). Countries with a largely public education system will therefore likely exhibit a convex shape of the intergenerational income elasticity. In countries with high privatization of the education system, a concave shape is presumed. In 2013, the share of private spending in the education system in Germany amounted to 13.5 percent and in the United States to 31.8 percent (OECD, 2016). If credit market constraints exist on top of this, the curve of intergenerational income elasticity should assume a convex shape in Germany and a concave shape in the United States. However, if the income of the father correlates with the unobservable talent of the son, a concave run of intergenerational income elasticity does not necessarily have to be driven by credit market constraints. In this case, poor fathers, regardless of whether credit market constraints exist, will reduce investments in their sons as a result of a lower expected human capital return, resulting in a concave curve (Grawe, 2004). Likewise, a convex shape of intergenerational income elasticity is not a clear indication for credit market constraints. The relationships can be triggered by institutional, social, or unobservable circumstances which influence poor and rich families in different ways.

In order to assess a non-linear relationship, estimates along the income distribution of the sons are necessary. The empirical literature with respect to non-linearities is mixed for both Germany and the United States. Lillard (2001) and Couch and Lillard (2004) find evidence of a non-linear curve of intergenerational income elasticity for both countries. In turn, Bratsberg et al. (2007) determine a more or less linear relationship for the United States. Schnitzlein (2009, 2016) also find no significant differences along the conditional income distribution in Germany. Therefore, the proposition of non-linearities among the income distribution will be re-examined using conditional and unconditional quantile regressions at selected percentiles of the income distribution of the sons.[77] The development of the estimation parameters proceeds differently for Germany and the United States (see Table 3.6). The results of the conditional quantile regression show a slightly hump-shaped run for the United States and a u-shaped curve for Germany over the conditional income quantiles of the sons.[78] Using conditional quantile regressions, however, statements about a nonlinear run of the intergenerational income elasticity can only be made when the monotonicity of the estimation parameter

[77] A detailed introduction, explanation and interpretation of the conditional or unconditional quantile regression can be found in Appendix A.1 and A.2.

[78] The conditional quantile regression defines the income quantile of the son conditional on the income of his father and estimates the intergenerational income elasticity on the conditional quantile of the income distribution of the son (Koenker and Bassett, 1978; Koenker, 2005).

Table 3.6: Quantile regressions of intergenerational income elasticity

	Germany				**United States**			
	CQR		*UQR*		*CQR*		*UQR*	
				20th Percentile				
IGE	0.311	(0.098)***	0.255	(0.100)***	0.447	(0.092)***	0.414	(0.091)***
Pseudo R^2	0.048		0.035		0.069		0.058	
				40th Percentile				
IGE	0.322	(0.089)***	0.416	(0.367)***	0.390	(0.090)***	0.377	(0.063)***
Pseudo R^2	0.063		0.088		0.064		0.091	
				50th Percentile				
IGE	0.352	(0.096)***	0.406	(0.071)***	0.346	(0.079)***	0.396	(0.057)***
Pseudo R^2	0.071		0.120		0.066		0.107	
				60th Percentile				
IGE	0.418	(0.091)***	0.395	(0.078)***	0.388	(0.061)***	0.391	(0.056)***
Pseudo R^2	0.070		0.110		0.071		0.095	
				80th Percentile				
IGE	0.374	(0.069)***	0.433	(0.106)***	0.512	(0.069)***	0.467	(0.077)***
Pseudo R^2	0.085		0.072		0.087		0.089	

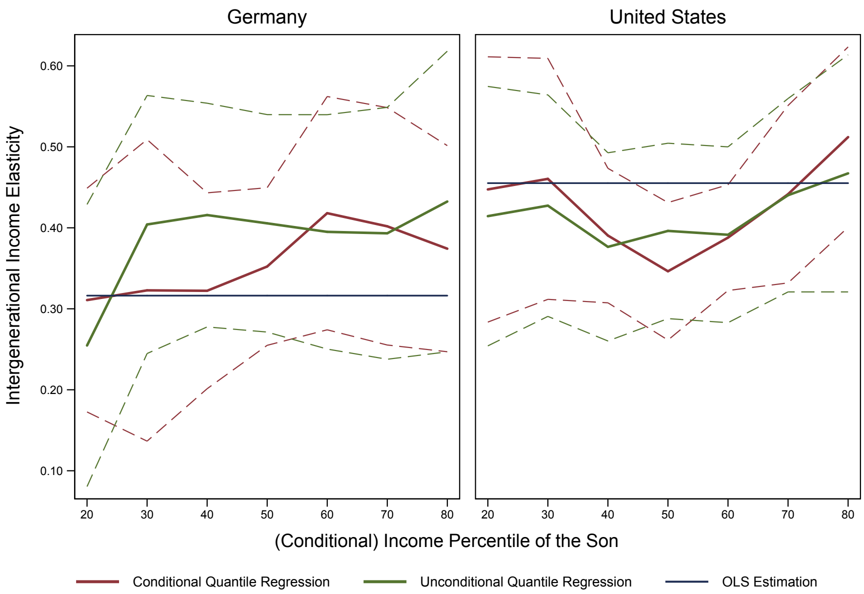
Source: SOEP (1984-2013), PSID (1984-2013)
Note: Standard errors are clustered at the family level and calculated using paired bootstrapped resampling with 1000 replications. Other controls include: polynomials for the father's and son's age and the number of valid observations for the son. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent. IGE: Intergenerational income elasticitiy, CQR: Conditional quantile regression, UQR: unconditional quantile regression.

along the income distribution is unambiguous.[79] Simple Wald tests show that the estimates for both countries do not differ significantly from one another across the percentiles.[80] For both Germany and the United States, the confidence bands almost completely overlap the OLS estimator of intergenerational income elasticity (see Figure 3.6). Thus, neither a concave nor a convex run of the intergenerational income elasticity in Germany and the United States can be verified so far. Using conditional quantile regressions, insights into how strong the effect of paternal income is for the sons at the selected quantiles of the marginal income distribution cannot be obtained. For such questions, the unconditional quantile regression or RIF regression is suitable (Firpo et al., 2009). In Germany, the intergenerational income elasticity assumes an s-shaped

[79] For example, monotonically increasing estimation parameters over the conditional quantiles would indicate that the income inequality is lower between the sons from low-income households than between the sons from high-income households. Thus, the intergenerational income elasticity would follow a convex function. The opposite occurs if the estimation parameters gradually decrease over the conditional quantiles and the intergenerational income elasticity takes a concave run.

[80] For the United States, a χ^2-value of 7.49 (p-value = 0.11) is obtained. For Germany, a χ^2-value of 2.07 (p-value = 0.72) is obtained.

Figure 3.6: Quantile regressions of the intergenerational income elasticity



Source: SOEP (1984-2013), PSID (1984-2013)
Note: Dashed lines represent the 90 percent confidence intervals of the corresponding estimations. In the case of the conditional quantile regressions, the income percentiles of the sons are the conditional percentiles, whereas in the case of the unconditional quantile regressions, the income percentiles of the sons are the marginal (unconditional) percentiles. Standard errors are clustered at the family level and calculated using paired bootstrapped resampling with 1000 replications. Other controls include: polynomials for the father's and son's age and the number of valid observations for the son.

curve along the ascending quantiles. Between the 40th and the 60th percentile, it is relatively constant at about 0.40, whereas it is lower for the 20th percentile and higher for the 80th percentile. The intergenerational income mobility is therefore higher at the lower end of the income distribution of the sons and slightly decreases when moving upward through the quantiles. In the United States, the development of the estimation parameters across the quantiles takes on a slightly u-shaped form. According to these results, intergenerational income mobility is higher in the middle range of the income distribution of the sons than at the two ends of the income distribution. While the curve for Germany indicates a convex development, the United States display an initially concave and then a convex course. However, the deviations from proportionality must be interpreted with caution since the confidence bands for both countries are relatively large and always contain the respective OLS estimator. Overall, the results of the conditional and unconditional quantile regression provide no clear indication of non-linearities in the development of intergenerational income elasticity over the income distribution of the sons for either Germany or the United States.

3.4.4 Decomposition of Intergenerational Income Inequality

Sons' income growth and changes in their income ranks have been considered separately from one another. While the intergenerational income elasticity measures the expected income of the son dependent on his father's income, the intergenerational rank mobility measures how many income ranks a son moves upward or downward as a function of his father's income position. If the fathers and their sons are interpreted as representatives of their family at two different points in time, sons' income growth and changes in income ranks can be considered together. This intergenerational, family-oriented perspective opens up two new questions: How strongly have the family's income grown between two generations? Is there upward or downward mobility of particular families between two generations?

Jenkins and Van Kerm (2006) offer a method to analyze income growth and changes in income ranks between a base and a reporting year simultaneously. Although this procedure was initially developed in order to investigate changes in annual income inequality, it can be applied to the difference in the income inequality of the sons' and the fathers' generation. Furthermore, the authors show that the change in income inequality, measured based on the Gini coefficient, between two points in time can be decomposed into a *pro-poor income growth* or progressivitiy and a *reranking* or income mobility component. The former measures to what extent the changes in family's income benefits the low-income families more strongly than high-income families of the base generation, i.e. the fathers' generation, or vice versa. The latter measures the magnitude of family's movement among the income distribution between fathers' and sons' generation. Applying the conventional Gini coefficient G in order to measure changes in income inequality, the decomposition can be expressed by[81]

$$\Delta G = G_c - G_p = R - P \,, \tag{3.9}$$

where G_c and G_p are the lifetime income inequality of the sons' and the fathers' generation, respectively. Furthermore, R and P are the reranking and the progressivity component, respectively, where the latter reduces the income inequality of families unless it is more than compensated by the accompanied former one. In Germany and in the United States, family-income inequality increased over the generations (see Table 3.7). The family-income mobility as well as the progressivitiy of family-income growth is higher in Germany than in the United States. Since the reranking index is a relative-family-income-weighted average of changes in the social weights of families between the fathers' generation and the sons' generation, a value of 78 percent implies that the family-income inequality in sons' generation would have been 78 percent higher (relative to the family-income inequality of the fathers' generation) if family-income growth had been equi-proportionate ($P = 0$), i.e. each family's income increase by the same percentage. Furthermore, the progressivitiy component takes positive values for both countries which indicates that the observed growth in family-incomes reduced family-income inequality of the sons' generation and is pro-poor, i.e. family-income

[81] A detailed derivation and explanation of the decomposition method is given in the Appendix A.3.2.

Table 3.7: Decomposition of the change in family-income inequality over two generations

	Germany	**United States**
Initial Gini coefficient of the fathers	22.78	33.28
Final Gini coefficient of the sons	25.87	40.91
Measures in Gini-Points		
Δ Gini coefficient	3.08	7.64
Mobility	17.72	23.21
Progressive family-income growth	14.63	15.57
Measures in Percent of the Initial Gini coefficient		
Δ Gini coefficient	13.54	22.95
Mobility	77.78	69.76
Progressive family-income growth	64.24	46.80

Source: SOEP (1984-2013), PSID (1984-2013)
Notes: Decomposition are based on family-incomes of the fathers' and the sons' generation, whereby the lifetime incomes of the sons who are members of the same family are averaged in order to measure the average family-income in the sons' generation.

growth is concentrated more among the low-income families than the high-income families. This index yields the decrease in the family-income inequality of the sons' generation in percentage of the value in the fathers' generation if there had been no reranking between the families over time ($R = 0$), i.e. the rank order of families does not change over the generations. In general, the income mobility in both countries overcompensates for pro-poor growth, so that income inequality between families increases. Nevertheless, the two countries differ in the strength of the components. Germany shows a higher income mobility as well as a more progressive income growth than the United States, measured as a percentage of the initial Gini coefficient of the fathers' generation. Moreover, the increase in family-income inequality in the United States is more strongly driven by a lower progressive family-income growth compared to Germany.

3.5 Recommendations for Economic Policy

The results presented suggest that paternal income has a strong influence on the future income of the sons in both Germany and the United States. Although there are no indications of credit market constraints, the substantially lower intergenerational income elasticity in, e.g., the Scandinavian countries indicates an additional influence of exogenous determinants on the success of children from poor households. Thus, measures to mitigate exogenous influences can reduce intergenerational income elasticity and facilitate a more efficient use of the total human capital of society.

However, stronger redistribution of income via the tax and transfer system does not necessarily have a positive effect on the level of social mobility. Although the disposable incomes of poor and rich families converge as a result of more redistribution, a more progressive tax and transfer system leads to a declining human capital return in the labor market, and thus to a reduction in the incentive to invest in education. While this is true for all families, it affects poor households relatively more strongly than it does rich households. In sum, higher redistribution could even reduce intergenerational income mobility. The method of choice should therefore be an improvement in the institutional design of the preschool and school system to increase equality of opportunity without severe distortion of market processes.

3.5.1 Early Childhood Education

The barriers to the future income of relatively poor children are not found in the late stages of education, but rather in early childhood care. Stimulations that children experience in the early stages of brain development greatly influence the limits of future mental capability. A stimulating environment results in improved cognitive development, better social skills, and better health (Knudsen et al., 2006).

While children whose families have above average incomes and human capital are able to receive these stimulants at home, this support often falls by the wayside in less well-off families. Thus, for children from socio-economically weak households opportunities must be created for their earlier attendance of public or private childcare facilities where they can be supported according to their abilities. This particularly applies to those children with an migration background who first come into contact with the German language at day care centers or in kindergarten. In 2016, however, only 21 percent of children under 3 years of age with a migration background visited day care, while 38 percent of under-3-year-olds with no migration background did so (Federal Statistical Office, 2017). Lee and Burkam (2002) show that there are already severe differences in education between children of different social backgrounds at the beginning of kindergarten. These differences continue to grow over the course of the children's education, which means that early childhood care is of great importance. An expansion of child care facilities for children under 3 years of age as well as a good staff-to-student ratio with well-trained educators would therefore be important for higher intergenerational income mobility.

3.5.2 Desegregation

Another starting point is the pronounced segregation of children according to social origin. This problem is particularly evident in the strong heterogeneity of the quality of schools in Germany. The variation in PISA scores between schools is 68 percent, which is well above the average (42 percent) for the OECD countries. At the same time, the variance in the results within the individual schools is only 45 percent, which is well below the OECD average of 65 percent (OECD, 2012). Thus, pupils at the respective schools are at a comparable level, but the variation between the performance of pupils in "good" and "bad" schools is immense.

The strong variation in school quality might be due to a higher demand for spots at good schools than capacities exist. In such a case, the risk of so-called cream skimming, i.e., the selection of subjectively better pupils, is high (Lubienski, 2006). Musset (2012) illustrates that a large part of this cream skimming can be traced back to local segregation. On the one hand, well-off families tend to avoid schools with a high number of children from socially vulnerable families. While wealthy families choose the subjectively best school for their children, families with a weaker socio-economic status tend to send children to the locally nearest school (Raveaud and Van Zanten, 2007; Schneider and Buckley, 2002). It has also been shown that families with a lower educational level spend less time choosing a school and suffer from a considerable information deficit with regard to the educational system and the quality of schools (Hastings et al., 2005). On the other hand, the location of an individual's home is an indicator of social status which can be used by schools as a basis for the selection of pupils. Thus, if cities become increasingly segregated by social background, this intensifies the problem of immobility.

However, a simple increase in investment in the school system is not an adequate means of increasing social mobility (Hanushek, 2003). The higher the average level of human capital, the more difficult the process of catching up is for pupils from disadvantaged families. Investments in the education system must therefore primarily promote equal opportunity and desegregation in the education system, provided that such investment is intended as an instrument for increasing social mobility. A so-called formula funding based on the Dutch model could help to decrease cream skimming and reduce the segregation of children according to social background. First, a weight is assigned to each student. The financial resources allocated to a certain school are then calculated based on the sum of the weights of its students. If pupils from disadvantaged families are assigned a higher weight, there is an incentive for schools to accept these pupils. This also takes account of the fact that due to the more intensive support they require, the admission of disadvantaged children may be more cost-intensive in some circumstances.

3.5.3 Secondary School Tracking

Another problem that is often discussed is the division of pupils into various secondary schools after only four years of elementary school, which happens in the German school system. Thus, the decision as to whether a child apprentices to learn a profession or attends university is, in most cases, made very early. However, reaching a high level of education is still the best insurance against unemployment. The unemployment rate of persons aged between 15 and 74 who have earned a degree below the secondary education level was 11.2 percent in Germany in 2015. The possession of secondary (4.3 percent) or tertiary education (2.3 percent) leads to a significantly lower probability of unemployment (European Commission, 2017). Furthermore, the decision about a particular type of school depends heavily on the income and education level of the parents. While 43.8 percent of parents of children at the Hauptschule also attended this institution, only 7.2 percent of pupils at the Gymnasium have parents who attended the Hauptschule (Federal Statistical Office, 2017). In German politics, therefore, later secondary school tracking, e.g., after the sixth grade, has been discussed for some time. A similar school reform in Finland has led to a reduction of intergenerational income elasticity by 23 percent (Pekkarinen et al., 2009).

3.6 Conclusion

The present study examines intergenerational income mobility with the help of different measures in Germany and the United States. In line with existing results, the average intergenerational income elasticity in the United States is higher than in Germany. While the results for the intergenerational rank mobility are relatively similar, the level of intergenerational income share mobility is higher in the United States than in Germany. There are no indications of a non-linear run of the intergenerational income elasticity. The decomposition of intergenerational income inequality shows both greater income mobility and stronger progressive income growth for Germany compared to the United States. In order to increase the currently low level of social mobility, policy needs to focus on equality of opportunity in the educational system, especially when it comes to pre-school care. This solution is more incentive-compatible in the long run than a policy of pure redistribution.

Appendix

Magnitude of Attenuation Bias

Income data of sons and fathers are measured at different times of life. Moreover, the number of valid observations varies between the sons' and the fathers' generation. Considering these two characteristics in the approximation of lifetime income, for each generation according to Solon (1992)

$$\frac{1}{T^g}\sum_{t=1}^{T^g} y_{it}^g = y_i^g + \gamma_1^g A_i^g + \gamma_2^g \left(A_i^g\right)^2 + v_i^g, \qquad g \in \{c, p\} \tag{3.10}$$

applies, where y_i^g is the age-adjusted, permanent income component of the son c and the father p, respectively. A_i^g yields the average age and T^g the number of valid annual observations. Substituting equation (3.10) in (3.1) yields

$$\frac{1}{T^c}\sum_{t=1}^{T^c} y_{it}^c = \beta_0 + \beta_1 \frac{1}{T^p}\sum_{t=1}^{T^p} y_{it}^p + \boldsymbol{A_i'}\boldsymbol{\gamma} + u_i^c, \tag{3.11}$$

where

$$\begin{aligned}
\boldsymbol{A_i} &= \left[A_i^p, (A_i^p)^2, A_i^c, (A_i^c)^2\right], \\
\boldsymbol{\gamma} &= \left[-\beta_1\gamma_1^p, -\beta_1\gamma_2^p, \gamma_1^c, \gamma_2^c\right], \\
u_i^c &= \epsilon_i^c + v_i^c - \beta_1 v_i^p,
\end{aligned}$$

applies. Thus, the estimated coefficient $\hat{\beta}_1$ is biased due to measurement errors in y_i^p. Assuming a serially uncorrelated error term, $\hat{\beta}_1$ takes the probability limit

$$\text{plim}\ \hat{\beta}_1 = \beta\left(\frac{\sigma_{y^p}^2}{\sigma_{y^p}^2 + \frac{\sigma_{v^p}^2}{T^p}}\right),$$

where $\sigma_{y^p}^2$ is the variance of the fathers' permanent component, $\sigma_{v^p}^2$ is the variance of the fathers' transitory component, and T^p is the number of fathers' valid income observations. If the number of paternal income observations increases the distortions of the estimates decrease.

Bias in the estimates due to divergent age-income profiles

Whether divergent age-income profiles of the fathers and the sons may cause a bias of the intergenerational income elasticity estimate, can be examined by the subsequent procedure (Fertig, 2003). First,

$$\frac{1}{T^g}\sum_{t=1}^{T^g} y_{it}^g = \gamma_1^g A_i^g + \gamma_2^g (A_i^g)^2 + \upsilon_i^g \tag{3.12}$$

is estimated separately for sons ($g = c$) and fathers ($g = p$), respectively, without an intercept. Then, the residuals $\hat{\upsilon}_i^p$ and $\hat{\upsilon}_i^c$ are used in order to estimate the intergenerational income elasticity by applying

$$\hat{\upsilon}_i^c = \beta_0 + \beta_1 \hat{\upsilon}_i^p + \epsilon_i^c. \tag{3.13}$$

Hereafter, Equation (3.13) is jointly estimated for the sons and the fathers. Then, the residuals are calculated and the estimation of the intergenerational income elasticity is replayed employing Equation (3.1). Therefore, if the estimates of the intergenerational income elasticity from both estimations significantly differ from one another the age-income profiles of the sons and the fathers might significantly differ and produce distortions in the estimates of the intergenerational income elasticity.

Table 3.8: Estimation of the intergenerational income elasticity with birth cohort controls

	United States	**Germany** *Without imputed Income Data*	**Germany** *With imputed Income Data*
	Panel A: Income > 1200 Euro / 1200 US-Dollar		
IGE	0.453	0.340	0.293
	(0.070)***	(0.080)***	(0.076)***
Obs.	617	361	401
R^2	0.139	0.082	0.086
	Panel B: Income > 6000 Euro / 6000 Dollar		
IGE	0.447	0.343	0.351
	(0.061))***	(0.072))***	(0.067))***
Obs.	599	355	396
R^2	0.171	0.112	0.133
	Panel C: Income > 12000 Euro / 12000 Dollar		
IGE	0.414	0.373	0.370
	(0.061))***	(0.068))***	(0.070))***
Obs.	570	344	385
R^2	0.16	0.141	0.158

Source: SOEP (1984-2013), PSID (1984-2013)
Note: Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1000 replications. Other control variables include: polynomials for the father's age and the son's age, the number of valid observations of the son, and father's and son's birth cohort. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent. IGE: Intergenerational income elasticity.

Table 3.9: Estimation of the intergenerational income elasticity; restricted to fathers' birth cohort from 1933 to 1945

	United States	Germany	
		Without imputed Income Data	*With imputed Income Data*
Panel A: Income > 1200 Euro / 1200 US-Dollar			
IGE	0.510	0.365	0.332
	(0.092)***	(0.081)***	(0.094)***
Obs.	328	286	322
R^2	0.176	0.074	0.078
Panel B: Income > 6000 Euro / 6000 Dollar			
IGE	0.478	0.355	0.384
	(0.081)***	(0.096)***	(0.087)***
Obs.	321	281	318
R^2	0.161	0.100	0.130
Panel C: Income > 12000 Euro / 12000 Dollar			
IGE	0.458	0.405	0.422
	(0.075)***	(0.095)***	(0.081)***
Obs.	309	271	307
R^2	0.151	0.127	0.155

Source: SOEP (1984-2013), PSID (1984-2013)
Note: Samples are restricted to fathers' birth cohorts from 1933 to 1945. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1000 replications. Other control variables include: polynomials for the father's age and the son's age, and the number of valid observations of the son. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent. IGE: Intergenerational income elasticity.

Table 3.10: Estimation of the intergenerational income elasticity, including unemployment periods

	United States	Germany	
		Without imputed Income Data	*With imputed Income Data*
IGE	0.452	0.323	0.332
	(0.047)***	(0.048)***	(0.047)***
Obs.	583	354	388
R^2	0.118	0.097	0.089

Source: SOEP (1984-2013), PSID (1984-2013)
Note: Samples include unemployment periods including labor income data of zero. Estimation are adjusted based on an outlier elimination procedure proposed by Belsley et al. (1980) using only income data of the fathers with a DFBETA-statistic lower than $\frac{2}{\sqrt{n}}$, whereby n represents the sample size. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1000 replications. Other control variables include: polynomials for the father's age and the son's age, and the number of valid observations of the son. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent. IGE: Intergenerational income elasticity.

Table 3.11: Estimation of sons' transition probabilities

	Germany		United States	
Father's 2nd quintile	0.116	(0.351)	0.618	(0.288)**
Father's 3rd quintile	0.797	(0.286)***	1.168	(0.279)***
Father's 4th quintile	1.045	(0.392)***	1.474	(0.273)***
Father's 5th quintile	1.602	(0.327)***	1.893	(0.301)***
Sons' age	1.206	(3.270)	-1.189	(2.428)
Sons's age^2	-0.015	(0.043)	0.016	(0.032)
Father's age	-0.024	(0.442)	-0.055	(0.228)
Father's age^2	0.001	(0.005)	0.001	(0.003)
Son's Obs.	0.058	(0.067)	0.172*	(0.102)
Obs.	361		617	
McFadden R^2	0.044		0.044	

Source: SOEP (1984-2013), PSID (1984-2013)
Note: Dependent variable is the sons' income rank, measured as income quintiles, and the raw coefficients of the ordered logistic regressions are reported. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1000 replications. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

Table 3.12: OLS estimation of the intergenerational rank mobility

	Germany				United States			
Father's Income Rank	-0.712	(0.053)***	-0.708	(0.052)***	-0.629	(0.045)***	-0.648	(0.046)***
Father's Age			-2.586	(6.063)			0.495	(3.431)
Father's Age^2			0.039	(0.068)			-0.003	(0.039)
Son's Age			38.117	(46.643)			-21.116	(34.334)
Son's Age^2			-0.493	(0.607)			0.281	(0.448)
Son's Obs.			0.769	(0.965)			3.372	(1.513)**
Obs	361		361		617		617	
R^2	0.372		0.400		0.277		0.293	

Source: SOEP (1984-2013), PSID (1984-2013)
Note: Dependent variable is the sons' income rank mobility. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1000 replications. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

Table 3.13: OLS estimation of the intergenerational income share mobility

	Germany				United States			
Father's Income Rank	-0.009	(0.001)***	-0.009	(0.001)***	-0.012	(0.003)***	-0.012	(0.003)***
Father's Age			-0.008	(0.107)			0.247	(0.265)
Father's Age^2			0.000	(0.001)			-0.003	(0.003)
Son's Age			0.120	(1.205)			-0.448	(1.751)
Son's Age^2			-0.001	(0.016)			0.007	(0.023)
Son's Obs.			0.033	(0.026)			0.016	(0.099)
Obs.	291		291		486		486	
R^2	0.186		0.217		0.048		0.061	

Source: SOEP (1984-2013), PSID (1984-2013)
Note: Dependent variable is the sons' income share mobility. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1000 replications. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

4
Intragenerational Wage Mobility and Tasks in Germany

In democracies, the tax and transfer system is to a greater or lesser extent static and rather slowly adjusted over longer time periods. Thus, in the expression of their preferences for redistribution, voters will take their current income position as well as their expected income position in the future into account. Based on the prospects of upward mobility hypothesis according to Benabou and Ok (2001), low-income earners who expect considerable income growth in the future will prefer less redistribution at the current time in order to prevent higher taxes in the future. As already pointed out by Hirschmann and Rothschild (1973), low-income earners are willing to accept a higher income inequality if they soundly believe that they will also benefit from a higher income inequality in terms of their income growth in the long run. This raises the question: how strongly is a worker's current wage associated with his or her wage in the future? Thus, the following chapter examines the determinants and development of intragenerational wage mobility in Germany. Among other things, there has been a decrease in wage mobility since the beginning of the 2000s, which has been accompanied by an increase in wage inequality.[82]

4.1 Introduction

The distribution of labor incomes and hourly wages has received much attention from policy makers, economists, and the general public in recent decades, since hourly wage and labor income inequality started to increase in the United States in the late 1970s and 1980s (Acemoglu, 2002; Alvaredo et al., 2013; Autor et al., 2008) and in most Western European countries, such as Germany, in the mid-1990s (Card et al., 2013; Dustmann

[82] A worker's income includes both labor income and capital income. Since the study analyzes the development of hourly wages, the term "income" always refers to labor income and the term "wage" refers to hourly wages based on labor incomes, unless otherwise stated.

et al., 2009; Gernandt and Pfeiffer, 2007). Several explanations have been developed to explain the increase in wage inequality. Hence, the divergent wage growth along the wage distribution in the United States in the 1980s is caused by the skill biased technical change, which reflects the increase in the relative demand for high-skilled workers, the supply of whom could not keep up (Acemoglu and Autor, 2012; Goldin and Katz, 2007; Katz and Autor, 1999). The diverging trends in wage growth along the wage distribution brought the literature about wage inequality to the nuanced version of the skill biased technical change hypothesis that suggests that the diffusion of computer technology in the production process in the 1990s induced the substitution of routine tasks and complementarity of non-routine tasks (Autor et al., 2003). Whereas the predictions of the routinization hypothesis can be confirmed for the United States in the 1990s (Autor et al., 2006, 2008), no wage polarization has been detected in Germany (Dustmann et al., 2009). Furthermore, explanations based on the contribution of the increase in international trade and de-unionization in the United States in the 1980s and 1990s were examined (Burtless, 1995; DiNardo et al., 1996). Additionally, Card et al. (2013) shows that the increased dispersion in West German wages between 1985 and 2009 was due to a combination of increased heterogeneity between workers, greater variance of wage premiums at different establishments, and better matching in the allocation of workers to plants.

Although the annual dispersion of wages is of particular interest, it is merely the static component of wage development. In order to complete the analysis on wage structure, changes in the relative wage position of workers have to be taken into account. Friedman (1962) and Shorrocks (1978) already pointed out that wage mobility can be interpreted as an equalizer of workers' long-term wages, since the movements of individuals along the wage distribution smooth their wage fluctuations over time. Thus, a high wage inequality accompanied by a high wage mobility is more acceptable for the contributors of the economy, since, in the case of perfect mobility, low-wage and high-wage earners have the same probability of receiving a high wage in the future. Therefore, the realization of high wage mobility or even the perception of a high wage mobility might reduce citizens' demand for more government interventions on the labor market or for more governmental redistribution (Benabou and Ok, 2001). However, employing labor income data, Burkhauser and Poupore (1997) find no strong relationship between income inequality and mobility in the United States and Germany. Bachmann et al. (2016) finds a weak relationship in a cross-section of European countries. Furthermore, based on post-government income data, most studies ascertain no clear relationship between inequality and mobility using cross-country or one country data (Aaberge et al., 2002; Gottschalk and Spolaore, 2002). Van Kerm and Pi Alperin (2013) reveal that despite large differences in income inequality across European countries, the patterns of income mobility are similar. Some countries with more unequal income distribution even exhibit slightly lower mobility rates.

In general, research on wage mobility can be arranged in three groups (Riphahn and Schnitzlein, 2016). The first group employs covariance structure models in order to decompose the trend in a worker's wage into the permanent and transitory component (Baker and Solon, 2003; Gottschalk and Moffitt, 1994; Myck et al., 2011). The second group provides evidence for wage mobility over time, across countries, or across different sub-groups of a country. In order to analyze the last, decompositions of the wage mobility for different types of income or wage (Chen, 2009), for specific sub-samples (Aretz, 2013; Gangl, 2005; Van Kerm, 2004), or for a differentiation in a between-group and a within-group component (Bachmann et al., 2016; Buchinsky and Hunt, 1999) were undertaken. Employing a decomposition of the variance in wage mobility in Germany over time, Riphahn and Schnitzlein (2016) show that the decline in wage mobility in the 2000s was mainly driven by structural shifts, i.e. changes in the returns to particular individual characteristics, instead of by the compositional changes of workers. The third group investigates the socio-economic and demographic determinants of individual wage or income mobility. These studies commonly use a basic set of individual determinants which are based on the covariates of the extended Mincer equation (Mincer, 1974) and build on the human capital model (Mincer, 1958). Using monthly gross earnings and employing wage growth regressions, Hunt (2001) detects that 60 percent of the East German workers changed their jobs between 1990 and 1996, but merely 25 percent of the Eastern income growth was attributable to these job changes. She concludes that especially women, low-wage earners, and low-educated East German workers gained the most after reunification. Since wage growth is originally a measure of structural mobility, Raferzeder and Winter-Ebmer (2007) analyze a worker's change in his or her relative income position based on the difference between his or her income rank in the base year t and the reporting year $t+s$. Based on Austrian income data between 1994 and 2001, they notice that the initial income percentile has a strong influence on a worker's wage mobility. In turn, Gernandt (2009) applies the same approach to West German data on workers' hourly wage mobility between 1984 and 2007 and receives similar results. In contrast, Finnie and Gray (2002) use a hazard model framework to analyze transitions between income quintiles in Canada in the 1980s and 1990s. Therefore, their measure of mobility can be interpreted as the conditional probability of transiting between quintiles. Furthermore, this enables the consideration of duration dependence, since a worker's probability of moving diminishes with the time he or she spent in a given quintile. The authors discover a strong decline in the baseline hazard rate, which indicates that there is high state dependence in both directions along the income distribution. Moreover, Bachmann et al. (2016) employ multinomial logit models to analyze whether there are asymmetries in the coefficients between upward and downward income mobile workers.

This study is related to the first and to the second groups described above, whereby descriptive evidence on the development of wage inequality is given. Since uncensored survey data on hourly wages in Germany are employed for an observation period of 30 years, the contribution to the literature on wage inequality and wage mobility is twofold. First, the commonly observed increase in wage inequality in the 1990s and 2000s is confirmed. However, wage inequality has started to stabilize in West and East Germany since 2006. Investigating the development in more detail uncovered a decrease of the 5/1 decile ratio and a polarization of wage growth along the wage distribution after the Hartz reforms. Since this trend in wage growth could be traced back to the predictions of the nuanced skill biased technical change according to (Autor et al., 2003), a newly available database is used to analyze the task-based explanations (Dengler et al., 2014). To the best of my knowledge, this is the first study employing an expert database in order to examine the impact of tasks on wages in Germany. However, the evidence of wage growth along the skill distribution of workers' occupations in the 2000s and early 2010s merely supports the routinization hypothesis in part. On the one hand, manual non-routine occupations are still the largest employment group in the middle of the skill distribution. On the other hand, cognitive routine occupations show a higher share of employment at the upper end, which is in contrast to the suggestions. Moreover, the employment share of cognitive routine occupations even increased at the top of the skill distribution between 2001 and 2013.

Second, some evidence on the evolution of aggregated wage mobility measures in East and West Germany is given. Using, among others, the Shorrocks mobility index, which can be interpreted as an equalizer index of long-term wages, there has been a decrease in wage mobility since the beginning of the 2000s in Germany. Thus, the contribution of overall wage mobility to the reduction of long-term inequality has fallen to 4.8 percentiles. Moreover, the correlation of individuals' wages across time increased by 10 percentage points, which indicates that there is increasing persistence in relative wages. Furthermore, this is reflected in the increasing state dependence of workers' initial wage ranks, where the aggregated measure is based on wage mobility estimations and introduced for the first time in this study. Therefore, the decline in intragenerational wage mobility and the increase of state dependence incite the following question: what determines a worker's wage mobility and did the impact of socio-economic and demographic characteristics change over time? The empirical results evince that worker's educational attainment, gender, labor market status, unemployment spells, firm size, place of residence, and occupations have an especially strong influence on his or her wage mobility. In particular, the length of unemployment spells within the fixed time windows and the kind of occupation have risen in importance, whereas the influence of gender, living in East Germany, and working part-time has decreased over time. On the one hand, this means that the depreciation of human capital during unemployment has a greater impact on a worker's re-entry wages. On the other hand, workers' wages depend more strongly on their occupation-specific human capital. Combing the latter with the wage polarization observed since 2006, a consequential follow-up question is whether these accompanied developments are attributable to the predictions of the routinization hypothesis. Employing tasks and task intensities of workers' occupation has been relatively neglected in the analysis of hourly wage mobility. This is, to the best of my knowledge, the first study that combines the task-based explanations of wage growth with wage mobility estimations. Two key findings can be identified. On the one hand, workers who perform mainly manual tasks have a lower wage mobility over the entire observation period. On the other hand, workers in cognitive routine occupations show a higher and also increasing wage mobility compared to manual non-routine workers. These results are in line with the descriptive evidence on wage growth along the skill distribution. Therefore, both types of manual workers have experienced losses in their wage mobility since 2000, whereas workers performing mainly abstract and cognitive routine tasks increased their wage mobility.

The rest of the chapter is organized as follows: Section 4.2 presents the data sources of employed variables. Section 4.3 gives descriptive evidence on wage inequality and mobility in West and East Germany based on different measures and concepts. Section 4.4 shows the basic results of wage mobility regressions and empirical extensions using a more detailed industry categorization. Furthermore, the influence of a worker's initial rank on wage mobility and an aggregate measure of state dependence are estimated. Subsequently, the impact of task types and task intensities on wage mobility are investigated. Additionally, differences in downward and upward mobility are examined. Finally, Section 4.5 concludes.

4.2 Data and Variables

In order to examine the intragenerational wage mobility empirically, suitable individual data are required for a person at least two times. For this purpose, the German Socio-Economic Panel (GSOEP) is used (Wagner et al., 2007). The GSOEP provides information on the socio-economic and the demographic characteristics of each households member as well as on some features of the household as a whole. Since the interviews are conducted annually, household members can be tracked over several years so that the development of their incomes, wages, and other peculiarities can be accurately observed. Furthermore, there are two advantages of the survey data compared to administrative data, such as the LIAB. First, the individual labor income is not censored by the social security ceiling. Therefore, the whole wage distribution can be observed and part-time workers can be taken into consideration. Second, the GSOEP includes information on contractual working hours as well as on effective working hours, which enables overtime work to be taken into account in the calculation of hourly wages (Grabka, 2014). Third, in contrast to administrative data, which normally includes daily wages, hourly wages can be directly computed based on an individual's monthly labor income and weekly working hours.

The analysis is based on individual labor income data from 1984 to 2014 and restricted to persons between the age of 25 and 60 for each employed time window. On the one hand, persons under the age of 25 are usually in schooling or vocational training. Thus, they do not earn regular labor income. On the other hand, persons above the age of 60 may be already retired or may strongly adjust their working hours due to early retirement programs. Therefore, students, trainees, employees in partial retirement, and retirees are dropped from the sample. Furthermore, civil servants and self-employed persons are not considered, since the former experience a strongly state-regulated wage development and the latter provide only imputed labor income. Thus, the analysis is based on the dependent labor force of the private sector, where workers in marginal or irregular employment are also removed from the sample.[83] To compute the real hourly wage, information on the individual gross monthly labor income and weekly working hours are used. In turn, working hours refer to an individual's effective working hours per week.[84] If there is no data on effective working hours or the extent of contractual hours exceed the values of effective working hours, the former is used instead. This procedure ensures that overtime work is taken into account as well as an individual's payment due to the contractual working hours if he or she reports less or no effective working hours. Ultimately, the division of the gross monthly labor income by monthly working hours, which equal weekly working hours times 4.2, yields the nominal hourly wage. For the calculation of the real hourly wage, the nominal wages are deflated to 2010 using the German Consumer Price Index, whereby separate indices are used in East and West Germany between 1991 and 2000 to account for reunification effects. In order to prevent distortions in the estimation due to misreporting gross monthly labor income and working hours, workers reporting real hourly wages less than 1 euro or more than 150 euros as well as reporting working hours less than 4 hours are excluded. Since the purpose of the study is to analyze wage mobility, an appropriate time span between two valid observations of a person's hourly wages has to be defined. If the time period is too short, the development and adjustments of a person's wages cannot be accurately observed. However, the longer the time span is, the higher the probability of panel attrition that may be correlated with certain individual characteristics. In line with the empirical literature, a 4-year time period is conducted in the estimations (Gernandt, 2009; Riphahn and Schnitzlein, 2016). Thus, workers have to be employed in the base year t and the reporting year $t+s$ as well as show valid

[83] In order to avoid distortions in the calculations and estimations, employees in sheltered workshops, military service, family workers, and other non-employed persons are excluded from the analysis.

[84] Note that the working hours are censored at 80 hours per week.

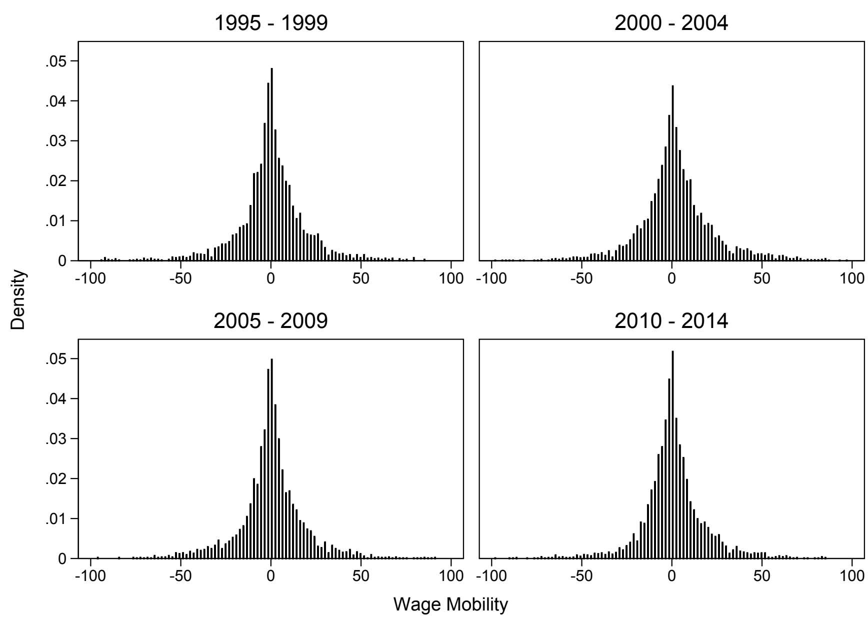
real hourly wages at both ends of the time span. Nevertheless, individuals have to meet the age restrictions across the time period and show a valid labor market status (employed or unemployed) in the meantime. The latter enables the consideration of unemployment spells in the estimations.

In the empirical literature, individual wage mobility mob_i is commonly defined as the difference in a worker's wage position in the the reporting year $t+s$ and the base year t, measured in percentiles pc (Gernandt, 2009; Riphahn and Schnitzlein, 2016):

$$mob_i = pc_{i,t+s} - pc_{i,t} \tag{4.1}$$

Thus, wage mobility can take values between -99 and +99. Due to the large definition set of the dependent variable, applying ordinary least squares regression is appropriate. Furthermore, the calculation of percentiles is based on longitudinal weights to account for panel attrition and to enable inference. Since the employed samples have to be balanced, i.e. only workers who have valid observations in the base and the reporting year are considered, for each worker moving up along the wage distribution, there must be another worker moving down. Therefore, the average wage mobility in a given time window equals zero. The majority of the workers show an upward or downward mobility of less than or equal to ten ranks within the 4-year time periods (see Figure 4.1). In the reunified Germany, there is a trend towards a more compressed distribution

Figure 4.1: Distribution of the changes in wage rank positions



Notes: Full samples, which include East and West German workers are employed. Calculation of ranks is based on frequency weights and measured as wage percentiles.

of rank changes over time. The standard deviation of the wage rank changes decreases from 20.01 in the base year 2000 to 17.15 in the base year 2010. Since a lower standard deviation indicates that there is less variation in the data, there is a first indication for a decreasing wage mobility in Germany since the beginning of the 2000s. Furthermore, there is slightly more upward mobility than downward mobility in the employed 4-year time periods. Since a worker's real hourly wage must be observed in both the base year and the reporting year, a positive selection towards those workers who have more stable employment situations might occur. Therefore, the estimations might be biased if the selection which is based on the labor market participation of workers in the reporting year is not random and correlates with observed or unobserved individual characteristics of the positively selected groups (Heckman, 1976). However, using a worker's marital status and the number of kids in his or her household as sufficient additional covariates of the selection equation, the application of Heckman selection regressions yielded no significant selection bias in almost each year, except for 1996 and 2006.[85]

Taking all employed 4-year time period samples together, there are 100,265 person-year observations in the data.[86] The basic set of covariates includes plenty of a worker's socio-economic and demographic characteristics which might affect his or her wage mobility. In turn, these predictors can be divided into three groups. First, *individual characteristics* are important drivers of the wage mobility. Thus, a worker's age, gender, educational attainment, and migration background may influence his or her wage development.[87] These variables are measured in the base year t. In order to avoid a distortion of the estimation results, a worker's initial rank is taken into account, since a low-wage earner cannot descend further along the wage distribution, whereas a high-wage earner cannot rise further. Second, *job stability* is typically associated with wage mobility. On the one hand, job changes can be accompanied by wage increases if employees harness lucrative outside options. On the other hand, a longer job tenure may lead to higher wages through learning curve effects and a longer accumulation of firm- and industry-specific human capital. The latter might also reason the difference in wage mobility between part-time and full-time workers. In turn, experiencing unemployment during the fixed time window can cause workers to return to the labor market at lower wages due to the depreciation of their human capital. Thus, the following three factors of job stability are taken into account: an indicator whether workers changed their job within the time period, an indicator whether a worker

[85] Marital status and number of kids are commonly used in wage regressions as selection variables, since they should have no direct effect on wages, but they might determine the labor market participation decision of workers. Estimates of the error term correlation are given in Table 4.6 in the appendix of this chapter

[86] The number of valid wage mobility observations for each 4-year time period is given in Table 4.4 in the appendix of this chapter.

[87] The education variable consists of three categories: "low-skilled", "medium-skilled", and "high-skilled". Its design is based on the CASMIN classification (König et al., 1987) and described in detail in Table 4.5 in the appendix of this chapter.

is part-time employed, the number of unemployment spells in the meantime, and the job tenure in the base year t. Third, *employment characteristics* are relevant to wage mobility through different mechanisms. In particular, unions can have a strong impact on workers' wage development if they have sufficient bargaining power. Since they are more strongly represented in larger companies, their wage claims may be higher in these firms. In 2014, 82 percent of workers employed in companies with more than 1000 employees received union wages, whereas only 20 percent of workers employed in companies with less than 50 employees obtained union wages (Federal Statistical Office, 2016). Furthermore, a worker's industry, occupation became more important due the increased relevance of industry-specific human capital (Firpo et al., 2011), the skilled biased technical change (Acemoglu and Autor, 2011), and increased specialization. Moreover, Gottschalk and Moffitt (2009) point out that the transfer of human capital between employment has become more difficult over time. In order to approximate these mechanisms, the following predictors are used: a worker's industry, and occupation, and size of his or her firm in the base year t as well as indicators whether a worker changed his or her industry and occupation in the meantime. Ultimately, an indicator whether a worker lives in East Germany in the reporting year $t+s$ is taking into account, in order to control for regional developments, such as unemployment and GDP growth, and for the different labor market circumstances in West and East Germany.

Based on the nuanced skill biased technical change hypothesis according to Autor et al. (2003), this study examines whether the performance of particular tasks in occupations has an impact on a worker's wage mobility. Since wage growth in occupations determines workers' movements along the wage distribution, the impact of tasks carried out in the base year of the time windows on a worker's wage mobility will be examined in more detail.[88] For this purpose, a newly available measurement method for the operationalization of tasks based on the expert database BERUFENET of the German Federal Employment Agency is applied (Dengler et al., 2014). Using expert knowledge about occupations' or professions' usual work activities in order to sort them into broad task categories is a well-established method in US-American research about wage growth. In German research on wage growth, survey data, without exception, has been used so far to carry out an operationalization of occupations or professions. However, expert databases have several advantages over survey data, such as the BIBB-IAB or BIBB-BAuA employee surveys. First, survey respondents describe the activities they usually perform in their jobs, whereas experts assess which competences and skills are usually attached to a particular profession or occupation. Thus, the latter is a more objective assessment of the tasks in a profession or occupation, independent of a worker's

[88]Since the task intensities and types of some occupations cannot be calculated due to compatibility problems, some observations are lost in the analysis. In order to prevent the loss of more observations by employing 4-year time periods, the time windows are shortened by one year.

industry or firm size. Second, survey responses can result in a larger variance in the measurement of tasks within and between occupations, since respondents describe their individual tasks which can vary widely for some occupations. Furthermore, error coding in the assignment of occupations during the interview can increase the variance. Third, surveys can only assign tasks to those occupations or professions which are already observed in the data. Therefore, rare or unrepresented occupations are not considered, which can lead to a distortion in the various task intensities of the labor force (Dengler et al., 2014). The expert database includes nearly all job titles used in Germany and link these job titles to approximately 3900 separate occupations. Following Spitz-Oener (2006), five task dimensions are differentiated, in order to ensure comparability with previous task operationalization which were based on survey data for Germany: (1) analytical non-routine tasks, (2) interactive non-routine tasks, (3) cognitive routine tasks, (4) manual routine tasks, and (5) manual non-routine tasks. Since Autor et al. (2003) subsume analytical and interactive tasks under abstract tasks, the employed five task dimensions are in line with the task operationalization in the US-American literature. Furthermore, the differentiation between routine and non-routine tasks is based on the substitutability of work activities by machines or computers. Thus, routine tasks follow certain programmable algorithms or rules, whereas non-routine tasks are supported and not replaced by computers or machines. Manual tasks, in contrast to analytical, interactive, and cognitive tasks, are work activities that are performed by hand. In order to calculate an occupation's *task intensities* and *main task type*, an occupation's core requirements given by the experts are used. Since there are five task types, five task intensities are calculated for each occupation, where an occupation's task intensities add up to one. Thus, an occupation's task intensity gives the share of core work activities which can be attributed to the corresponding task, e.g. an analytical task intensity of 0.25 means that a quarter of the work activities in the occupation are analytical in nature. In turn, task intensities can take values between zero and one, where a zero value indicates that a specific task is not performed in the occupation and a value of one indicates that no task other than the one observed is performed in the occupation. Furthermore, the task type with the highest intensity or share for each occupation is defined as main task type.[89]

Occupations' main task type and task intensity are based on the 3-digit code of KldB 2010 classification. Since the GSOEP does not provide information on a respondent's KldB 2010 level 3 occupation until 2014 and reported respondents' occupation based on the 5-digit code of KldB 1992, which is the previous version of occupational classification, the information on the latter are converted into KldB 2010 level 3 according to official conversion tables. Based on the KldB 2010 level 3 occupations, the task information for 2011 are matched to the individual data of workers between 2000 and

[89]A detailed description of the calculation method and the database can be found in Dengler et al. (2014).

2014.[90] The assumption that occupations' task intensities from 2011 are valid for the entire observation period from 2000 to 2014 can be justified twofold. First, occupations do not experience changes in their task compositions on an annual basis. Thus, the adjustment of tasks and work activities takes place slowly over time and depends on the introduction of new technologies. Since computerization of production already mature at the end of the 1990s (Autor, 2015; Beaudry et al., 2016), it can be assumed that task composition of occupations have been relatively stable in Germany since 2000. Second, the task information is based on experts' evaluation of occupations' core requirements, which follow institutionally codified requirements profiles. Thus, an occupation's main task type and task intensity change only slowly over time when data on experts' assessment are applied.

4.3 Descriptive Evidence

The individual determinants of wage mobility as well as the development of the overall wage mobility within a country are of particular interest in the empirical literature. Measuring the wage mobility in more aggregate levels allows for the investigation of the development of an average workers' wage mobility over time in a country or in particular subgroups. Since a worker's downward and upward mobility depends on his or her wage increases or losses as well as on the wage changes of the other workers in the country, there is a logical link between wage mobility and wage inequality. Therefore, the development of wage inequality and wage mobility for Germany between 1984 and 2014 is described below.[91]

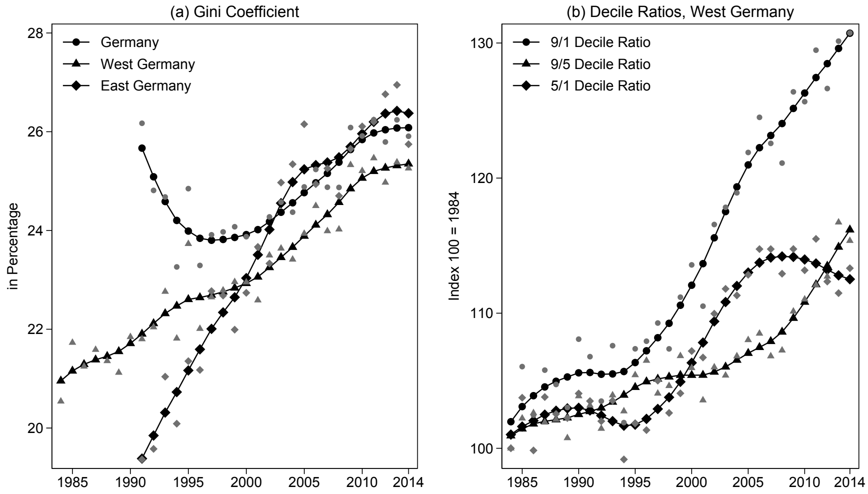
4.3.1 Wage Inequality

There has been a sprouting interest in wage inequality in Germany as well as in most industrialized countries since the 1990s. After the German reunification and the collapse of the Soviet Union, the impact of globalization and the skill biased technical change on the development of the national labor markets increased, which was accompanied by changes in wages and the unemployment rate. Thus, taking a closer look at the development of the wage inequality in West Germany in the 1980s, there are merely moderate increases in the Gini coefficient (see Figure 4.2, panel (a)). However,

[90] According to the official conversion tables, some KldB 1992 level 5 occupations cannot be uniquely matched to KldB 2010 level 3 occupations. This entails a loss of around 17.5 percent of observations in each 3-year-time period. Various matching procedures have been applied in order to the reduce the loss of observation, though they yielded very similar results. Therefore, the estimations are carried out based on uniquely matched occupational data. Estimation results based on matching procedures which match occupations based on likelihoods are available upon request.

[91] Employed inequality and mobility measures are presented and explained in more detail in the Appendix A.2 and A.3. Statistical and distributional basics for the derivation of these measures are given in Appendix A.1.

Figure 4.2: Development of the real hourly wage inequality (various samples)



Notes: Gini coefficients are calculated separately for the full sample, which includes East and West German workers, the West German sample, and the East German sample. Panels (a) and (b) are based on real hourly wages weighted with the corresponding cross-sectional weights. Solid lines represent the trend component of the applied Hodrick-Prescott filter (Hodrick and Prescott, 1997). Since annual data are applied, the smoothing parameter is $\lambda = 6.25$ according to the rule-of-thumb in Ravn and Uhlig (2002).

wage inequality has increased more strongly since the end of the 1990s. In turn, East Germany has experienced a strong growth in wage inequality since the start of data collection in 1991. Whereas wage inequality was 19.4 Gini points in 1991 and below the West German value of 21.8 at that time, the East German values are above the West German ones since 2001. Interestingly, in the first years after the reunification, the overall wage inequality was initially higher than both regional wage inequality values, decreased in the subsequent years, and then has been increasing again since 2000. This pattern of the overall wage mobility indicates that the between-region wage inequality converges over time. The decomposition of the overall mean logarithmic deviation by the two regions shows that between-region and within-region inequality contributed 30 and 70 percent, respectively, to the overall wage inequality in 1991.[92] In turn, the contribution of the between-inequality gradually diminished and has had a value of around 4.5 percent since 2000. Since a between-region inequality of zero means that the average wages in both regions are the same, there is strong convergence between the two regions, at least in average wages, since 1991. Thus, the overall inequality is mainly driven by the within-region inequality.

Furthermore, in order to obtain a more detailed picture of the wage distribution, the common decile ratios are calculated for West Germany between 1984 and 2014 and indexed to 1984 (see Figure 4.2, panel (b)). Whereas there are merely slight changes in

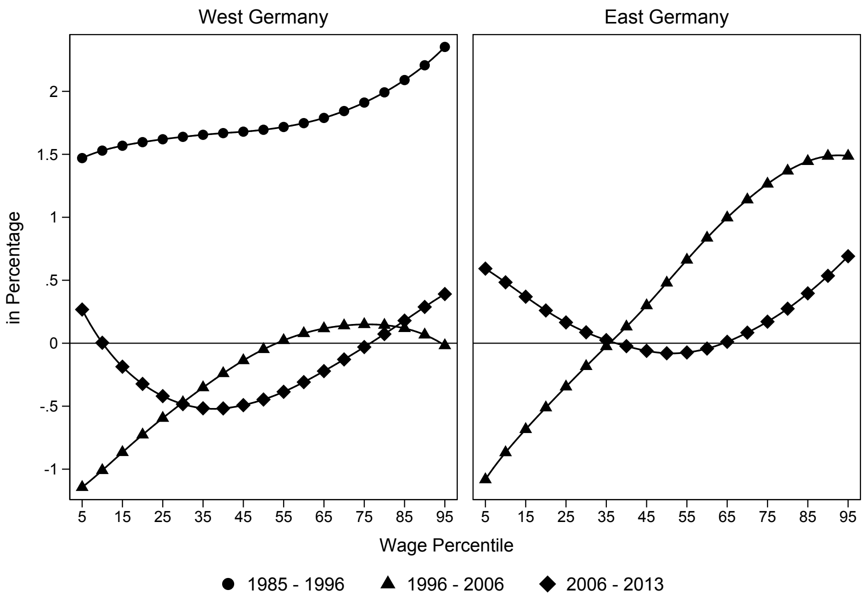
[92]The full results of the decomposition by regions based on the mean logarithmic deviation are given in Table 4.7 in the appendix of this chapter. Since a decomposition based on the Theil index produced very similar results, they are not reported.

the decile ratios until 1995, the indexed 9/1 and 5/1 decile ratios experiences a rapid growth after 1996 and the 9/5 decile ratio after 2000.[93] Due to the persistent increase in unemployment since 1990, low economic growth and the recessions in 1992,1993, and 2003, several reforms were undertaken between 1996 and 2005 in order to increase the flexibility of the labor market and reduce unemployment. Furthermore, unions have lost bargaining power since the mid 1990s due to a sharp decrease in amount of members and the decline in the share of workers covered by any kind of union agreement. This political and economic process supported and partly promoted the establishment and the expansion of a low-wage sector in Germany (Dustmann et al., 2014). Therefore, the low-wage earners experience less wage growth compared to the middle-wage and the high-wage earners. However, the increase of the 9/5 decile ratio since 2002 shows that the middle-wage earners experience less wage growth compared to the high-wage earners. This trend has strengthened since 2008 and shows a similar pattern to the 9/1 decile ratio. Interestingly, the development of the 5/1 decile ratio reverses precisely at this point in time and there has even been a decline in the ratio since 2008. Thus, two general conclusions can be drawn. First, the wage gap between low-wage as well as middle-wage earners to high-wage earners has increased rapidly since 2000. Second, the wage gap between low-wage and middle-wage earners has declined since 2008 and is currently even smaller than the gap between the middle-wage and high-wage earners.

Based on these results, a natural follow-up question arises: Is wage inequality more pronounced in certain parts of the wage distribution and how has it changed over time? This question can be answered, at least in a descriptive manner, by investigating the annual wage growth among the percentiles of the wage distribution in the base year (see Figure 4.3). Utilizing the development of the 5/1 wage decile ratio over time, the observation period is divided into three non-equal-sized time periods. Since there is no data available for East Germany in the 1980s, wage growth between 1985 and 1996 is restricted to West German workers. In this period, the slight increase in the 9/1 and 9/5 decile ratios as well as the relatively constant trend of the 5/1 decile ratio are reflected in wage growth. The increase in wages between the 20th and 60th percentile is between 1.6 and 1.75 percent, whereas wage growth is slightly lower at the lower bound and somewhat higher at the upper bound. Thus, the rise in wage inequality in the 1980s and mid 1990s is due to a stronger wage growth at the top of the wage distribution (Dustmann et al., 2009). However, there is a monotonic function of wage growth over the wage distribution between the mid 1990s and mid 2000s. In West Germany (East Germany), wage losses occur up to the 54th percentile (35th percentile), whereas workers at the top experience slight wage increases. In particular, the large slope of East German wage growth along the wage distribution explains the rise of overall wage inequality in part during this period. Interestingly, in the

[93]The development of the decile ratios in East Germany are similar, though, the growth rates are greater (see Figure 4.16 in the appendix of this chapter).

Figure 4.3: Annual real hourly wage growth in West and East Germany



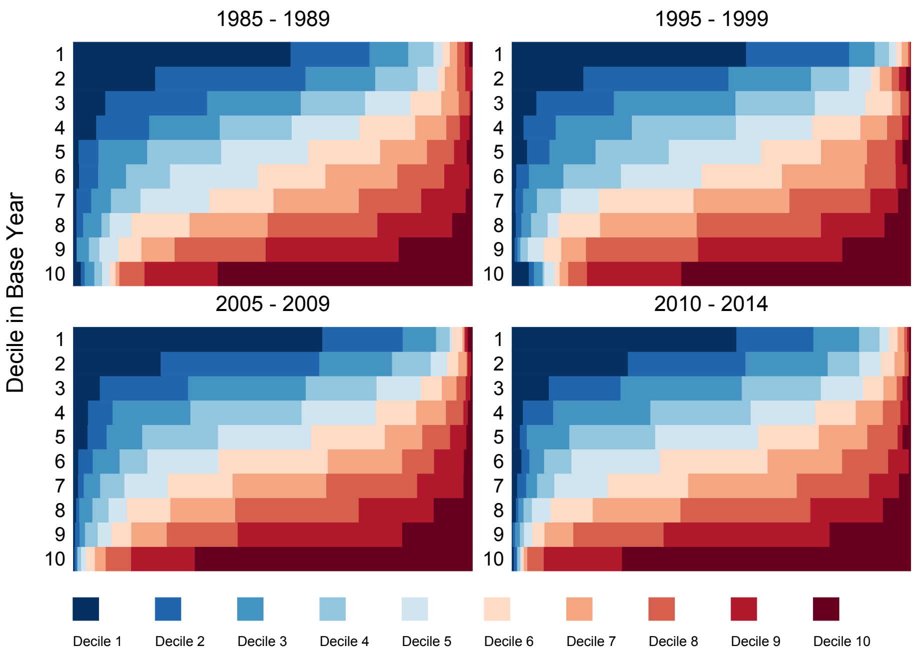
Notes: The data are pooled using three-year moving averages (i.e. the year 1996 includes data from 1995, 1996, and 1997) in order to prevent distortions in wage percentiles caused by outliers in a given year. Using locally weighted smoothing regressions (bandwidth 0.8 with 100 observations), both panels represent the annual change in logarithmic wages by the wage percentile in the base year.The wage distribution in both panels is based on the ranking of real hourly wages weighted by cross-sectional sample weights.

aftermath of the Hartz reforms, there is a wage polarization along the wage distribution in West and East Germany. This result brings the nuanced version of the skill biased technical change hypothesis or polarization hypothesis according to Autor et al. (2003, 2006, 2008) back to wage structure debate in Germany. In previous studies, no wage polarization has been identified for the German wage growth either in the 1990s or in the early 2000s (Dustmann et al., 2009; Antonczyk et al., 2009). Since current research re-evaluates the polarization hypothesis for the 2000s and 2010s in the United States (Green and Sand, 2015; Beaudry et al., 2016) and in Germany (Pikos and Thomsen, 2015), the Subsection 4.4.2 focuses on two particular questions. To what extent is the observed wage polarization along the wage distribution attributable to the polarization hypothesis? Is the wage polarization and the performance of different tasks reflected in a worker's wage mobility?

4.3.2 Wage Mobility

The growth of wage inequality between the mid 1980s and mid 2000s implies that the wage gaps between the percentiles of the wage distribution have increased over time. This trend has been slowing down slightly in West and East Germany since 2006 due to less wage growth in the middle of the wage distribution relative to the lower and upper end. However, higher wage growth or less wage losses of particular wage percentiles do not ensure that workers in these percentiles experience an improvement in their relative wage position. On the one hand, workers' movement along the wage distribution depends on their own wage growth. On the other hand, the wage growth along the entire wage distribution determines whether a worker's own wage growth is sufficient to rise in ranks. Thus, the paradox case of a worker's downward mobility despite his or her own wage growth can occur if workers with a lower wage in the base year experience a much stronger wage growth and pass him or her in ranks. In general, wage mobility can be defined and illustrated in different ways, depending on the aim of the research. A commonly used illustration to show wage mobility in ranks is the descriptive transition matrix which measures the probability to move from a particular wage quantile, such as quintile, decile, or percentile, in the base year t to a certain quantile in the reporting year $t+s$. In Germany, workers in the lowest and in the top wage decile show a very high persistence in their wage ranks (see Figure 4.4). The probability of staying in these wage deciles even after four years is between

Figure 4.4: Descriptive transition probabilities between base and reporting year



Notes: Full samples, which include East and West German workers, are employed for fixed time windows since 1990. The time window before 1990 corresponds to the West German sample. The colors of the transition colorplot represent the wage deciles in the reporting year. The longer the colored bars of the illustration are, the higher is the probability to move to the particular wage decile in the reporting year. Wage distribution in both years is based on the ranking of real hourly wages weighted by cross-sectional sample weights.

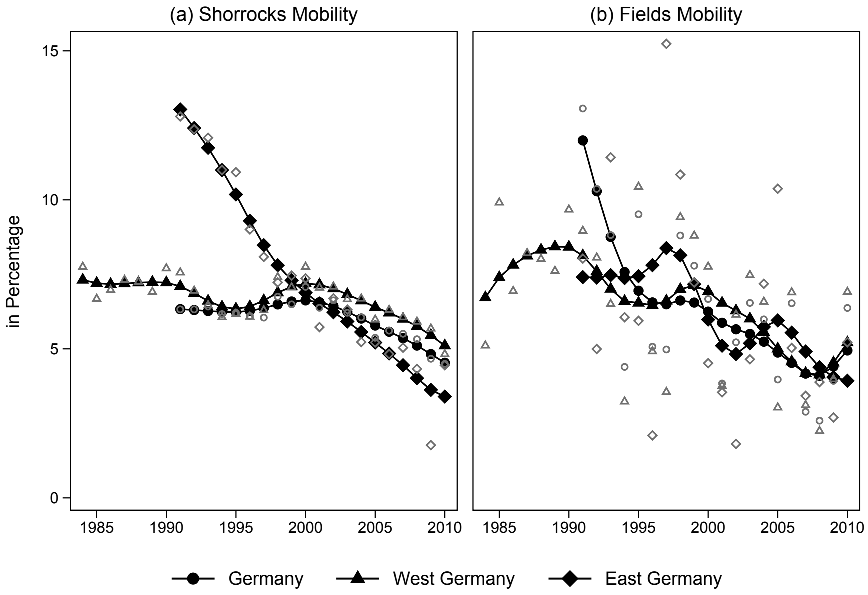
54 and 72 percent over the observation period, whereby the probabilities of workers in the top decile are higher. Considering the wage mobility of workers who are in the lower (upper) three deciles in the base year, their probability of receiving a wage above (below) the median wage after four years are merely between 2 and 15.4 percent. This indicates that the likelihood of workers' downward or upward movement in deciles diminishes rapidly with increasing or decreasing wage deciles. In total, a decrease in

upward mobility of low-wage earners and downward mobility of high-wage earners can be detected since the mid 1990s. Whilst transition matrices measure the transition probabilities between base year and reporting year deciles, they neglect three notable issues. First, a worker's downward or upward mobility within a decile is not taken into account in the calculation of transition probabilities. Second, overall wage growth along the entire wage distribution leaves the probabilities unchanged if the initial ranking of workers does not not change. Third, transition matrices do not directly consider the development of wage mobility over time.

The latter points to the issue that there is no generally accepted and unambiguous definition of intragenerational mobility in the empirical literature. In his pioneering work, Shorrocks (1978) defines mobility as the circumstance that reduces long-term inequality as it smoothes the individual wage or income fluctuations over time. Based on this idea, the Shorrocks mobility index is defined as the difference between the average of cross-sectional wage inequality and long-term wage inequality, which is the inequality of average individual wages over time. Thus, the index measures to what extent wage mobility reduces average cross-sectional wage inequality and can be interpreted as an *equalizer index*. However, Fields (2010) postulates that the wage inequality in the base year should be related to the long-term inequality instead of the average in annual wage inequality. Both measures are calculated and illustrated by applying a moving fixed time window of 4 years over the observation period, whereby it is apparent that the Fields mobility index is more volatile over time (see Figure 4.5).

Furthermore, the mobility indexes strongly differ for East Germany and for Germany as a whole. Whereas the Shorrocks mobility index yields a high wage mobility in East Germany and a relatively constant overall wage mobility after the reunification, the Fields mobility index returns exactly the reverse pattern. Since the numerators of both indexes are the same, the difference is due to divergent denominators. Thus, the Shorrocks mobility index captures the effect of an increasing wage inequality in East Germany and decreasing overall wage inequality between 1991 and 1996. Therefore, in the aftermath of the reunification, the average annual wage inequality over the 4-year time periods is higher (lower) in East Germany (Germany as a whole) than the values in the corresponding base years. This leads to the reverse development of the two indexes and shows the main drawback of the Fields mobility index, which attributes the high wage mobility in East Germany to the overall wage mobility and claims that there was almost no change in wage mobility in East Germany between 1991 and 1996. Hereinafter, the explanations of the wage mobility patterns refer to the Shorrocks mobility index, which enables an accurate distinction between different regional patterns of wage mobility. In West Germany, wage mobility is relatively constant, with values of around 6.5 percent between 1984 and 2000. However, since 2000, wage mobility has gradually decreased, indicating that wage mobility reduced the

Figure 4.5: Wage Mobility as an equalizer of long-term wages between base and reporting year



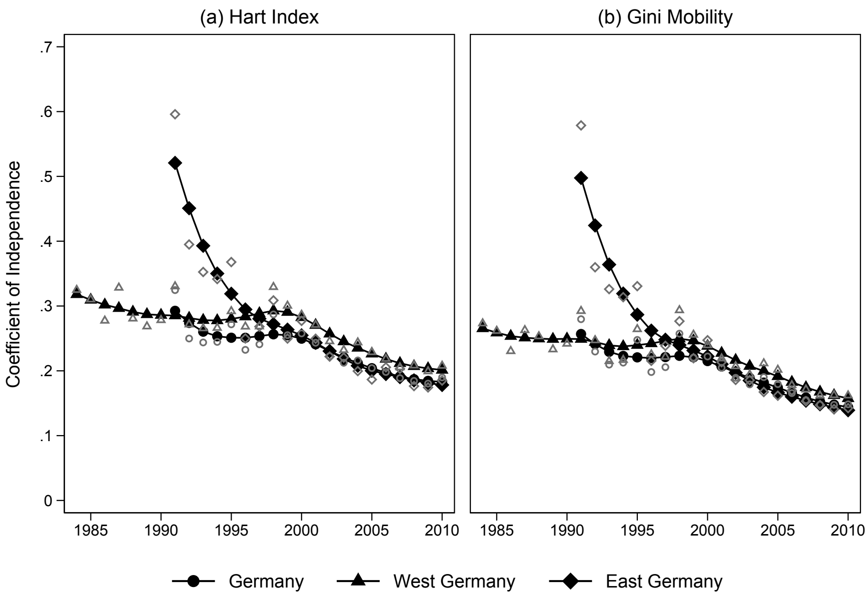
Notes: Mobility measures are calculated separately for the full sample, which includes East and West German workers, the West German sample, and the East German sample, by applying 4-year time periods. Thus, for example, the point estimates for 1984 yield the wage mobility between 1984 and 1988. Panel (a) and (b) are based on real hourly wages weighted with the corresponding cross-sectional weights. Solid lines represent the trend component of the applied Hodrick-Prescott filter (Hodrick and Prescott, 1997). Since annual data are applied, the smoothing parameter is $\lambda = 6.25$, according to the rule-of-thumb in Ravn and Uhlig (2002).

long-term wage mobility by merely 4.8 percent in 2010. The same pattern is detected for the development of overall wage mobility. East Germany started with very high values of wage mobility in 1991, but experienced a sharp decline in the ongoing years. Since 2000, wage mobility in East Germany has even been significantly lower than in West Germany. Currently, merely 3.4 percent of the long-term wage inequality can be reduced through wage mobility in East Germany. Since the Shorrocks mobility index is nondirectional and scale invariant, i.e. only relative income changes matter in the calculation, state dependence in wage ranks strongly increased after 2000 in West and East Germany. Therefore, a worker's probability to move in ranks along the wage distribution diminished over time.

Another group of mobility measures takes this idea of dependency on wages from two different points in time and defines wage mobility as a measure or concept of the independence of cross-sectional incomes. Thus, the Hart Index (Hart, 1976) and the Gini Mobility index (Yitzhaki and Wodon, 2004) measure the correlation between wages at different points in time, where the former is based on the Pearson correlation and the latter on the correlation of Gini coefficients. Therefore, the independence of a worker's wages over time is interpreted as complete wage mobility, since the wage position in the base year does not determine the wage position in the reporting year.

Whereas the Hart index ranges between −1 and +1 and takes the value zero if there is complete immobility, the Gini mobility index ranges between zero and 2 and takes the value 0 if there is complete immobility. Complete mobility is present if the Hart index or the Gini mobility index equals 1, whereas there is complete rank reversal if the Hart index equals −1 and the Gini mobility equals 2. It is apparent that both measures show similar values for West and East Germany, since they are based on wage correlation (see Figure 4.6).

Figure 4.6: Wage Mobility as a measure of independence between base and reporting year wages



Notes: Mobility measures are calculated separately for the full sample, which includes East and West German workers, the West German sample, and the East German sample by applying 4-year time periods. Panel (a) and (b) are based on real hourly wages weighted with the corresponding cross-sectional weights. Solid lines represent the trend component of the applied Hodrick-Prescott filter (Hodrick and Prescott, 1997). Since annual data are applied, the smoothing parameter is $\lambda = 6.25$, according to the rule-of-thumb in Ravn and Uhlig (2002).

Furthermore, both indexes show a similar pattern to the Shorrocks mobility index. However, they differ in their interpretation. For example, in West Germany, the Hart index takes values of around 0.3 between 1984 and 2000, indicating that there is a strong correlation of 0.7 between a worker's wage in the base and reporting year. However, the positive Hart index implies that high-wage earners in the reporting year will not be as "rich" as in the base year and vice versa. Since the Hart index is very similar to one minus the slope parameter of a least-squares regression of the logarithmic wage in the base year on the logarithmic wage in the reporting year, it can also be interpreted as measure of predicted change in wages. For example, a Hart index value of 0.3 indicates that a 1 percentage increase in a worker's base year wage predicts a 0.7 percent increase in his or her reporting year wage. Therefore, the Hart index and the Gini mobility index can be either interpreted as wage independence measures or as indicators for the prediction of percentage changes in individuals' wages.

The measures presented so far depict the change in relative incomes and the movements of individuals along the wage distribution in ranks, such as percentiles and deciles. However, an individual's movements depend on his or her wage growth and on wage distance between two or more adjacent ranks or percentiles. The latter implies that the extent of wage inequality is logically related to the extent of particular wage mobility measures. Jenkins and Van Kerm (2006) offer a method to analyze wage growth and changes in wage ranks between the base and the reporting year simultaneously. Furthermore, they show that the change in the Gini coefficients between two points in time can be decomposed into a pro-poor growth and a reranking or mobility component. The former measures to what extent the changes in wages or wage growth in general benefits the low-wage earner more strongly than high-wage earners of the base year or vice versa. The latter measures the magnitude of individuals' movement along the wage distribution between the base and the reporting year. Applying the conventional Gini coefficient G in order to measure changes in wage inequality, the decomposition can be expressed by:[94]

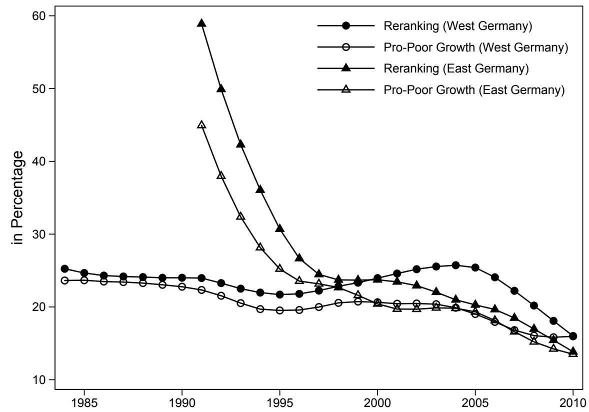
$$\Delta G = G_{t+s} - G_t = R - P \tag{4.2}$$

where R and P are the reranking and progressivity component, respectively, whereby the latter reduces wage inequality, unless the former overcompensates for it. In West Germany, wage mobility as well as the progressivity of wage growth decrease slightly between 1984 and 1996 from 25.2 and 23.6 percent to 22.2 and 20 percent, where both components are measured relative to the Gini coefficient in the base year and reported in percentage (see Figure 4.7).

Since the reranking index is a relative-wages-weighted average of changes in the social weights of individuals between the base and the reporting year, a value of 20 percent implies that wage inequality in the reporting year would have been 20 percent higher (relative to the base year) if wage growth had been equi-proportionate $P = 0$, i.e. each worker's wage increased by the same percentage. Furthermore, the progressivity component takes consistently positive values in East and West Germany over time, which indicates that observed wage growth reduces wage inequality and is pro-poor, i.e. wage growth is concentrated more among the low-wage earner than the high-wage earner. This index yields the decrease in cross-sectional wage inequality in percentage of the base year value if there had been no reranking $R = 0$, i.e. the rank order of workers does not change between the base and the reporting year. Whereas the difference in the reranking and the progressivity component are relatively constant in East Germany, the two components start to diverge in West Germany between 2000 and 2005. The fairly constant progressivity combined with increasing mobility indicates that the growth in

[94]A detailed derivation and explanation of the decomposition method is given in Appendix A.3.2.

Figure 4.7: Decomposition of Gini coefficient changes in wages between base and reporting year



Notes: Decompositions are calculated separately for the West German and the East German sample applying 4-year time periods. Reranking and pro-poor growth index are given in percentage of the base year wage inequality, whereby the calculation of the conventional Gini coefficients is based on real hourly wages weighted with the cross-sectional weights of the base year. Solid lines represent the trend component of the applied Hodrick-Prescott filter (Hodrick and Prescott, 1997). Since annual data are applied, the smoothing parameter is $\lambda = 6.25$, according to the rule-of-thumb in Ravn and Uhlig (2002).

wage inequality between 2000 and 2009 is mainly driven by wage mobility. However, it is to an extent counterintuitive that wage inequality increase despite pro-poor growth in both regions due to the overcompensating effect of reranking. Since the decomposition method is based on tracking individuals' wage position over time, low-wage earners in the initial year might move towards middle-wage jobs in the reporting year due to pro-poor growth, but they are simultaneously replaced by new low-wage earners who were middle- or high-wage earners in the base year. If the new set of low-wage earners in the reporting year have, on average, a lower wage than the previous set of low-wage earners in the base year, the reranking index will exhibit the pro-poor growth index, which leads to an increase in cross-sectional wage inequality. Therefore, the decomposition method measures wage changes of a fixed wage group, whose membership is defined by the base year (progressivity) and adds a term that accounts for membership changes (reranking). As the 9/5 decile ratio has increased more strongly since 2000, after a rather flat phase before, and there was no considerable change in the growth pattern of the other decile ratios, the increase in wage inequality might be due to a higher reranking in the middle of the wage distribution. This is all the more likely because the conventional Gini coefficient is more sensitive to changes in the middle of the distribution.

4.4 Empirical Results

The empirical analysis evaluates the influence of individual characteristics, job stability variables, and employment characteristics on a worker's wage mobility in Germany.

For this purpose, rolling 4-year time periods between 1993 and 2010 are used. Due to the reunification effects, the first two years after the reunification are not considered within the estimations in order to prevent distortions. Although the presentation of the estimation results is limited to three selected 4-year time periods, the conclusions are drawn taking the whole observation period into account.[95] Hence, a worker's age has a negative impact on his or her wage mobility, i.e. older workers show, on average, a lower wage mobility (see Table 4.1). The magnitude of this effect is relatively constant over time and ranges between 0.1 and 0.2 percentiles per year over the entire observation period. In contrast, a worker's job tenure in the base year has no significant impact on his or her wage mobility in two out of three presented time periods. Although job tenure did not have a significant impact in the 1990s, there has been a significant positive association between job tenure and wage mobility since 1999. The results for the 1990s can be due to a higher correlation between a worker's age and his or her job tenure, which might lead to insignificant coefficients of one of the two covariates.[96] Since the estimations control for plenty of socio-economic characteristics, a worker's migration background does not cause significant differences in wage mobility.[97] Furthermore, a job change within the 4-year time periods has no significant influence on a worker's wage mobility. On the one hand, workers who have better alternatives might change their workplace to achieve higher wages. On the other hand, workers might involuntarily switch to low-wage employment due to family reasons or imminent unemployment. Thus, the lack of job change effect could be due to these two mutually compensating causes. Moreover, a worker's unemployment experience within the time period has a highly significant negative impact on his or her wage mobility. An additional month of unemployment between 2010 and 2014 lowers an employee's wage mobility by 0.5 percentiles. Across the presented time periods, there is an increase in the importance of unemployment spells for wage mobility. Since the considered base years are respectively in economic upturns, the three time periods start in comparable points of the business cycle.[98]

Additionally, wage mobility increases with firm size.[99] Employees who work in firms with more than 2000 employees show a wage mobility of almost 6 percentiles higher than similar employees who work in firms with less than 20 employees. There

[95]The estimation results of the remaining time periods are available upon request.

[96]Neither age nor job tenure show a significant quadratic effect on the workers' wage mobility. Thus, there is no curvilinear relationship for both covariates.

[97]In the estimations, workers with a migration background and workers with migration experience are combined. People with migration experience are foreign-born persons, whereas people with migration background are born in Germany and have parents or grandparents who are foreign-born.

[98]The previous recessions were in the following periods: January 1991 - April 1994, January 2001 - August 2003, and April 2008 - January 2009.

[99]The positive association between wages and the firm size was first discovered by Moore (1911) who investigated the daily wages of Italian women in textile mills.

Table 4.1: Determinants of wage mobility in different 4-year time periods

	1995-1999		2005-2009		2010-2014	
Individual Characteristics						
Age	-0.122	(0.039)***	-0.115	(0.038)***	-0.146	(0.034)***
Female	-5.340	(0.831)***	-4.296	(0.655)***	-3.993	(0.608)***
Migration Background	-1.285	(0.778)*	-0.677	(0.710)	-0.873	(0.620)
Low-Skilled			*reference*			
Medium-Skilled	2.172	(1.004)**	2.571	(1.003)**	3.112	(1.010)***
High-Skilled	7.867	(1.455)***	7.385	(1.276)***	8.153	(1.227)***
Job Stability						
At Least 1 Job Change	-1.075	(0.861)	-0.712	(0.788)	0.617	(0.649)
Unemployment Experience	-4.085	(1.359)***	-5.269	(1.656)***	-6.217	(1.348)***
Job Tenure	0.052	(0.040)	0.035	(0.036)	0.068	(0.032)**
Employed Part-Time	-3.144	(1.075)***	-2.774	(0.788)***	-1.633	(0.685)**
Employment Characteristics						
Firm Size: < 20			*reference*			
Firm Size: 20-200	1.584	(0.867)*	2.413	(0.743)***	1.643	(0.686)**
Firm Size: 200-2000	4.649	(0.918)***	4.880	(0.839)***	3.960	(0.747)***
Firm Size: > 2000	6.778	(0.955)***	6.655	(0.860)***	5.863	(0.763)***
Manufacturing			*reference*			
Agriculture	-7.699	(2.552)***	-7.203	(2.399)***	-2.175	(2.485)
Energy	4.345	(2.803)	-0.943	(2.492)	-2.380	(2.258)
Mining	-0.613	(3.560)	1.608	(4.441)	12.431	(4.979)**
Construction	-0.631	(0.861)	-0.533	(0.828)	-0.445	(0.743)
Trade	-2.274	(1.150)**	-5.998	(0.946)***	-5.534	(0.877)***
Transport	-2.286	(1.394)	-2.623	(1.303)**	-2.463	(1.126)**
Bank,Insurance	2.513	(1.473)*	2.914	(1.203)**	0.235	(1.186)
Services	0.133	(0.887)	-2.458	(0.741)***	-2.513	(0.706)***
Legislators/Senior Officials/Managers			*reference*			
Professionals	3.904	(1.873)**	-0.263	(1.180)	1.197	(1.099)
Technicians/Associate Professionals	-2.324	(1.730)	-4.830	(1.177)***	-2.733	(1.094)**
Clerks	-3.256	(1.819)*	-8.324	(1.322)***	-6.208	(1.235)***
Service Workers/Shop and Market Sales Workers	-7.909	(2.122)***	-11.436	(1.444)***	-7.729	(1.430)***
Skilled Agricultural/Fishery Workers	-7.927	(3.210)**	-13.083	(3.421)***	-12.766	(2.509)***
Craft and Related Trades Workers	-7.976	(1.814)***	-11.223	(1.364)***	-9.535	(1.263)***
Plant and Machine Operators and Assemblers	-8.855	(1.873)***	-13.713	(1.485)***	-10.980	(1.401)***
Elementary Occupations	-11.546	(2.100)***	-13.300	(1.606)***	-10.023	(1.542)***
Change of Occupation	0.011	(0.647)	-0.512	(0.553)	0.268	(0.511)
Change of Industry	0.463	(0.711)	0.173	(0.631)	-0.648	(0.590)
East Germany	-10.704	(0.969)***	-6.224	(0.690)***	-6.012	(0.612)***
R^2	0.269		0.234		0.230	
Obs.	3323		4096		4571	

Notes: Estimations are based on the full sample, which indcludes East and West German workers. Wage mobility is calculated using cross-sectional weights. Classification of industries is based on ISIC Rev. 3 and classification of occupations is based on ISCO88. Workers' initial wage percentiles or ranks are included, but not reported. Robust standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

are several causes for such an positive association between firm size and wage mobility or wages, in general.[100] First, larger firms show a more unionized workforce that can bargain for higher wages than comparable workers in smaller firms. Second, the capital to labor ratio is higher in larger firms. Thus, a worker's productivity and wage is higher

[100] See Brown and Medoff (1989), Abowd et al. (1999), and Oi and Idson (1999) for a review of the literature on the firm size wage premium.

in larger firms. Furthermore, large firms tend to adopt new technologies and process innovations more quickly than small firms, which increases workers' productivity (Idson and Oi, 1999). Third, larger firms are more likely to fill their vacancies internally than externally. Thus, workers could receive higher wages due to changing their position within the firm. Additionally, this reduces a firm's searching and hiring costs (Gerlach and Schmidt, 1989). Fourth, firms with many employees are more likely to have a higher survival rate and invest more in training their workers (Brown and Medoff, 2003). Moreover, the firm size wage premium can be driven to some extent by the self-selection of less able workers into small, unstable, and low-paying firms (Winter-Ebmer, 1995).

Taking a closer look at the effect of a worker's occupation on his or her wage mobility shows declining coefficients with descending categories, since managers are the reference category. This is due to the classification scheme of the occupations that is based on an occupation's skill requirements and the degree of specialization. Thus, the occupation variable covers the specific part of a worker's human capital, whereas the educational attainment measures his or her general human capital. Therefore, workers in elementary occupations and plant or machine operators have around a 10 percentiles lower wage mobility than managers. In particular, professionals and clerks suffered a loss in their wage mobility compared to managers. Whereas professionals show a 3.8 percentiles higher wage mobility than managers in 1993, the wage mobility difference between both occupations has not been significantly different from zero since the beginning of the 2000s. Furthermore, clerks' estimation coefficient decreased from -1.6 in 1993 to -6.2 in 2010.

Additionally, a worker's industry affiliation partly affects his or her wage mobility. In particular, workers in the trade industry have been significantly less mobile in terms of wage percentiles than workers in manufacturing since the beginning of the 2000s. Over time, the negative effect is relatively stable and ranges between 5 and 6 percentiles. The same applies for the transport industry. Although workers in the mining industry experience a significantly upward mobility in the last 4-year time period, this result is only an outlier. In previous years, there is no significant difference in the wage mobility of workers of the manufacturing and mining industry.

Whereas workers in the service industry did not significantly differ in their wage mobility from workers of the manufacturing industry until 1999, their wage mobility slightly decreased several years after 2000. As the service industry includes various sub-industries, which can be different in their qualification and employment structure, the estimations are repeated using a more detailed industry definition (see Table 4.2).[101] Applying the NACE Rev. 1 level 1 industry categories enables the detailed breakdown of the service sector, whereby some industries, such as agriculture, fishing, and mining,

[101] Full estimation results are in Table 4.8 in the appendix of this chapter.

Table 4.2: Effect of detailed industry categories on the wage mobility in different 4-year time periods

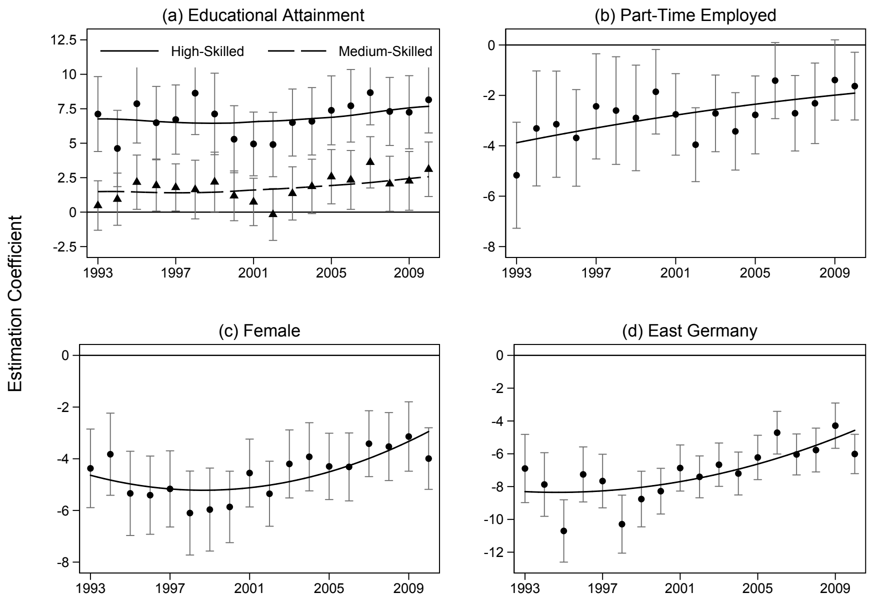
	1995-1999		2005-2009		2010-2014	
Manufacturing			*reference*			
Agriculture/Fishing/Mining	-5.674	(2.140)***	-3.873	(2.318)*	-0.542	(2.362)
Electricity/Gas/Water	3.948	(2.771)	-0.735	(2.479)	-2.493	(2.245)
Construction	-2.150	(1.075)**	-0.624	(1.240)	-3.468	(1.012)***
Wholesale And Retail Trade	-2.789	(1.179)**	-5.830	(0.935)***	-5.706	(0.873)***
Hotels And Restaurants	-3.815	(2.548)	-7.804	(1.882)***	-8.691	(1.824)***
Transport, Storage, and Communication	-2.698	(1.382)*	-2.512	(1.275)**	-2.745	(1.094)**
Financial Intermediation	2.053	(1.465)	3.048	(1.164)***	0.118	(1.148)
Real Estate, Renting, and Business Activities	2.871	(1.443)**	-1.456	(1.004)	-1.393	(0.872)
Public Administration/Social Security	-1.709	(1.280)	-1.373	(1.076)	-1.554	(0.992)
Education	0.090	(1.566)	-1.332	(1.407)	0.389	(1.226)
Health And Social Work	-2.201	(1.241)*	-3.874	(0.997)***	-4.674	(0.874)***
Other Industries	1.705	(1.852)	-2.338	(1.484)	-3.452	(1.322)***

Notes: Estimations are based on the full sample, which includes East and West German workers. Wage mobility is calculated using cross-sectional weights. Classification of industries is based on NACE Rev. 1, where “agriculture”, “fishing”, and “mining” are combined into a category and “other community activities”, “private households”, and “extra-territorial organization” are combined into “other industries”. The classification of occupations is based on ISCO88. Workers’ initial wage percentiles or ranks are included, but not reported. Robust standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

are grouped together due to a small number of valid observations in the corresponding cells. Workers of the “wholesale and retail trade” and “hotels and restaurants” industry which were aggregated to the previous “trade” industry show significantly less wage mobility than workers in manufacturing. With respect to the sub-industries of the service sector, the results show that the negative effect for the service sector is driven by the sub-industry “health and social work”. Here, workers’ wage mobility declines relative to workers in the manufacturing industry over time. Their difference in wage mobility to workers in manufacturing increased from 2 percentiles in 1993 to 4.6 percentiles in 2010. The workers of the other sub-industries of the service sector do not show a significant difference in their wage mobility to workers in manufacturing. This has especially applied since the 2000s. Ultimately, neither a worker’s change in occupation nor change in industry within the time periods have a significant influence on his or her wage mobility. Here, the same reasons apply as for a worker’s job change.

Some covariates show a clear trend in the extent of their effect on a worker’s wage mobility over the entire observation period (see Figure 4.8). Hence, women have a lower wage mobility than men over time. Whereas at the beginning of the 1990s, this difference slightly increased due to reunification effects, the effect of a worker’s gender on the wage mobility has gradually declined since 1998. However, this convergence of women and men occurs relatively slowly. In 2010, women were still, on average, 4 percentiles less mobile in wage ranks than men. A similar trend can be detected for workers living in East Germany. There is a slow convergence between East and West German workers in their wage mobility. In particular, since 2001 the wage mobility gap between West and East Germany has gradually declined. However, the difference in

Figure 4.8: Development of selected estimation coefficients over time (full sample)



Notes: Solid and dashed lines are local polynomial smooth functions of degree 3, whereas spikes and cap lines represent the 95 percent confidence limits of estimation coefficients. Estimations are based on the full sample, which includes East and West German workers. Wage mobility is calculated using cross-sectional weights.

wage mobility was still 6 percentiles in 2010. Thus, the labor market adjustments in East Germany occur very slowly with regard to wage mobility and wage development, although 25 years have already passed since reunification (Gernandt and Pfeiffer, 2008). In turn, the negative impact of part-time employment on a worker's wage mobility diminishes over time. In contrast to the trend of previous covariates, the convergence between part-time and full-time workers' wage mobility is almost entirely completed at the end of the observation period. Between 1993 and 2010, the wage mobility gap decreased from 5.1 percentiles to 1.6 percentiles.

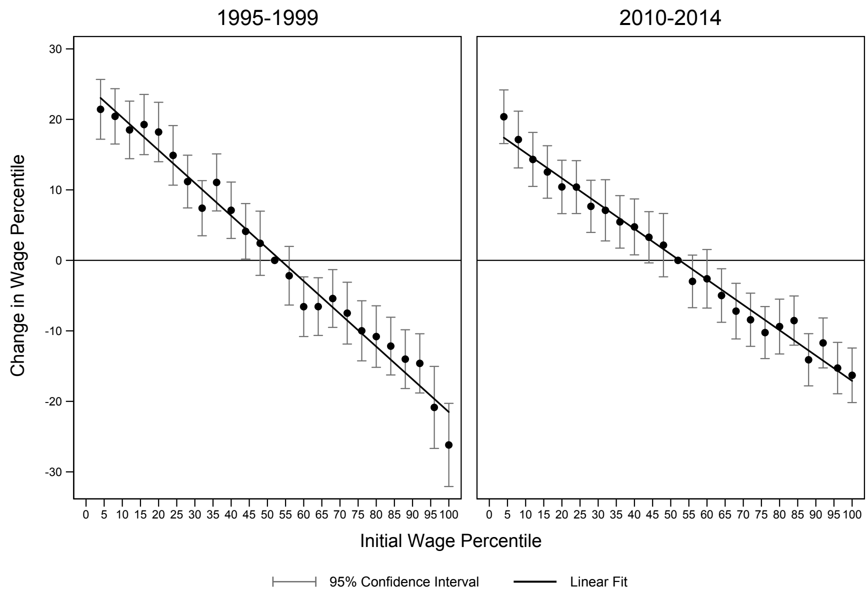
Taking a closer look at educational attainment's impact on a worker's wage mobility, wage mobility increases with increasing educational degree. In 2010, high-skilled workers and medium-skilled workers were more mobile than low-skilled workers by 8 and 3 percentiles, respectively. Over time, the extent of these effects has been relatively constant, however there has been a slightly rising trend in the estimation coefficients of both education categories since the beginning of the 2000s. At first glance, a relatively constant effect of educational attainment on workers' wage mobility might not coincide with the skill biased technical change hypothesis, which implies that industrialized countries, such as Germany, have experienced a rise in the relative demand for high-skilled employees since the 1980s or 1990s (Katz and Autor, 1999). The skill biased technical change is based on the introduction of computer technology in the workplace and the greater digitization of work. In turn, the workforce is affected differently by this development, since computer technology favors high-skilled jobs and disadvantages low-skilled jobs. Thus, the larger productivity increases of human capital relative to the productivity gains of the other production factors should result in larger increases in high-skilled wages relative to increases in low-skilled wages (Hornstein et al., 2005; Acemoglu and Autor, 2011). Whether the relative wages of high-skilled and low-skilled workers increase in the long run depends on the productivity effect and the relative labor supply. If the latter shifts towards high-skilled labor, it partly compensates for the productivity effect on relative wages (Acemoglu, 1998, 2002).[102] As wage inequality has strongly increased in Germany since the beginning of the 1990s, this development can be partly attributed to the skill biased technical change (Dustmann et al., 2009; Antonczyk et al., 2009). In turn, a higher wage inequality entails the expansion of the wage thresholds between the percentiles along the wage distribution. Since wage growth increases along the wage distribution due to skill biased technical change (Card et al., 2013), high-wage earners have to generate stronger wage increases than low-wage earners in order to ascend along the wage distribution. As high-skilled workers tend to be at the upper end and low-skilled workers at the lower end of the wage distribution, a constant estimation coefficient across the educational categories over time implies a stable influence on wage mobility, though the effect of education on a worker's wage growth has to be increased.

4.4.1 State Dependence in Wage Mobility

In addition to the socio-economic and demographic characteristics, a worker's wage mobility depends on his or her initial wage percentile in the base year. Workers who are at the lower end of the wage distribution experience an upward mobility relative to median workers, whereas workers who are at the upper end of the wage distribution show a downward mobility relative to median workers (see Figure 4.9). This relationship applies to all employed 4-year time periods. In relation to the median worker, a worker who started in the bottom four percentiles in 1995 moved, on average, by 21.2 percentiles upward, whereas a worker starting in the top four percentiles moved, on average, 26.2 percentiles downwards. Thus, there were several rank changes between workers at both ends of the wage distribution as well as in middle of the wage distribution. However, workers' wage mobility depending on their initial rank changed in 2010. Although the impact of the initial percentile at the lower end of the wage distribution is only slightly smaller, workers from above-median percentiles show significantly less downward mobility. A worker starting in the top four percentiles experiences merely a downward mobility of 16 percentiles relative to the median worker.

[102] In his pioneering work, Tinbergen (1974) had already suggested that the technological trend will increase the demand for more skilled labor and characterized the development of the wage structures as a "race between demand for third-level manpower due to technological development and supply of it due to increased schooling".

Figure 4.9: Change in wage percentiles due to a worker's initial wage percentile



Notes: Estimations are based on the full sample, which includes East and West German workers. Solid lines are linear fits, whereas spikes and cap lines represent the 95 percent confidence limits of the estimation coefficients. Wage mobility is calculated using cross-sectional weights. The reference point is a worker who is between the 48th and 52nd percentile of the wage distribution in the base year.

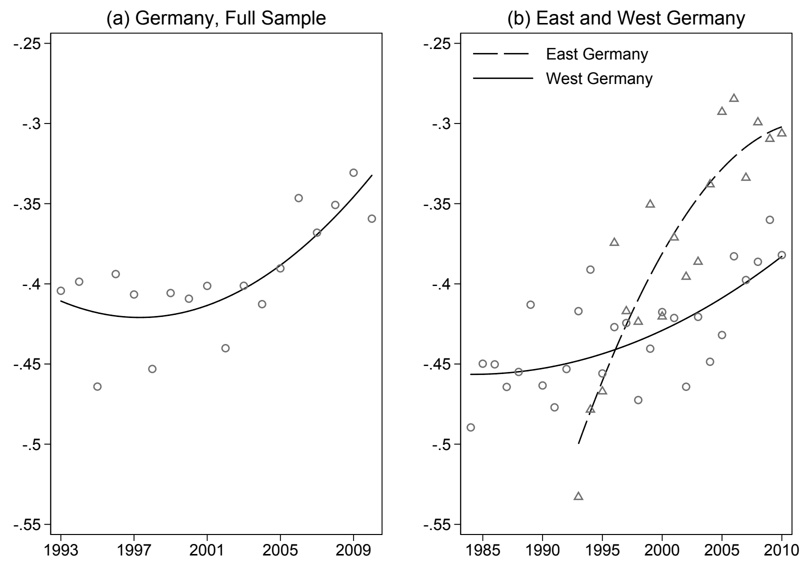
Thus, high-wage earners show less downward mobility or have a lower probability to move downwards along the wage distribution. Therefore, the closer the estimation coefficients of the initial wage percentiles are to the zero value, the smaller is the impact of a worker's initial wage percentile on his or her wage mobility. This relationship can be graphically represented by a linear fit over the estimation coefficients of the particular initial ranks. Thus, two polar cases can be distinguished from the slope of the linear fit. First, if the slope of the linear fit is equal to a value of one, workers at the bottom of the wage distribution swap their position with workers at the top of the wage distribution. The top wage-earner becomes the bottom wage-earner after four years and vice versa. Second, if the slope of the linear fit is equal to zero, the initial wage percentiles have no significant impact on a worker's wage mobility after controlling for the basic set of covariates. Both high-wage and low-wage earners remain in the same wage rank after four years. Since no worker moves depending on his or her initial wage percentile, this can be interpreted as an extreme form of state dependence.

State dependence, in general, occurs if a person's economic status exhibits substantial serial persistence over time and transitions between different economic status are lowered. [103] In general, there are two explanations for serial dependence (Heckman,

[103] State dependence is investigated in studies about a person's transition probability from welfare receipt to no welfare receipt (Jenkins and Cappelari, 2014; Königs, 2014), from unemployment to employment (Wunder and Riphahn, 2014), and from low-wage employment to high-wage employment (Mosthaf et al., 2011; Aretz and Gürtzgen, 2012).

1981). On the one hand, persistence might be the result of "true dependence", i.e. the current position of a person directly affects his opportunities or preferences to take another position. On the other hand, the persistence might occur due to genuine state dependence, i.e. there is observed or unobserved individual heterogeneity that drives the observed persistence. However, the extent of genuine state dependence can be considerably reduced if observable individual characteristics and selection into the observed position is accounted for (Stewart and Swaffield, 1999; Cappellari, 2007). Since plenty of socio-economic and demographic covariates are used within the estimations, the slope of the linear fit should reflect true state dependence to a major extent. Furthermore, a greater slope in absolute terms implies less aggregate state dependence in workers' wage mobility. Over the observation period, the aggregate state dependence generally increased in the full sample, which includes East and West German workers. Between 1993 and 2004, state dependence was relatively constant around the value -0.4, except for the outliers in 1995, 1998, and 2002 (see Figure 4.10). However, since 2005, the impact of a worker's initial wage percentile on his or

Figure 4.10: Development of the aggregated state dependence over time



Notes: Estimations based on the full sample includes East and West German workers and a region dummy for East Germany. Estimation based on West or East German Samples include federal state dummies. West German Samples additionally includes a dummy for whether workers migrated from East to West Germany. Wage mobility is based on 4-year time periods and calculated using cross-sectional weights. The reference point for estimation coefficients of the initial wage percentiles is a worker who is between the 48th and 52nd percentile of the wage distribution in the base year.

her wage mobility has gradually declined and state dependence reached a value of -0.36 in 2010. A similar trend can be detected separately for West German workers. There, between 1984 and 2004, the state dependence does not take any value below -0.5 or above -0.4. Thus, there is no clear trend initially apparent. However, since 2005, the -0.4 mark has been continuously surpassed and the aggregate state dependence amounted to -0.38 in 2010. A rise in workers' persistence probability in their initial wage percentile can also be ascertained for East German workers. In the first years after reunification, state dependence in East Germany was even lower than in West Germany, which can be attributed to reunification effects and has already been mirrored in a higher aggregate wage mobility in East Germany during that time. However, since 1996, the state dependence of wage mobility has been higher in East Germany than in West Germany. In particular, since 2005, East German values have been around the -0.3 mark. Although the average difference in the wage mobility of East and West German workers has declined since 2001 due to the estimation results, an East German worker's probability of persistence in his or her initial wage percentile is higher. This indicates that workers' wage mobility along the entire wage distribution is lower in East Germany than in West Germany. Workers at the lower end of the wage distribution move upwards by less percentiles, whereas workers at the upper end of the wage distribution move downwards by less percentiles. Ultimately, workers' probability of persistence in their initial wage percentiles increased overall, but more so in East Germany than in West Germany.

4.4.2 Tasks, Task Intensity, and Wage Mobility

The skill biased technical change predicts that wages have increased monotonously over employees' educational degree since the introduction of computer technology at workplaces. Therefore, low-skilled workers' jobs can be replaced more easily by new technologies and experience wage losses or lower wage growth over time, whereas high-skilled jobs are complemented and extended, which leads to higher wages or greater wage growth. However, Autor et al. (2003) point out that the substitution process does not address the general level of education, but rather draws on specific work activities. By aggregating the work activities of different occupations to tasks, they show that the diffusion of computer technology in the production process induced a substitution of routine cognitive and routine manual tasks which follow explicit rules and a complementation of non-routine problem-solving and complex communications tasks. Furthermore, Autor et al. (2006, 2008) discover that low-skilled workers' wages and employment did not decline in the United States in the 1990s, but rather these changes occurred to middle-skilled workers. Additionally, they show that, in general, workers performing mainly routine jobs are located in the middle of the wage distribution, whereas workers performing mainly non-routine jobs are at the upper and lower end. Therefore, the nuanced version of the skill biased technical change predicts a polarization of wage and employment growth along the wage distribution. In a follow-up paper, Autor and Dorn (2013) show that wage and employment polarization at the lower end of the skill distribution between 1980 and 2005 is mainly driven by service occupations in the United States. Since routine tasks were substituted through computerization, low-skilled workers re-allocated themselves into service occupations which require direct physical proximity and flexible interpersonal contact. Goos and Manning (2007) receive similar results with regard to the employment growth pattern, but different results for the wage growth in the United Kingdom between 1975 and 1999. Whereas workers at the lower end of the skill distribution show wage losses relative to workers at the middle, employment polarization explains one-third of the rise in the 5/1 wage decile ratio wage and one-half of the rise in the 9/5 wage decile ratio.

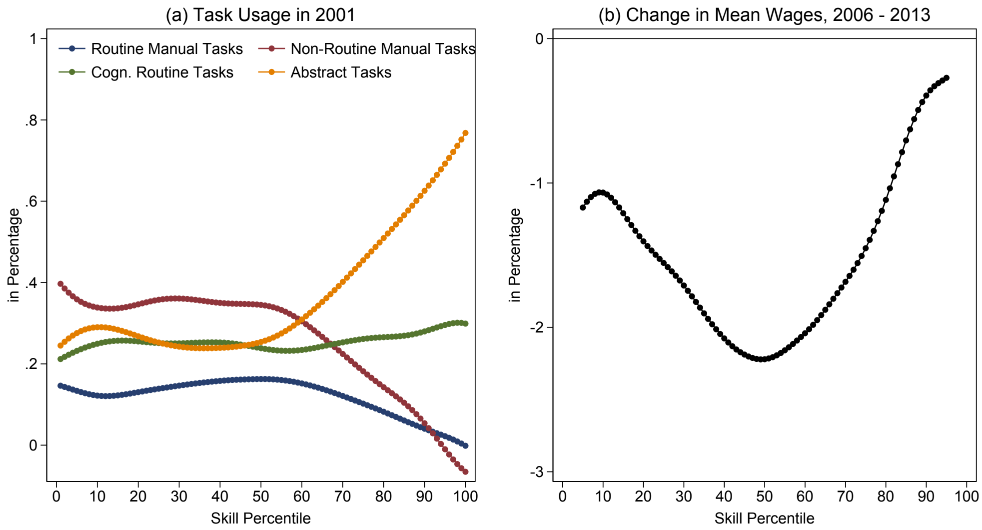
In Germany, Spitz-Oener (2006) examined the routinization hypothesis and detects an employment polarization irrespective of the educational degree between 1979 and 1999. The first skill decile (including mainly non-routine manual tasks) and the top three skill deciles (including mainly non-routine analytic and interactive tasks) experienced employment growth, whereas the second and third deciles (including mainly routine manual and cognitive tasks) evinced employment losses. Dustmann et al. (2009) confirm the employment polarization in the 1980s and 1990s. However, they find no evidence of a wage polarization in either of the two decades. Whereas average wages in skill percentiles above the median are positively correlated with employment changes, average wages in skill percentiles below the median are negatively correlated. Therefore, the increase in wage inequality in the early 1990s, especially at the lower end of the wage distribution, can be better explained by temporary events, such as de-unionization and supply shocks (reunification and stark inflow of low-skilled Eastern Europeans). Antonczyk et al. (2009) support these results and conclude that the task-approach can explain the wage growth at the upper end of the distribution, but not the wage changes at the lower end. Thus, the rise in wage inequality can only partly explained by the relative task demand shifts.

Recent studies question the wage polarization as a long-term phenomenon, claiming that wage polarization was limited to the labor market in the United States and is merely an exception rather than a rule (Green and Sand, 2015). Beaudry et al. (2016) detect that there has been no wage growth or slight wage growth for abstract tasks in the United States since 2000, whereas workers performing mainly routine and manual tasks have experienced no wage changes or slight declines in their wages. In Germany, Pikos and Thomsen (2015) find an employment polarization from 1979 to 1999 and a substitution of routine tasks by non-routine tasks. However, the pattern is reversed from 1999 to 2012. There is considerable employment growth in routine tasks and losses in non-routine tasks, which is in line with the demand reversal results according to Beaudry et al. (2016). Thus, the extent to which the substitutability of routine tasks by the computer technology affects wage growth after the turn of the century can be questioned. Since wage growth of certain occupations or workers determines their movements along the wage distribution, the impact of tasks carried out in the base year of the 3-year-time periods on a worker's wage mobility will be examined in more detail.

For this purpose, a newly available measurement method for the operationalization of tasks based on the expert database BERUFENET of the German Federal Employment Agency is applied (Dengler et al., 2014). According to Autor et al. (2003, 2006, 2008) the technical change has a non-monotonic effect on the wage growth along the skill distribution due to the implementation of computer technology. The nuanced version of the skill biased technical change predicts that workers in manual non-routine and abstract occupations are more strongly represented at the lower and upper end of the skill or wage distribution, whereas employees performing mainly cognitive routine and manual routine occupations are mainly located in the middle. Since computer technology substitutes routine tasks and complements non-routine tasks, wage growth along the skill distribution should be polarized, i.e. the wage growth at both ends of the skill distribution is higher than in the middle. In order to test both assumptions of this simple demand-based explanation of the skill biased technical change, the distribution of task usage, and the polarized wage growth, the skill distribution is prepared following the calculation methods outlined in Goos and Manning (2007) and Autor and Dorn (2013). Data on the 3-digit KldB 2010 occupations are combined with information on workers' industry based on the NACE level 1 classification, whereby there are 259 occupation-industry categories in 2001.[104] These occupations are ranked according to their skill level and grouped into 100 equally-sized groups, where skill ranks are approximated by the average wage of workers in the occupations in 2001. Furthermore, each percentile of the skill distribution corresponds to percentiles of the overall employment, i.e. each skill percentile polls the same nominal amount of employment, measured in working hours. Ultimately, the task usage (task intensity) and wage growth are calculated for each skill rank and the estimates of the locally weighted smoothing regressions are plotted over the skill distribution (see Figure 4.11). Taking a closer look at the task usage along the skill distribution shows that the share of workers performing abstract tasks increases strongly as of the 51st skill percentile from 26 percent to 77 percent, whereas the share is relatively constant in the middle and slightly higher at the lower end. Although the share of non-routine manual workers is highest at the bottom of the skill distribution (around 37.5 percent), the shares in the middle are of comparable size (around 35 percent). Ultimately, the shares decrease rapidly as of the 50th percentile. In turn, routine manual occupations are, in general, more frequently located in the middle, but their employment shares are relatively small along the entire skill distribution. In contrast to the routinization hypothesis, cognitive routine task intensity increases from 23 percent in the 60th skill percentile up to 30 percent in the top skill rank. Moreover, their employment shares are relatively constant in the lower end and the middle (around 25 percent). Thus, the predicted distribution of tasks along the skill distribution can be confirmed merely in part for

[104]For the sake of readability, the term "occupation" is used instead of "occupation-industry category" in the following explanations.

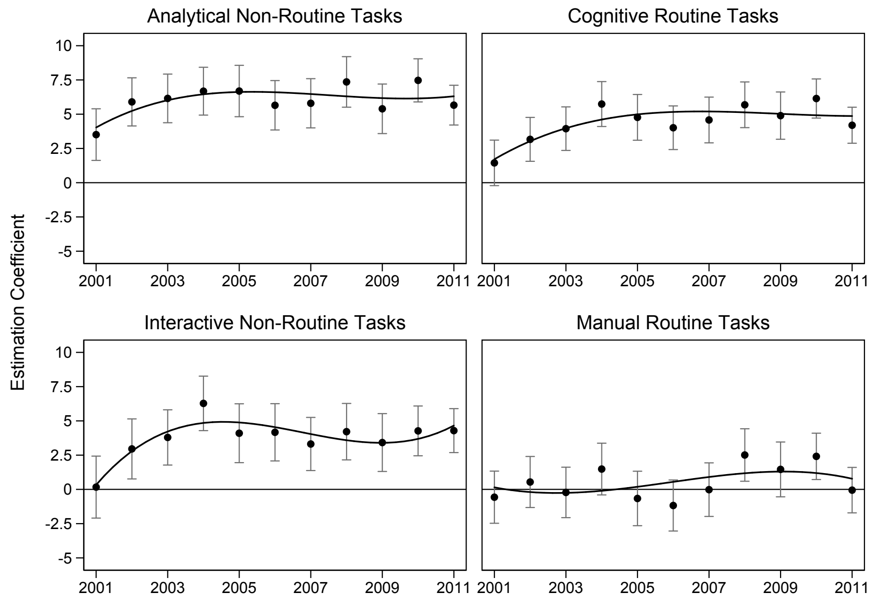
Figure 4.11: Annual wage growth and task usage along skill distribution in 2001



Notes: The data are pooled using three-year moving averages (i.e. the year 2001 includes data from 2000, 2001, and 2002) in order to prevent distortions in skill percentiles caused by outliers in a given year. Using locally weighted smoothing regressions (bandwidth 0.8 with 100 observations), Panel (a) depicts the share of workers performing various task types by 2001 skill percentile and Panel (b) represents the 100 times change in logarithmic mean wages by 2001 skill percentile. The skill distribution in both panels is based on the ranking of 3-digit KldB 2010 occupations combined with NACE level 1 industry information according to mean wages weighted by working hours times cross-sectional sample weights in 2001 and on the subsequently grouping into 100 equal-sized groups with regard to overall employment. The full sample is employed, which includes East and West German workers.

Germany in 2001. Since there was some descriptive evidence on the polarization of wage growth along the wage distribution as of 2006, the average wage growth in occupations along the skill distribution based on 2001 is examined. In general, all occupations experience, on average, wage losses in this period. In contrast to the assumptions about the task distribution, the wage polarization is still maintained using the skill distribution instead of the wage distribution. However, this pattern can be explained merely in part by the routinization hypothesis. The greater wage growth at the upper end of the skill distribution is due to the higher employment share of abstract tasks. This development might also be encouraged by an increasing employment share of cognitive routine tasks. In turn, wage growth at the lower end of the distribution might be explained by the lower wage losses of non-routine manual workers. However, abstract and cognitive routine tasks' usage is slightly higher at the lower end of the skill distribution than in the middle, which might also drive the observed wage pattern in part. Ultimately, the high wage reductions in the middle of the skill distribution suggest that this result is driven by higher employment shares of routine manual tasks. However, non-routine manual tasks make up the highest employment share in that part of the distribution. In a recent work, Pikos and Thomsen (2015) ascertain two aspects of wage development in Germany between 1999 and 2012 that explain the observed wage pattern so far. First, for occupations which consist of cognitive tasks, they detect a rise in wages, which was slightly greater for routine cognitive tasks than for non-routine cognitive tasks. Second, occupations where routine manual tasks are performed experienced wage decreases, whereas slight wage increases were observed for occupations where non-routine manual tasks are performed. Therefore, the wage losses seen for occupations consisting of routine manual tasks might overcompensate the slight wage growth experienced by occupations where other tasks are mainly performed in the middle of the distribution, although they might be not able to offset the wage growth at the lower end of the distribution, since their employment share is lower and the employment share of abstract and routine cognitive tasks is higher relative to the middle of the distribution. Putting the focus back on wage mobility, the evidence of wage changes across the occupations where various tasks are performed is reflected in the estimations (see Figure 4.12).

Figure 4.12: Development of tasks' impact on wage mobility over time

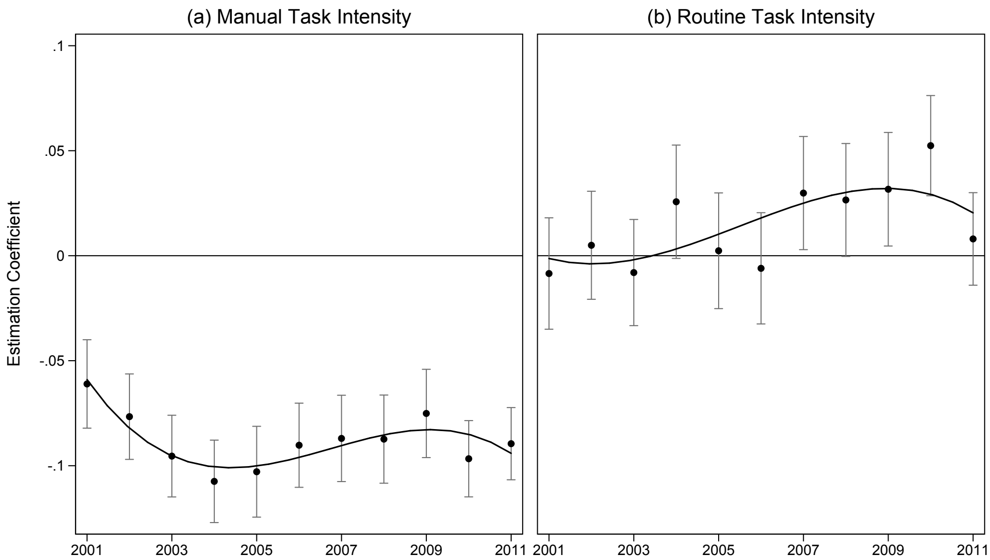


Notes: Solid lines are local polynomial smooth functions of degree 3, whereas spikes and cap lines represent the 95 percent confidence limits of estimation coefficients. Estimations are based on the full sample, which includes East and West German workers. Wage mobility is based on 3-year-time periods and calculated using cross-sectional weights.

As workers' wage growth directly affects their movement along the wage distribution, the main task type of occupations is additionally considered in the estimates for wage mobility. Since occupations which contain mainly manual non-routine work activities are the base category, estimated coefficients are interpreted in relation to this category. Both types of abstract tasks, analytical non-routine and interactive non-routine, continuously show a higher wage mobility. Over time, the estimates for analytical non-routine tasks have remained relatively constant at between 3.5 and 7.3 percentiles of increased wage mobility. In turn, interactive non-routine tasks show an increase in their impact on a worker's wage mobility between 2001 and 2004. Employees performing interactive non-routine tasks have experienced higher wage mobility by around 4 percentiles since 2005. Since abstract tasks are more present at the top of the skill distribution, the higher wage mobility is in line with the descriptive evidence as well as with the skill biased technical change hypothesis. However, the estimated coefficients of both of the remaining task types, cognitive routine and manual routine tasks, show an interesting empirical pattern. On the one hand, employees in manual routine occupations do not have a significantly different wage mobility compared to workers in manual non-routine occupations. On the other hand, workers performing cognitive routine tasks have a higher wage mobility and their wage mobility gap to workers in manual non-routine occupations has increased from 1.4 to 4.2 percentiles over time.

These findings indicate that the distinction in tasks does not depend on whether they are routine or non-routine, but rather depends on whether tasks are manual or non-manual. Since the task data set contains the task intensities for each occupation, this information is picked up in a further estimation instead of occupation's main task type (see Figure 4.13).

Figure 4.13: Development of task intensity's impact on wage mobility over time

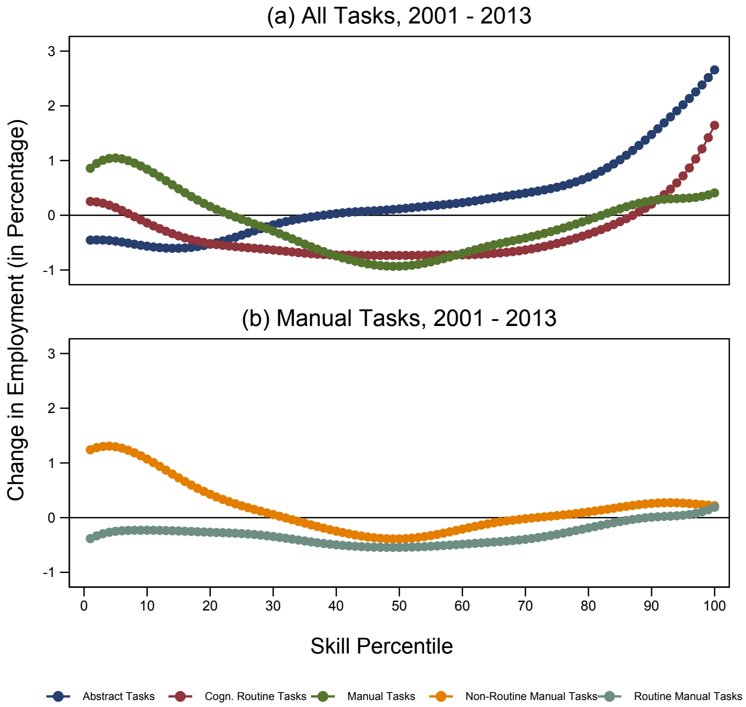


Notes: Solid lines are local polynomial smooth functions of degree 3, whereas spikes and cap lines represent the 95 percent confidence limits of estimation coefficients. Estimations are based on the full sample, which includes East and West German workers. Wage mobility is based on 3-year-time periods and calculated using cross-sectional weights.

In Panel (a), occupations' manual and non-manual task intensity are grouped together, whereas in Panel (b), distinction is made between an occupation's routine and non-routine task intensity. As a quick reminder, the sum of the five task intensities is equal to one for each occupation. Thus a decrease in, for example, routine task intensity is always accompanied by an increase in non-routine task intensity. Hence, if a worker's manual task intensity increases by one percentage point, his or her wage mobility decreases by around 0.1 percentile point in 2011. Whereas there is a drop in the value of the estimation coefficient in Panel (a) at the beginning of the observation period, some recovery has occurred since 2004. However, the initial values can no longer be achieved. Switching the analysis to the distinction between routine and non-routine tasks, the effect of the routine tasks' intensity is mostly insignificant. Over time, however, the estimation coefficient slightly increases year by year. Combining both results, two conclusions can be drawn. First, workers who perform mainly manual tasks in their occupations show less upward wage mobility, regardless of whether their work activities consist of non-routine or routine-tasks. Since workers in manual routine and manual non-routine occupations do not differ significantly in their wage mobility, the prediction of the nuanced skill bias technical change hypothesis that manual non-routine workers should be beneficiaries of the computer and automation revolution can be denied. Furthermore, this might be due to the contemporaneously high proportion of manual and non-manual tasks in occupations which are mainly in the middle of the skill distribution and experienced greater wage losses in the 2000s. Second, routine and non-routine workers do not significantly differ in their wage mobility, on average. Since manual routine workers experience losses in their wage mobility and cognitive routine workers gain wage mobility, the observed insignificant effect is driven by these compensating effects. Ultimately, the suggestion that routine workers should experience less wage growth and consequently less wage mobility is true merely for manual routine workers. However, the increasing coefficient in Panel (b) indicates a rising wage mobility for cognitive routine workers over time.

Moreover, the routinization hypothesis predicts that the computerization of production processes triggers a polarization of employment along the skill distribution. Therefore, the employment shares of mainly manual non-routine and abstract occupations should increase, whereas shares of manual routine and cognitive occupations should decrease over time. Plotting the change in task usage along the skill distribution between 2001 and 2013 shows that there are considerable shifts in employment (see Figure 4.14). Since the skill distribution is based on 2001, the point estimates yields the change in employment by tasks for each percentile. Hence, abstract tasks follow a monotonically increasing curve along the skill distribution, indicating an increasing usage of abstract tasks at the top of the skill distribution. Manual and cognitive routine tasks follow a u-shaped curve, with increasing employment shares at both ends of the distribution. However, the rise of cognitive employment is higher relative to manual employment at the upper end, whereas the rise of manual employment is higher relative to cognitive employment at the lower end. Furthermore, the polarization is more strongly pronounced for manual employment. Dividing manual employment into non-routine and routine manual employment instantly shows that the increase in employment shares at the bottom of the skill distribution is completely driven by an

Figure 4.14: Change of task usage over the skill distribution, 2001-2013



Notes: The data are pooled using three-year moving averages (i.e. the year 2001 includes data from 2000, 2001, and 2002) in order to prevent distortions in skill percentiles caused by outliers in a given year. Using locally weighted smoothing regressions, both panels depict the percentage point change in task usage over the skill distribution between 2001 and 2013 due to changes in employment shares and occupational composition of the respective skill percentiles. The skill distribution in both panels is based on the ranking of 3-digit KldB 2010 occupations according to median wages weighted by working hours times cross-sectional sample weights in 2001 and 2013 and on the subsequently grouping into 25 equal-sized groups with regard to overall employment. The observed 3-digit KldB 2010 occupations are the same in 2001 and 2013. The full sample is employed, which includes East and West German workers.

increase of non-routine manual task intensive occupations. In turn, manual routine employment decreased almost along the entire distribution. Thus, the observed higher wage growth at the lower end of the skill distribution (see Figure 4.11) is accompanied by higher manual non-routine employment, which indicates that wage growth is driven by less wage losses of non-manual workers at the lower end. Given these facts, why is there no significant difference in wage mobility between manual routine and manual non-routine workers in spite of the latter's greater wage growth? Since the employment share of manual non-routine occupations is very high in the middle of the skill distribution, the wage losses of these occupations compensate for the wage gains of manual non-routine occupations at the lower end of the distribution. Furthermore, the higher employment shares of abstract and cognitive routine tasks at the upper end of the skill distribution indicate that more workers in these occupations experienced higher wage growth over time and moved upwards along the wage distribution.

4.4.3 Upward and Downward Mobility

In the previous analyses, wage mobility was measured as the difference between a worker's wage position in the base and the reporting year. Thus, the empirical results were interpreted as ceteris paribus effects on wage mobility over the whole wage mobility distribution. Since ordinary least squares estimations were applied, the impact of socio-economic and demographic characteristics was assumed to be constant across different wage mobility patterns. The following is an analysis of the extent to which there are asymmetries in the effects of the basic covariates on a worker's downward and upward wage mobility. For this purpose, the workers' wage mobility is measured as the difference in their wage decile between the base and the reporting year. In turn, the new dependent variable y_i aggregates these movements into three groups based on the aims of the investigation:

$$y_i = \begin{cases} 1 & \text{(downward mobility),} & \text{if} \quad mob_i \in [-9, -1] \\ 2 & \text{(same decile/no mobility),} & \text{if} \quad mob_i = 0 \\ 3 & \text{(upward mobility),} & \text{if} \quad mob_i \in [1, 9] \end{cases} , \tag{4.3}$$

where mob_i represents a worker's movement in wage deciles.[105] Thus, a distinction is made between workers who move to a lower decile, remain in the same decile, or move to an upper decile. Since these three categories are mutually exclusive, a multinomial logit model that estimates the effects of the covariates on a worker's probability of experiencing the respective wage mobility types is applied. This enables the detection of divergent effects of covariates on a worker's probability of upward and downward wage mobility. In order to obtain a unique parameter identification in the multinomial logit models, the category "same decile/no mobility" is selected as the base category. The probability of a worker i to be in one of the left categories can be expressed by

$$\Pr(y_i = j|\boldsymbol{x_i}) = \Pr{}_{ij} = \frac{\exp(\boldsymbol{x_i'\beta_j})}{1 + \exp(\boldsymbol{x_i'\beta_1}) + \exp(\boldsymbol{x_i'\beta_3})}, \qquad j = 1, 3 \quad , \tag{4.4}$$

where $\boldsymbol{x_i}$ represents the set of basic covariates and the initial wage decile of workers in the base year. As multinomial logit models assume independently distributed error terms, the odds between two categories should not depend on the other alternatives (*independence of irrelevant alternatives assumption*), i.e. adding or deleting alternative categories does not affect the odds among the remaining categories. Since the employed categories cover all possible wage pattern alternatives and the three categories are always observed within the time periods, the independence of irrelevant alternatives assumption is already met by the construction of the dependent variable. In turn,

[105] The measurement of mob_i differs from the original definition, since movements in wage percentiles lead to an insufficient number of observations in the middle category "same decile/no mobility".

the estimated coefficients $\boldsymbol{\beta_j}$ are difficult to interpret and their magnitude has no meaning. Therefore, the average marginal effects AME_k of a particular covariate x_k on the respective probabilities are presented and obtained by

$$AME_k = \frac{\partial \Pr(y = j|\boldsymbol{x} = \boldsymbol{x_i})}{\partial x_k} = \left[\frac{1}{n}\sum_{i=1}^{n} \Pr{}_{ij}\right] \cdot \left[\beta_{k,j} - \sum_{s=1}^{3} \beta_{k,s} \cdot \left(\frac{1}{n}\sum_{i=1}^{n} \Pr{}_{is}\right)\right], \tag{4.5}$$

where $\beta_{k,j}$ and $\beta_{k,s}$ correspond to the coefficient of the covariate x_k in the probability estimation of the wage mobility category j and s, respectively. Furthermore, n is the total observation number and $\beta_{k,2} = 0$ due to identification. Thus, the average marginal effects of a particular covariate on downward and upward mobility can be compared with one another in their magnitude, since they have content-related and substantive meaning (see Table 4.3).[106] In principle, the marginal effects on downward and upward mobility should have the opposite sign, since a positive impact on the probability of downward mobility should be accompanied by a negative impact on the probability of upward mobility. Thus, working in an occupation other than manager increases (decreases) a worker's probability of downward (upward) mobility. However, some workers experience a higher impact in absolute terms on their upward mobility than their downward mobility. Whereas clerks and service workers have a 21.5 to 27 percent lower probability of upward mobility than managers, they have merely a 13 to 17.5 percent higher probability of downward mobility. Therefore, working as a clerk or a service worker has slightly higher relevance in relation to the chance to move upwards. The opposite applies to employees in the service industry. Their probability of downward (upward) mobility is 8.4 (5.7) percent higher (lower) than the respective probabilities of workers in the manufacturing industry. Interestingly, the impact of the firm size on downward and upward mobility is almost the same in absolute terms. The impact of unemployment experience on the probability of downward mobility is much higher than on the probability of upward mobility. Since unemployment experience almost exclusively takes positive values for downwards mobile and immobile workers, the results confirm that unemployment spells are highly correlated with downward mobility and accompanied with wage losses. Furthermore, a job change has significant effect on the probability of downward and no mobility, but no significant impact on upward mobility. This confirms the insignificant effect of job changes on a worker's wage mobility at the beginning of the section and provides more detailed information. On the one hand, a positive correlation between job changes and upward mobility is expected due to the standard job search theory, which predicts that job-to-job transitions are mainly voluntary and are accompanied by wage increases (Pissarides, 1994). On the other hand, workers might switch to low-wage employment due to family reasons or

[106] The estimation results for the other two time periods, 1995-1999 and 2010-2014, are given in Table 4.9 in the appendix of this chapter.

Table 4.3: Average marginal effects on upward and downward wage mobility in the 2005-2009 time period

	Downward Mobility		Same Decile		Upward Mobility	
Individual Characteristics						
Age	0.001	(0.001)	0.001	(0.001)	-0.002	(0.001)**
Female	0.085	(0.018)***	0.002	(0.019)	-0.087	(0.017)***
Migrational Background	0.021	(0.018)	-0.033	(0.019)*	0.011	(0.018)
Low-Skilled			*reference*			
Medium-Skilled	-0.054	(0.029)*	-0.006	(0.028)	0.061	(0.023)***
High-Skilled	-0.166	(0.034)***	0.031	(0.036)	0.135	(0.032)***
Job Stability						
At Least 1 Job Change	0.062	(0.020)***	-0.088	(0.019)***	0.026	(0.019)
Unemployment Experience	0.198	(0.050)***	-0.134	(0.047)***	-0.065	(0.035)*
Job Tenure	0.001	(0.001)	-0.001	(0.001)	0.000	(0.001)
Employed Part-Time	0.070	(0.021)***	-0.070	(0.020)***	0.000	(0.019)
Employment Charateristics						
Firm Size: < 20			*reference*			
Firm Size: 20-200	-0.050	(0.022)**	0.004	(0.021)	0.046	(0.017)***
Firm Size: 200-2000	-0.087	(0.022)***	0.001	(0.023)	0.086	(0.020)***
Firm Size: > 2000	-0.122	(0.022)***	0.000	(0.024)	0.122	(0.022)***
Manufacturing			*reference*			
Agriculture	0.163	(0.109)	-0.035	(0.091)	-0.128	(0.072)*
Energy	-0.027	(0.056)	-0.088	(0.060)	0.115	(0.077)
Mining	0.108	(0.102)	-0.305	(0.063)***	0.197	(0.095)**
Construction	0.002	(0.021)	0.016	(0.025)	-0.018	(0.024)
Trade	0.139	(0.027)***	-0.013	(0.027)	-0.125	(0.024)***
Transport	0.061	(0.032)*	-0.031	(0.033)	-0.030	(0.032)
Bank,Insurance	-0.031	(0.031)	0.011	(0.038)	0.019	(0.041)
Services	0.084	(0.020)***	-0.027	(0.022)	-0.057	(0.021)***
Legislators/Senior Officials/Managers			*reference*			
Professionals	0.042	(0.027)	0.009	(0.034)	-0.051	(0.041)
Technicians/Associate Professionals	0.088	(0.025)***	0.052	(0.032)	-0.140	(0.037)***
Clerks	0.133	(0.030)***	0.082	(0.036)**	-0.215	(0.039)***
Service Workers/Shop and Market Sales Workers	0.175	(0.036)***	0.093	(0.040)**	-0.268	(0.041)***
Skilled Agricultural/Fishery Workers	0.230	(0.131)*	0.069	(0.130)	-0.299	(0.093)***
Craft and Related Trades Workers	0.254	(0.032)***	0.018	(0.036)	-0.272	(0.039)***
Plant and Machine Operators and Assemblers	0.310	(0.036)***	-0.017	(0.039)	-0.292	(0.040)***
Elementary Occupations	0.277	(0.045)***	0.039	(0.046)	-0.316	(0.042)***
Change of Occupation	0.028	(0.015)*	-0.030	(0.015)**	0.002	(0.015)
Change of Industry	0.013	(0.017)	-0.025	(0.018)	0.011	(0.017)
East-Germany	0.120	(0.019)***	-0.016	(0.018)	-0.104	(0.015)***
McFadden R^2			0.171			
AIC			7573.486			
BIC			8091.543			
Obs.			4096			

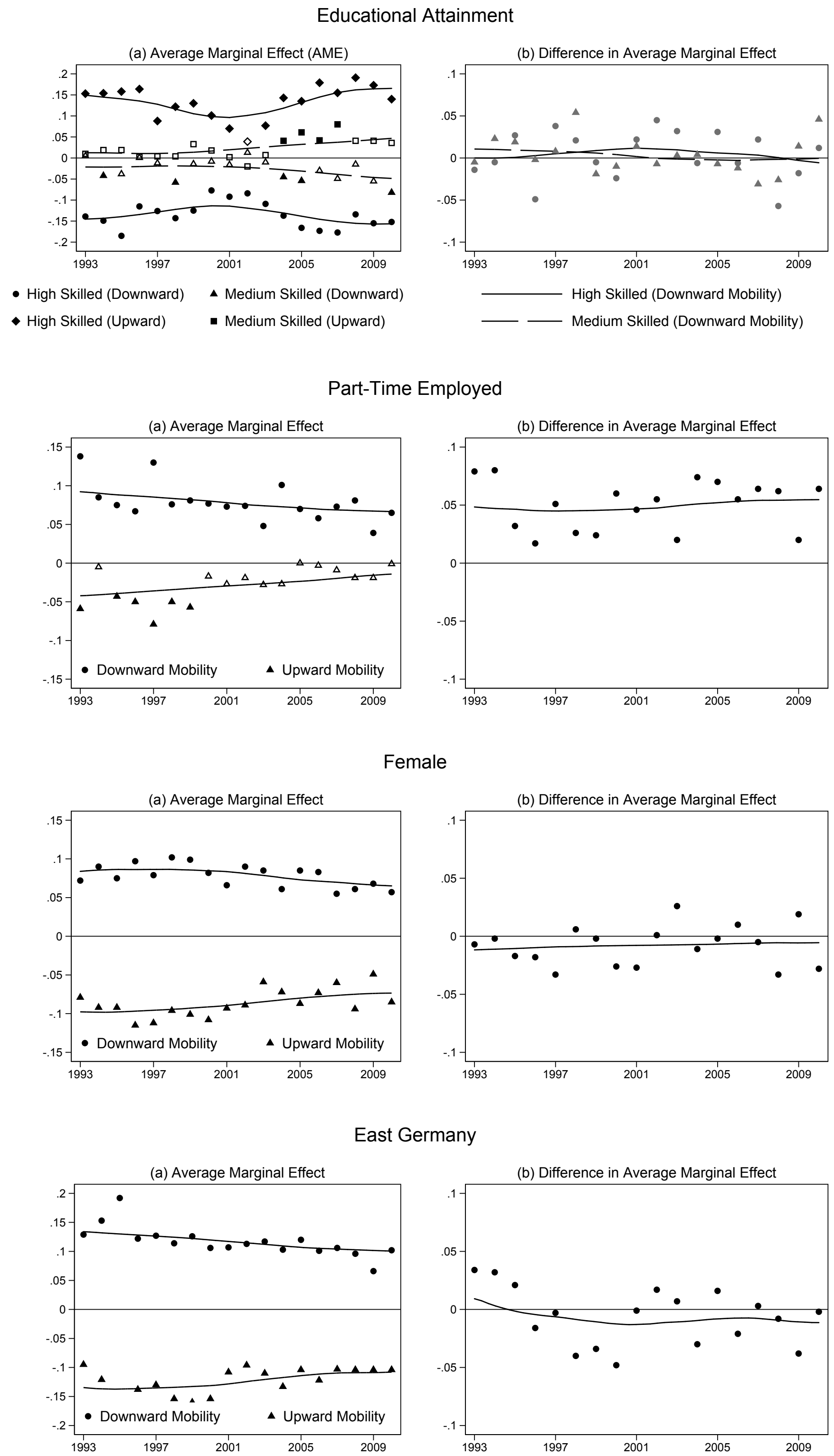
Notes: Multinomial logit estimations are applied to the full sample, which includes East and West German workers. Wage mobility categories are based on movements between deciles which are calculated using cross-sectional weights. Classification of industries is based on ISIC Rev. 3 and classification of occupations is based on ISCO88. Workers' initial wage deciles are included, but not reported. Robust standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

imminent risk of unemployment, which is correlated with downward mobility. Since only the marginal effects on downward mobility and no mobility are significant, the explanations are twofold. First, a positive correlation of job changes with downward mobility indicates that a significant fraction of workplace changes are involuntary due to family reasons or unemployment risks. Second, the negative correlation with immobility suggests that voluntary job changes in order to achieve higher wages do not even guarantee moving up within the same decile.[107] Thus, the results indicate that job changes tend to be associated with a loss in wages and a downward wage mobility.

In order to compare the estimation results of wage mobility patterns with the estimation results of wage mobility, the development of the marginal effects of selected covariates is illustrated (see Figure 4.15). Panel (a) shows the average marginal effects of the respective exogenous variables on the probabilities and Panel (b) represents the difference in average marginal effects on downward and upward wage mobility. Considering the development of the average marginal effects of a worker's educational attainment on his or her wage mobility, the previous findings can be confirmed. High-skilled workers and medium-skilled workers have a lower (higher) probability of downward (upward) wage mobility than low-skilled workers. The average marginal effects are greater, in absolute terms, for the high-skilled than for the medium-skilled. Furthermore, both smoothed functions of the difference in average marginal effects are close to zero. Thus, there is no clear difference in the magnitude of the average marginal effects on downward and upward mobility. Moreover, average marginal effects of high-skilled workers show a slight hump shape (u-shape) with respect to downward (upward) wage mobility, which has already been detected in the estimation of wage mobility. Additionally, there is no clear difference in the average marginal effects of the gender variable. Women had an 8.5 (8.7) higher (lower) probability of downward (upward) wage mobility than men in 2010. Living in East Germany increases (decreases) a worker's probability of downward (upward) mobility. However, the marginal effects on downward mobility were higher at the beginning of the observation period. Taking a comparison between the marginal effects of part-time employment on downward and upward mobility detects that both effects decreased in magnitude over time. In turn, the difference in the marginal effects is consistently positive, i.e. the marginal effects on downward mobility are higher than on upward mobility. Since a convergence between part-time and full-time employment in wage mobility has been detected earlier, the results of the wage mobility patterns suggest that this development is mainly driven

[107] A positive effect on the immobility would be consistent with voluntary and involuntary job changes. On the one hand, a worker's wage increase due to the job change is too small to push him or her into the next decile. On the other hand, a worker's wage loss due to a job change is small enough to keep him or her within the same decile.

Figure 4.15: Development of selected estimation coefficients of upward and downward wage mobility over time



Notes: Multinomial logit estimations are applied to the full sample, which includes East and West German workers. Wage mobility categories are based on movements between deciles which are calculated using cross-sectional weights. Hollow circles represent insignificant average marginal effects, whereas filled circles represent average marginal effects which are at least significant at 10 percent. Solid and dashed lines are local polynomial smooth functions of degree 3.

due to a convergence in the probability of upward mobility. Hence, part-time workers still have a higher probability of downward mobility than full-time workers, but with regard to upward mobility, both worker types have nearly identical probabilities at the present time.

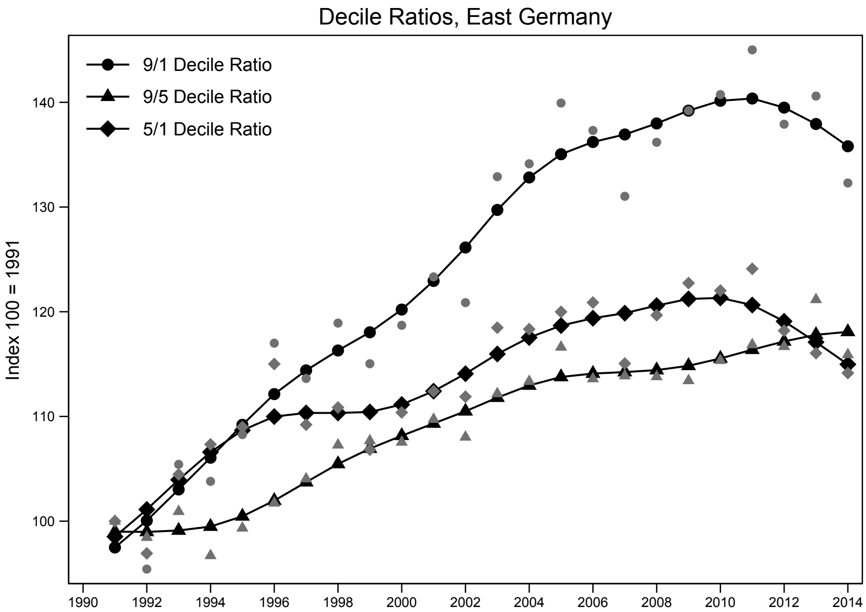
4.5 Conclusion

As the importance of wage inequality and that of wage mobility have increased since the 1990s and 2000s, respectively, the aim of this study is to illustrate the development of these two concepts in Germany over an observation period of 30 years, and to combine the empirical results for the determinants of a worker's wage mobility with the trend in wage inequality. In particular, in the aftermath of the financial crisis, the trend in German wage inequality received international attention, since wage inequality had started to stabilize in Germany at this point, in contrast to other industrialized countries. The descriptive evidence shows that wage growth was polarized along the wage distribution between 2006 and 2013, which is reflected in a decline of the 5/1 wage decile ratio as well as in stable wage inequality. Meanwhile, the intragenerational wage mobility is a less studied object in the empirical literature, since access to individual panel data is a requirement for its investigation. However, the combination of wage inequality and wage mobility is of both theoretical and economic interest. First, increasing wage inequality implies that the wage limits of the percentiles are starting to diverge. This, in turn, hinders a worker's improvement of his or her relative wage position over time. Second, a society is more willing to accept higher annual wage inequality if the long-term wage inequality is reduced due to the intragenerational wage mobility of workers over their working life. However, the contribution of overall wage mobility to the reduction of long-term inequality has been decreasing since the beginning of the 2000s. This is also true for years with stagnating wage inequality. Thus, wage mobility has become less important as an equalizer of long-term wages over time, and workers' prospective wages depend more strongly on wages in the current year. The correlation of individuals' wages over time increased by 10 percentage points, which indicates that the persistence in relative wages is increasing. This is further reflected in the increasing state dependence on initial wage ranks, where the aggregate measure is based on wage mobility estimations and introduced for the first time in the literature in this study. Therefore, the decline in intragenerational wage mobility and the increase in state dependence motivate the following question: what determines a worker's wage mobility, and has the impact of socio-economic and demographic characteristics changed over time? The empirical results reveal that a worker's educational attainment, gender, labor market status, length of unemployment spells, firm size, place of residence, and occupations have a particularly strong influence on his or her wage mobility. In particular, the length of unemployment spells within fixed 4-year time periods and the type of occupation have gained in importance, whereas the influence of gender, living in East Germany, and being employed part-time has diminished over time. On the one hand, this means that the depreciation of human capital during unemployment has a greater impact on a worker's re-entry wages. On the other hand, workers' wages depend more strongly on their occupation-specific human capital. Combining the latter with the wage polarization observed since 2006, a logical follow-up question is whether these accompanying developments relate to the predictions of the routinization hypothesis. However, the descriptive evidence as well as the results of the wage mobility estimations only partially support the hypothesis. On the one hand, workers who mainly perform manual tasks have a lower wage mobility over the entire observation period. On the other hand, workers from cognitive routine occupations show a higher and also increasing wage mobility compared to manual non-routine workers. The former is due to the fact that manual non-routine occupations are still the largest employment group in the middle of the skill distribution. The latter is due to a higher proportion of cognitive routine occupations at the upper end, contrasting with predictions of the routinization hypothesis. Furthermore, the employment share of cognitive routine tasks at the top has, in fact, increased over time. Therefore, both types of manual workers have experienced reductions in their wage mobility since 2000, whereas workers performing primarily abstract and cognitive routine tasks were able to increase their wage mobility. Moreover, multinomial logit estimations were applied in order to examine asymmetries in the effects of the basic covariates on a worker's downward and upward wage mobility. The results show that job changes within the time fixed periods have a significant impact on downward mobility and no impact on upward mobility. This indicates that job changes do not guarantee movement upward in relative wage ranks, measured in deciles, and that workplace changes might be mainly involuntary, being the result of family issues or unemployment risks. Furthermore, the convergence between part-time and full-time workers in Germany over time is mainly driven by the convergence in their upward mobility. However, there is still a significant difference between worker types with regard to downward mobility. Ultimately, the length of unemployment spells has a greater impact on downward mobility than on upward mobility.

In particular, the increasing influence of unemployment experience within the fixed 4-year time periods is ground for some concern about the benefits of re-employment and necessitates a re-examination of labor market policies in Germany. Although some fundamental reforms were made at the beginning of the 2000s, and the current unemployment rate is at a historically low level, the increasing wage mobility penalty for each additional month of unemployment indicates that even short periods of unemployment might strongly reduce a worker's potential to reach his or her initial relative wage position after four years. Since short periods of unemployment are more pronounced for part-time workers than full-time workers in Germany, the increasing impact of unemployment experience on a worker's wage mobility might be due to the institutional setting of the labor market. In particular, the design of the so-called mini- and midijobs, as well as the unemployment benefit system, create incentives to remain in lower-paying, part-time jobs because the transition to a better paying, full-time job would result in lower net incomes, especially for secondary earners of a household, due to the expiry of tax advantages and the loss of advantages of the social security system (Berthold and Coban, 2013). Furthermore, attention should be given to the significant difference in wage mobility between men and women. Although there has been a decline in the gender wage mobility gap over time, men still had a 4 percentile higher wage mobility than women in 2010. Since a worker's wage mobility depends, among other things, on his or her wage growth within the fixed time period, this indicates that there is a discrepancy in the wage growth rate between the sexes. Therefore, future research should supplement the analysis of the cross-sectional gender wage gap with the gender wage mobility gap.

Appendix

Figure 4.16: Development of real hourly wage decile ratios, East Germany



Notes: Decile ratios are indexed on 1991 and are based on real hourly wages weighted with the corresponding cross-sectional weights. Solid lines represent the trend component of the applied Hodrick-Prescott filter (Hodrick and Prescott, 1997). Since annual data are applied, the smoothing parameter is $\lambda = 6.25$ according to the rule-of-thumb in Ravn and Uhlig (2002).

Table 4.4: Number of wage mobility observations per 4-year time period

Base Year	West Germany	East Germany	Total
1984	2669		
1985	2563		
1986	2462		
1987	2559		
1988	2467		
1989	2460		
1990	2371		
1991	2413	1243	3656
1992	2350	1150	3500
1993	2307	1084	3391
1994	2211	1045	3256
1995	2380	1057	3437
1996	2332	1025	3357
1997	2295	954	3249
1998	2463	993	3456
1999	2432	958	3390
2000	3880	1328	5208
2001	3753	1262	5015
2002	3921	1259	5180
2003	3802	1212	5014
2004	3586	1183	4769
2005	3252	1113	4365
2006	3270	1116	4386
2007	3183	1124	4307
2008	2833	1031	3864
2009	2642	955	3597
2010	3680	1136	4816

Notes: Only workers who have valid real hourly wages in both the base year and the reporting year are taken into account.

Table 4.5: Definition of the educational attainment in the estimations

Educational Category	Feature	CASMIN categories	
Low-Skilled	no completed apprenticeship	1a	inadequately completed
	or	1b	general elementary school
	no high school diploma	2b	intermediate general qualification
Medium-Skilled	completed apprenticeship or high school diploma	1c	basic vocational qualification
		2a	intermediate vocational
		2c(voc)	vocational maturity certificate
		2c(gen)	general maturity certificate
High-Skilled	university degree	3a	lowert tertiary education
		3b	higher tertiary education

Notes: Design is based on Zenzen (2013).

Table 4.6: Results of the Heckman selection regressions

	Correlation		Selection Equation			
	atan ρ		*Married*		*Number of Kid(s) at Home*	
1993	-.277	(.263)	-.156	(.072)**	.155	(.03)***
1994	-.083	(.187)	-.104	(.074)	.091	(.03)***
1995	-.153	(.186)	-.115	(.073)	.159	(.033)***
1996	-.444	(.155)***	-.201	(.077)***	.109	(.034)***
1997	-.209	(.287)	-.074	(.076)	.106	(.037)***
1998	-.137	(.28)	-.104	(.076)	.051	(.037)
1999	-.036	(.952)	.033	(.071)	.01	(.034)
2000	-.126	(.161)	.145	(.056)**	.035	(.028)
2001	-.136	(.178)	.182	(.059)***	.04	(.029)
2002	-.232	(.153)	.219	(.06)***	.045	(.03)
2003	-.235	(.208)	.132	(.07)*	.015	(.035)
2004	-.084	(.547)	.063	(.079)	.021	(.039)
2005	-.027	(.605)	.094	(.087)	.03	(.046)
2006	-.374	(.154)**	.066	(.077)	.055	(.041)
2007	.098	(.294)	.096	(.087)	.074	(.049)
2008	.093	(.22)	.288	(.09)***	.047	(.054)
2009	-.266	(.193)	.127	(.095)	.148	(.062)**
2010	.101	(.288)	.223	(.087)**	.017	(.04)

Notes: Estimations are based on the full sample, which includes East and West German workers. Wage mobility is calculated using cross-sectional weights. Selection variables are a worker's marital status and the number of kids in his or her household. Correlation of the error terms between wage mobility and labor market participation (in the reporting year) equation is represented by atan $\rho = \frac{1}{2}\ln\left(\frac{1+\rho}{1-\rho}\right)$, which yields the inverse hyperbolic tangent of ρ. Classification of industries is based on NACE Rev. 1, where "agriculture", "fishing", and "mining" are combined into a category and "other community activities", "private households", and "extra-territorial organization" are combined into "other industries". The classification of occupations is based on ISCO88. Workers' initial wage percentiles or ranks are included, but not reported. Standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

Table 4.7: Decomposition of the overall wage inequality by West and East Germany

	Mean Logarithmic Deviation			Contribution to Overall Inequality	
Year	*Germany*	*East Germany*	*West Germany*	*Between-Region Inequality*	*Within-Region Inequality*
1991	0.12	0.06	0.08	33.19	66.81
1992	0.11	0.07	0.09	21.93	78.07
1993	0.11	0.08	0.09	15.97	84.03
1994	0.09	0.07	0.08	13.50	86.50
1995	0.11	0.08	0.10	11.39	88.61
1996	0.09	0.08	0.09	11.36	88.64
1997	0.10	0.09	0.09	8.84	91.16
1998	0.10	0.09	0.09	9.25	90.75
1999	0.10	0.08	0.09	9.98	90.02
2000	0.10	0.09	0.09	7.51	92.49
2001	0.10	0.09	0.09	7.02	92.98
2002	0.10	0.09	0.10	6.23	93.77
2003	0.10	0.11	0.10	5.82	94.18
2004	0.10	0.11	0.10	5.04	94.96
2005	0.11	0.12	0.10	4.77	95.23
2006	0.11	0.10	0.11	5.26	94.74
2007	0.11	0.11	0.10	5.72	94.28
2008	0.11	0.10	0.10	6.16	93.84
2009	0.12	0.11	0.11	5.43	94.57
2010	0.12	0.12	0.11	4.49	95.51
2011	0.12	0.12	0.11	5.36	94.64
2012	0.11	0.12	0.11	4.06	95.94
2013	0.12	0.12	0.11	4.64	95.36
2014	0.11	0.11	0.11	4.41	95.59

Notes: Calculations are based on the mean logarithmic deviation as a measure of wage inequality. Full, West German, and East German samples are applied separately. Contributions are expressed in percentage.

Table 4.8: Determinants of the wage mobility in different 4-year time periods using detailed industries

	1995-1999		**2005-2009**		**2010-2014**	
Individual Characteristics						
Age	-0.124	(0.040)***	-0.115	(0.038)***	-0.142	(0.034)***
Female	-5.395	(0.844)***	-4.250	(0.661)***	-4.105	(0.614)***
Migrational Background	-1.350	(0.793)*	-0.692	(0.715)	-0.967	(0.625)
Low-Skilled			*reference*			
Medium-Skilled	2.130	(1.017)**	2.542	(1.009)**	2.962	(1.008)***
High-Skilled	7.740	(1.487)***	7.382	(1.289)***	7.875	(1.227)***
Job Stability						
At Least 1 Job Change	-1.132	(0.880)	-0.729	(0.803)	0.814	(0.658)
Unemployment Experience	-3.951	(1.371)***	-5.258	(1.666)***	-6.149	(1.361)***
Job Tenure	0.045	(0.040)	0.034	(0.036)	0.074	(0.033)**
Employed Part-Time	-3.083	(1.083)***	-2.866	(0.801)***	-1.689	(0.690)**
Employment Characteristics						
Firm Size: < 20			*reference*			
Firm Size: 20-200	1.729	(0.879)**	2.662	(0.762)***	1.782	(0.699)**
Firm Size: 200-2000	4.786	(0.933)***	5.262	(0.873)***	4.280	(0.771)***
Firm Size: > 2000	7.090	(0.972)***	6.777	(0.886)***	5.909	(0.778)***
Manufacturing			*reference*			
Agriculture/Fishing/Mining	-5.674	(2.140)***	-3.873	(2.318)*	-0.542	(2.362)
Electricity/Gas/Water	3.948	(2.771)	-0.735	(2.479)	-2.493	(2.245)
Construction	-2.150	(1.075)**	-0.624	(1.240)	-3.468	(1.012)***
Wholesale and Retail Trade	-2.789	(1.179)**	-5.830	(0.935)***	-5.706	(0.873)***
Hotels and Restaurants	-3.815	(2.548)	-7.804	(1.882)***	-8.691	(1.824)***
Transport, Storage, and Communication	-2.698	(1.382)*	-2.512	(1.275)**	-2.745	(1.094)**
Financial Intermediation	2.053	(1.465)	3.048	(1.164)***	0.118	(1.148)
Real Estate, Renting, and Business Activities	2.871	(1.443)**	-1.456	(1.004)	-1.393	(0.872)
Public Administration/Social Security	-1.709	(1.280)	-1.373	(1.076)	-1.554	(0.992)
Education	0.090	(1.566)	-1.332	(1.407)	0.389	(1.226)
Health and Social Work	-2.201	(1.241)*	-3.874	(0.997)***	-4.674	(0.874)***
Other Industries	1.705	(1.852)	-2.338	(1.484)	-3.452	(1.322)***
Legislators/Senior Officials/Managers			*reference*			
Professionals	3.552	(1.901)*	-0.442	(1.200)	0.927	(1.101)
Technicians/Associate Professionals	-2.756	(1.766)	-4.660	(1.192)***	-2.661	(1.104)**
Clerks	-3.842	(1.861)**	-8.326	(1.336)***	-6.251	(1.260)***
Service Workers/Shop and Market Sales Workers	-7.755	(2.168)***	-10.817	(1.467)***	-6.884	(1.446)***
Skilled Agricultural/Fishery Workers	-10.241	(3.183)***	-15.387	(3.417)***	-14.030	(2.491)***
Craft and Related Trades Workers	-8.593	(1.847)***	-11.071	(1.382)***	-9.331	(1.279)***
Plant and Machine Operators and Assemblers	-9.701	(1.909)***	-13.556	(1.505)***	-11.064	(1.425)***
Elementary Occupations	-12.123	(2.138)***	-13.316	(1.617)***	-10.042	(1.573)***
Change of Occupation	-0.005	(0.655)	-0.582	(0.560)	0.223	(0.513)
Change of Industry	-0.157	(0.746)	-0.191	(0.663)	-0.734	(0.602)
East-Germany	-10.585	(0.981)***	-6.190	(0.703)***	-5.961	(0.620)***
R^2	0.275		0.235		0.236	
Obs	3263		4035		4469	

Notes: Estimations are based on the full sample, which includes East and West German workers. Wage mobility is calculated using cross-sectional weights. Classification of industries is based on NACE Rev. 1, where “agriculture”, “fishing”, and “mining” are combined into a category and “other community activities”, “private households”, and “extra-territorial organization” are combined into “other industries”. The classification of occupations is based on ISCO88. Workers’ initial wage percentiles or ranks are included, but not reported. Robust standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

Table 4.9: Average marginal effects on upward and downward wage mobility in the 1995-1999 and 2010-2014 time periods

	1995 - 1999						2010 - 2014					
	Downward Mobility		Same Decile		Upward Mobility		Downward Mobility		Same Decile		Upward Mobility	
Individual Characteristics												
Age	0.001	(0.001)	0.003	(0.001)***	-0.005	(0.001)***	0.002	(0.001)**	0.002	(0.001)**	-0.004	(0.001)***
Female	0.075	(0.020)***	0.017	(0.021)	-0.092	(0.020)***	0.057	(0.017)***	0.028	(0.018)	-0.085	(0.016)***
Migrational Background	0.016	(0.019)	0.006	(0.020)	-0.022	(0.020)	0.006	(0.017)	0.019	(0.018)	-0.025	(0.016)
Low-Skilled							*reference*					
Medium-Skilled	-0.038	(0.024)	0.019	(0.025)	0.019	(0.023)	-0.082	(0.031)***	0.045	(0.029)	0.036	(0.024)
High-Skilled	-0.185	(0.031)***	0.027	(0.036)	0.158	(0.036)***	-0.152	(0.036)***	0.012	(0.035)	0.140	(0.031)***
Job Stability												
At Least 1 Job Change	0.061	(0.021)***	-0.058	(0.020)***	-0.003	(0.020)	0.000	(0.017)	-0.050	(0.017)***	0.050	(0.016)***
Unemployment Experience	0.142	(0.032)***	-0.060	(0.032)*	-0.082	(0.030)***	0.235	(0.046)***	-0.077	(0.045)*	-0.158	(0.037)***
Job Tenure	0.000	(0.001)	-0.001	(0.001)	0.000	(0.001)	0.000	(0.001)	-0.001	(0.001)	0.000	(0.001)
Employed Part-Time	0.075	(0.026)***	-0.033	(0.024)	-0.043	(0.024)*	0.065	(0.019)***	-0.064	(0.019)***	-0.001	(0.017)
Employment Characteristics												
Firm Size: < 20							*reference*					
Firm Size: 20-200	-0.034	(0.023)	-0.019	(0.023)	0.053	(0.020)**	-0.031	(0.020)	-0.004	(0.020)	0.035	(0.016)**
Firm Size: 200-2000	-0.089	(0.024)***	-0.017	(0.025)	0.106	(0.023)***	-0.079	(0.021)***	-0.006	(0.022)	0.084	(0.019)***
Firm Size: > 2000	-0.133	(0.025)***	-0.018	(0.026)	0.151	(0.025)***	-0.121	(0.021)***	-0.004	(0.022)	0.125	(0.020)***
Manufacturing							*reference*					
Agriculture	0.238	(0.069)***	-0.059	(0.057)	-0.179	(0.051)***	0.028	(0.081)	0.031	(0.075)	-0.059	(0.063)
Energy	-0.064	(0.050)	-0.096	(0.073)	0.160	(0.070)**	0.043	(0.049)	-0.065	(0.053)	0.022	(0.054)
Mining	-0.006	(0.094)	0.001	(0.116)	0.004	(0.091)	-0.139	(0.014)***	-0.398	(0.016)***	0.536	(0.016)***
Construction	0.012	(0.022)	-0.019	(0.025)	0.006	(0.025)	0.028	(0.021)	-0.021	(0.024)	-0.007	(0.023)
Trade	0.078	(0.030)**	-0.042	(0.030)	-0.036	(0.029)	0.115	(0.026)***	-0.029	(0.026)	-0.085	(0.023)***
Transport	0.038	(0.037)	-0.041	(0.037)	0.003	(0.035)	0.058	(0.031)*	-0.049	(0.032)	-0.009	(0.032)
Bank,Insurance	-0.009	(0.038)	-0.003	(0.043)	0.012	(0.043)	0.033	(0.032)	-0.009	(0.037)	-0.024	(0.037)
Services	0.005	(0.022)	-0.019	(0.025)	0.015	(0.024)	0.074	(0.020)***	-0.024	(0.021)	-0.050	(0.020)**
Legislators/Senior Officials/Managers							*reference*					
Professionals	-0.035	(0.037)	0.020	(0.044)	0.015	(0.057)	-0.030	(0.028)	0.017	(0.034)	0.012	(0.042)
Technicians/Associate Professionals	0.054	(0.036)	0.091	(0.040)**	-0.145	(0.051)***	0.034	(0.028)	0.040	(0.032)	-0.075	(0.038)**
Clerks	0.003	(0.038)	0.148	(0.043)***	-0.151	(0.052)***	0.119	(0.032)***	0.041	(0.036)	-0.161	(0.040)***
Service Workers/Shop and Market Sales Workers	0.188	(0.047)***	0.050	(0.047)	-0.238	(0.054)***	0.153	(0.039)***	0.043	(0.040)	-0.196	(0.041)***
Skilled Agricultural/Fishery Workers	0.135	(0.109)	0.086	(0.109)	-0.221	(0.102)**	0.398	(0.089)***	-0.111	(0.070)	-0.287	(0.062)***
Craft and Related Trades Workers	0.167	(0.038)***	0.039	(0.041)	-0.206	(0.052)***	0.202	(0.034)***	-0.007	(0.036)	-0.195	(0.039)***
Plant and Machine Operators and Assemblers	0.163	(0.042)***	0.076	(0.044)*	-0.239	(0.053)***	0.215	(0.040)***	0.006	(0.040)	-0.221	(0.041)***
Elementary Occupations	0.196	(0.047)***	0.083	(0.048)*	-0.279	(0.054)***	0.216	(0.045)***	0.008	(0.044)	-0.225	(0.042)***
Change of Occupation	0.002	(0.016)	-0.016	(0.018)	0.014	(0.017)	-0.015	(0.014)	0.010	(0.015)	0.005	(0.014)
Change of Industry	-0.001	(0.017)	-0.020	(0.018)	0.020	(0.018)	0.019	(0.016)	-0.020	(0.017)	0.001	(0.015)
East-Germany	0.192	(0.021)***	-0.021	(0.020)	-0.171	(0.018)***	0.102	(0.018)***	0.003	(0.018)	-0.104	(0.014)***
McFadden R2			0.176						0.167			
AIC			6175.153						8488.382			
BIC			6676.061						9009.008			
Obs.			3323						4571			

Notes: Estimations are based on the full sample, which includes East and West German workers. Wage mobility categories are based on movements between deciles which are calculated using cross-sectional weights. Classification of industries is based on ISIC Rev. 3 and classification of occupations is based on ISCO88. Workers' initial wage deciles are included, but not reported. Robust standard errors are in parentheses. ***significant at 1 percent, **significant at 5 percent, *significant at 10 percent.

A
Measuring Inequality and Mobility

In the last decades, the access to individual data has improved in most industrialized and emerging countries, which fostered researchers to analyze individual socio-economic and demographic characteristics in more detail. In particular, individual incomes, wages, wealth, and other nearly continuous variables are more precisely aggregated to various spatial dimensions, such as neighborhoods, municipalities, regions, and countries. Furthermore, employing standardized surveys and administrative data enabled the reduction of measurement errors in variables and the harmonization of calculation methods across countries as well as across different research fields, such as economics, politics, and sociology. This especially applies to the measurement of income inequality and income mobility. On the one hand, cross-sectional surveys and administrative data enable the computation of various inequality measures for a particular point in time. On the other hand, surveys which track respondents over time can be employed in order to determine an individual's changes in particular variables. Thus, the latter enables the calculation of various mobility measures. Some basic principles for the representation of distributions are briefly explained below. Thereafter, different measures of income inequality and income mobility are introduced. Although explanations relate to income, these measures, in principle, can be applied to any nearly continuous variable, such as hourly wages or wealth.

A.1 Basics

The analysis of distributions is based on the probability theory, since any variable can be initially defined as a random experiment, which yields characteristic values with particular probabilities. Based on the probabilities, the distribution of a variable's realizations can be compared with its hypothetical probability distribution. Furthermore, if the probability of the characteristic values depends on the characteristic values of another variable, the distribution of these two variables can be set in relation to one another.

Thus, the statistical and distributional principles are the base for the determination of empirical distributions and the calculation of aggregated inequality and mobility measures.

A.1.1 Statistical Basics

Below, some basic concepts of descriptive statistics and probability theory will be clarified and combined. The focus here is on the frequency distribution of one or more variables. A frequency distribution involves the representation of the ordered characteristic values of a random variable Y with the relative or absolute frequency assigned to it. In turn, a random variable is defined as a quantifiable function

$$Y : \omega \rightarrow y(\omega) \in \mathcal{R}$$

that assigns a real number from the set $\mathcal{R}$ to every atomic event ω from the sample space Ω ($\omega \in \Omega$). Thus, the relative frequency $f(\cdot)$ of a particular characteristic value y_i of the random variable Y is expressed by

$$f(y_i) = \frac{h(y_i)}{n} \,,$$

wherein $h(y_i)$ is the absolute frequency of the characteristic value y_i and n yields the total number of observations. Therefore, the relative frequency can be combined with the statistical definition of the probability that a characteristic value will appear by

$$\Pr(y_i) = \lim_{n \to \infty} f_n(y_i) \,,$$

where $f_n(y_i)$ denotes the relative frequency for the appearance of the characteristic value y_i after nth trial of the experiment. The function $\Pr(\cdot)$ assigns a real number $\Pr(y_i)$ to every possible characteristic value from a system $\mathcal{R}$, thus yielding the probability. Bernoulli's law of large numbers, expressed by

$$\lim_{n \to \infty} \Pr(|f_n(y_i) - \Pr(y_i)| > \epsilon) = 0 \quad , \epsilon > 0 \,,$$

implies that the probability limit of the appearance of a characteristic value y_i is in accordance with its relative frequency. For a given random variable Y, which can take on the realizations $y_1, y_2, \ldots, y_n$ with the probabilities $\Pr(Y = y_i) = \Pr(y_i)$, the function

$$f_Y(y_i) = f(y_i) = \Pr(Y = y_i) = \Pr(y_i) \,,$$

which assigns the probability $f(y_i)$ to each y_i, is called a *probability function* for discrete random variables and a *probability density function* for continuous random variables. Furthermore, the following properties apply for discrete and continuous variables, respectively:[108]

$$0 \leq f(y_i) \leq 1 \qquad \text{, or rather} \qquad f(y_i) \geq 0 \, ,$$
$$\sum_i f(y_i) = 1 \qquad \text{, or rather} \qquad \int f(y) = 1 \, .$$

The related *cumulative distribution functions* of the discrete or continuous variables are then

$$F_Y(y) = F(y) = \Pr(Y \leq y) = \sum_{y_i \leq y} f(y_i)$$

and

$$F_Y(y) = F(y) = \Pr(Y \leq y) = \int_{-\infty}^{y} f(s)\,ds \, .$$

The cumulative distribution functions are monotonically increasing and continuous on the right. Furthermore, their limit of sequence is given by

$$\lim_{y \to -\infty} F(y) = 0 \qquad \text{and} \qquad \lim_{y \to +\infty} F(y) = 1$$

The considerations thus far can also be applied to multidimensional frequency distributions, whereby the following explanations are limited to two dimensions. Thus, a random variable Y with the characteristic values $y_i (i = 1, \ldots, m)$ and a random variable X with the characteristic values $x_j (j = 1, \ldots, r)$ are surveyed for the same statistical units, e.g. persons, households, and others. The total of all of the possible combinations of characteristic values (y_i, x_j) and their particular absolute or relative frequency define the two-dimensional frequency distribution $f(y_i, x_j)$. Thus, the relative frequency of a particular combination of characteristic values (y_i, x_j) is given by

$$f(y_i, x_j) = \frac{1}{n} h(y_i, x_j) \, ,$$

where $h(y_i, x_j)$ yields the absolute frequency of the particular combination and n is the total number of observations. Therefore, the probability of the appearance of a particular combination (y_i, x_j) of the two-dimensional random variable (Y, X) is defined for discrete variables as

$$f(x_i, y_j) = \Pr(Y = y_i, X = x_j) \qquad , i = 1, \ldots, m \, ; \; j = 1, \ldots, r$$

[108] For simplification proposes, hereinafter, integrals without specified integral limits always denote indefinite integrals: $\int_{-\infty}^{+\infty} = \int$.

and for continuous variables as

$$f(x,y) = \Pr(Y = y, X = x)\,.$$

Thus, the probability functions of discrete variables or the probability density functions of continuous variables have the following properties:

$$\begin{aligned} 0 \le f(y_i,x_j) \le 1 \qquad &\text{or} \qquad f(y,x) \ge 0 \\ \sum_{i=1}^{m}\sum_{j=1}^{r} f(y_i,x_j) = 1 \qquad &\text{or} \qquad \int\!\!\int f(y,x)\,dy\,dx = 1\,. \end{aligned}$$

Furthermore, in a given two-dimensional distribution of Y and X, the one-dimensional distribution of the random variable Y (or X), whereby the appearance of the other random variables is not taken into account, is called the *marginal distribution* of Y (or X). Thus, the marginal distribution of Y of the discrete probability function or continuous probability density function is given by

$$f(y_i) = \sum_{j=1}^{r} f(y_i,x_j) \quad i = 1,\ldots,m \qquad \text{or} \qquad f(y) = \int f(y,x)\,dx\,.$$

Additionally, the frequency distribution of Y (or X), which applies to a particular characteristic value of the respective other random variable, is called the *conditional distribution*. Thus, the conditional distribution of Y of the probability function or continuous probability density function is denoted by

$$f(y_i|X = x_j) = \frac{f(y_i,x_j)}{f(x_j)} \qquad \text{or} \qquad f(y|X = x) = \frac{f(y,x)}{f(x)}\,.$$

The conditional distribution functions directly correspond to probability theory, since the conditional probability $\Pr(y_i|Y = y_i, X = x_j)$ or $\Pr(y|Y = y, X = x)$ is the probability of the occurrence of y_i or y under the condition that x_i or x occurs. Therefore,

$$\Pr(y_i|Y = y_i, X = x_j) = \frac{\Pr(Y = y_i, X = x_j)}{\Pr(Y = y_i)},$$

applies for discrete random variables, whereas

$$\Pr(y|Y = y, X = x) = \frac{\Pr(Y = y, X = x)}{\Pr(Y = y)}$$

applies for continuous random variables. Based on the probability calculus, the two random variables can be examined for *stochastic independence*. Two random variables are empirically independent if the relative frequency of each conditional distribution of Y (or X) is the same:

$$f(y_i|x_k) = f(y_i|x_l) \qquad \forall\ k,l = 1,\ldots,r\ ;\ i = 1,\ldots,m$$

Therefore, if the two random variables are stochastically independent, the conditional distribution is expressed for discrete variables by

$$f(y_i|x_k) = f(y_i) \qquad \text{and} \qquad f(x_j|y_i) = f(x_j) \qquad \forall\ i = 1,\ldots,m\ ;\ j = 1,\ldots,r$$

and for continuous variables by

$$f(y|X = x) = f(y) \qquad \text{and} \qquad f(x|Y = y) = f(x)\,.$$

If stochastic independence is present, the unconditional relative frequency of a particular combination of characteristic values (y_i, x_j) is equivalent to the product of the relative frequencies of the marginal distributions $f(y_i)$ and $f(x_j)$, which results in

$$f(y_i, x_j) = f(y_i) \cdot f(x_j) \qquad \text{or} \qquad f(y,x) = f(y) \cdot f(x)\,.$$

A.1.2 Distributional Basics

Let $\mathcal{F}$ be the space of all univariate probability distributions with the support $\mathcal{Y} \subseteq \mathcal{R}$, where $\mathcal{R}$ denotes real numbers and $\mathcal{Y}$ is a proper interval. If $\mathcal{F}$ is used in order to describe the income distributions, $y \in \mathcal{Y}$ represents a particular income value and $F \in \mathcal{F}$ is one possible distribution of income in the population. Therefore, F denotes the *cumulative distribution function (cdf)* and $F(y_0)$ captures the proportion of the population with an income less than or equal to some income y_0. If income is treated as a random variable, the cdf of incomes can be represented in probability terms by

$$F(y_0) = F(y \leq y_0) = \Pr(y \leq y_0)\,,$$

where $\Pr(\cdot)$ yields the probability that a person has an income less than or equal to y_0. If $F \in \mathcal{F}$ is absolutely continuous over some interval $\mathcal{Y}' \subseteq \mathcal{Y}$ and is differentiable over $y \in \mathcal{Y}'$, then the density function is expressed by

$$f(y) = \frac{dF(y)}{dy}$$

and represents the *probability density function (pdf)* in a stochastic manner. Furthermore $\underline{y} := \inf(\mathcal{Y})$ defines the infimum of $\mathcal{Y}$ and yields the lower bound of the income distribution or incomes. Additionally, the mean of an income distribution F is given by

$$\mu(F) = \int y \, dF(y) \, .$$

Moreover, population quantiles are another piece of information, which can be derived from distribution functions. The qth population quantile divides the population into two groups based on the corresponding income value y_q, such that $q \cdot 100$ percent of the population earns an income less than or equal to the income value y_q and the rest of the population generates a higher income. Thus, a particular quantile $q \in [0,1]$ is expressed by

$$q = \Pr(y \le y_q) = F(y_q) \, ,$$

where $\Pr(y \le y_q)$ yields the probability that a population unit earns an income less than or equal to y_q (Cameron and Trivedi, 2005). Furthermore, Pen (1971) recommends quantile curves, which are the inverse of the cumulative distribution functions, to illustrate the distribution of incomes:

$$y_q = F^{-1}(q) = \inf \left[y | F(y) \ge q \right] \, .$$

For example, a value of $y_{0.1} = 25$ for the income distribution indicates that the poorest 10 percent of the income earners have an income less or equal to 25, whereas 90 percent of income earners generate higher income. Therefore, the probability that a randomly selected worker of the population earns an income less than or equal to 25 is 10 percent.

In particular, in the analysis of the income or wage distribution, the application of the *cumulative income function GL* is common:

$$GL(F,q) = \int_{\underline{y}}^{y_q} y \, dF(y) \, ,$$

where $GL(F,0) = 0$ and $GL(F,1) = \mu(F)$ hold by definition (Cowell, 2000). The cumulative income function in discrete notation is given by

$$GL(F,q) = q \cdot \mu_q = q \cdot \frac{1}{qn} \sum_{i=1}^{qn} y_i = \frac{1}{n} \sum_{i=1}^{qn} y_i \, .$$

Thus, the function yields the average income that would be achieved if merely the poorest $q \cdot 100$ percent of the population generates the total income for each quantile q. Ultimately, plotting the function $GL(F,q)$ against q yields the *generalized Lorenz curve*. However, in the empirical literature, the conventional *Lorenz curve* or relative Lorenz curve is more common for illustrating the income distribution. The Lorenz curve or the Lorenz ordinates can be obtained by normalizing the cumulative income function by the average income of the entire population

$$L(F,q) = \frac{GL(F,q)}{\mu(F)} = \int_{\underline{y}}^{y_q} \frac{y\,dF(y)}{\mu(F)} = \int_{\underline{y}}^{y_q} \frac{ny\,dF(y)}{n\mu(F)}\,, \tag{A.1}$$

where $\int_{\underline{y}}^{y_q} ny\,dF(y)$ is the total income of the $100 \cdot q$ percent persons at the lower end of the income distribution and $n\mu(F)$ is the total income of the entire population. The conventional Lorenz curve can be illustrated by plotting the Lorenz ordinates $L(\cdot)$ against the quantiles q. If the incomes are equally distributed among the population, the Lorenz curve is equivalent to the bisectors of an angle ($L(F,q) = q$). Taking a closer look at the derivatives of the Lorenz curve

$$L'(F,q) = \frac{y_q}{\mu(F)}\,,$$
$$L''(F,q) = \frac{1}{\mu(F)f'(y)}$$

yields that the Lorenz curve has a positive slope and is convex (Cowell, 2000). Therefore, income distributions can be compared to one another based on the properties of their Lorenz curves. Thus, the income inequality of an income distribution D is lower than the income inequality of an income distribution E if

$$L(D,q) \geq L(E,q) \quad \forall q \in (0,1)$$

holds, i.e. the Lorenz curve of the income distribution D is closer to the uniform distribution q than the Lorenz curve of the income distribution E along all quantiles. Therefore, if the Lorenz curves of the two income distributions intersect, an unambiguous comparison between them with regard to income inequality is no longer possible.

A.2 Measurement of Inequality

The measurement of inequality is an important subject in order to compare two or more distributions of income, wages, and other nearly continuous variables and to aggregate the findings to uni- or multidimensional measures.[109] Since the main purpose of the measurement is a comparison over time or across statistical units, the empirical literature has given particular interest to the derivation and calculation of scalar indexes. However, for example, the measurement of income inequality as well as the term “income inequality” have no natural definition. Thus, the formulation of an income inequality index is always bound to normative criteria and desirable properties. Therefore, a researcher cannot refer to a “correct” or “justified” income distribution

[109]For the sake of simplicity, the explanations and employed measures refer to incomes. In principle, the remarks can also applied to wages and other nearly continuous variables with a logical order.

after the calculation of an inequality measure. A distinct evaluation of an income distribution would be given if all members of a society agree unanimously on one or more criteria for the assessment of the income distribution. Since *Arrow's impossibility theorem* has shown that the derivation of a distinct social welfare function for the society is impossible, there can be no uniformly "justified" or "correct" income distribution for a society (Arrow, 1951).

A.2.1 Desired Properties of Inequality Measures

In the theoretical and mathematical literature on income inequality, five properties are postulated to the inequality indexes (Jenkins and Van Kerm, 2009):

i) *Scale invariance*
If each individual's income is increased equiproportionately, the inequality index does not change

ii) *Replication invariance*
A simple replication of the population of individuals and their incomes does not change the aggregate income inequality

iii) *Symmetry / Anonymity property*
The calculation of inequality index does only depend on the incomes and their ranking. Additional information about an individual's reputation in the society or resource of income combined with his or her income position are not taken into account.

iv) *Principle of transfer*
A Pigou-Dalton transfer or progressive transfer decreases the overall income inequality. Therefore, a financial transfer from a rich person i to a poor person j without changing the ranking order of the respective persons is called a progressive transfer that decreases the inequality index. This property can be derived from marginal utility theory. If a poor person's marginal utility of the increase in income is higher than a rich person's marginal loss of the decrease in income, the social welfare of a society increases.

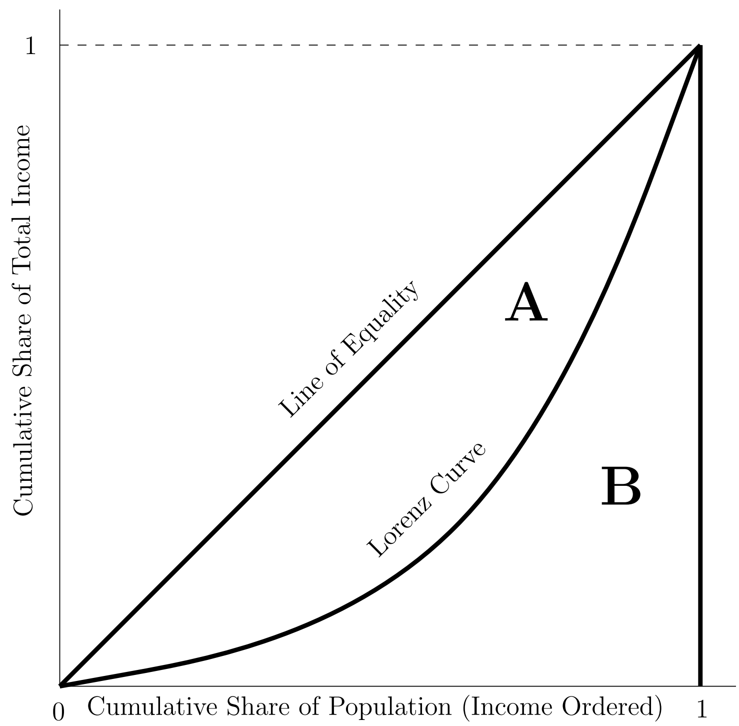
v) *Transfer sensitivity*
Taking two pairs of individuals with the same income distance, where one pair is at the upper end of the income distribution and the other pair is at the lower end of the income distribution, the property of transfer sensitivity is fulfilled if progressive transfer between the individuals of the pair at the lower end of the income distribution leads to a stronger decrease in income inequality than the same transfer between the individuals of the pair at the upper end of the income distribution (see Shorrocks and Foster, 1987, for a more detailed explanation).

The Gini coefficients and the generalized entropy indexes which are explained in the following satisfy the properties i) to iv). Only the Atkinson indexes, except the half the squared coefficient of correlation, satisfy all properties. Since the last property is also the most controversial one, the Atkinson indexes are rarely used in the empirical literature.

A.2.2 Unidimensional Inequality Measures

The derivation of unidimensional inequality measures has been necessary because the relative and the generalized Lorenz curves have two serious deficits despite their vivid illustration of the income distribution. First, the Lorenz curves of two income distributions cannot be compared with one another with respect to income inequality once they intersect. Second, the comparison of several income distributions at a given time based on the Lorenz curves overloads the graphical illustration and hampers the ranking of the corresponding income distributions with regard to income inequality. These aspects substantiate the aggregation of information about the income distribution to one single unidimensional index that is comparable both over time and across different units of observation. In particular, the Gini coefficient has successfully prevailed in the empirical literature, since its derivation and interpretation is straightforward.[110] Furthermore, the Gini coefficient can be directly derived from the graphical representation of the Lorenz curve $L(F,q)$ and the uniform distribution curve q (see Figure A.1).

Figure A.1: Graphical representation of the Gini coefficient



[110]The Gini coefficient is named after the Italian statistician and economist *Corrado Gini* who developed the final index in Gini (1914).

Thus, the Gini coefficient $G(y)$ corresponds to the ratio of the area between the uniform distribution q and the Lorenz curve (A) to the entire surface below the uniform distribution that equals $\frac{1}{2}$ per definition:

$$G(y) = \frac{A}{A+B} = 1 - 2B\,. \tag{A.2}$$

Therefore, the Gini coefficient measures the average distance between the Lorenz curve $L(F,q)$ and the diagonal q, whereby the diagonal is the benchmark in the calculation of the "deficit". Moreover, considering income as a continuous variable, the Gini coefficient of an income distribution F can be determined by integration over the Lorenz curve employing (Lambert, 1993)

$$G(y) = 1 - 2\int_0^1 L(F,q)\,dq\,, \tag{A.3}$$

where $G(y)$ can take values between zero and one. Thus, if all individuals have the same value of income, the Lorenz curve and the diagonal overlap completely and the Gini coefficient equals zero (minimum inequality). On the other hand, if one single individual owns the economy's total income while remaining individuals have zero income, the Lorenz curve overlaps completely with the two axes and Gini coefficient is one (maximum inequality). Since individual income data are practically discrete, the Gini coefficient can be also represented in discrete notation:

$$G(y) = \frac{1}{2n^2\mu} \cdot \sum_{i=1}^{n}\sum_{j=1}^{n} \left|y_i - y_j\right| \quad ,\forall i \neq j \tag{A.4}$$

where i and j are two individuals from the society. The average income is given by μ and n yields the total number of individuals. Thus, the Gini coefficient is the average absolute distance between the incomes of all pairs of individuals normalized by the average income of the economy. Therefore, this inequality measure is a measure of dispersion divided by the mean of the income distribution (Cowell, 2000). Interestingly, the Gini coefficient can be expressed as the covariance between an individual's income and his or her fractional rank in the income distribution by

$$G(y) = \frac{2}{\mu}\,\mathrm{Cov}(y, F(y)) \tag{A.5}$$

, where the covariance between an individuals income y_i and his or her fractional rank $\frac{i}{n}$ in the income distribution is divided by the average income (Lerman and Yitzhaki, 1984, 1985). After some transformations of the expression which are explained in detail in Yitzhaki (1982), it can be shown that the Gini coefficient is most sensitive to income changes around the median income and places stronger weight on the middle of the income distribution. In order to achieve a higher flexibility in the sensitivity, the class of *generalized Gini coefficients* (S-Gini) that additionally include an aversion to inequality parameter ν were introduced (Donaldson and Weymark, 1980; Yitzhaki, 1983):

$$S_\nu(y) = 1 - \int_0^1 \nu(\nu-1)(1-q)^{\nu-2} L(F,q)\, dq\,, \tag{A.6}$$

where $\nu > 1$ holds. Thus, due to the weighting function $W(\nu,q) = \nu(\nu-1)(1-q)^{\nu-2}$, higher values of ν determine that a given income difference between two persons at the bottom of the income distribution receives a higher weight in the calculation of the overall income inequality than the same income difference between two persons at the top of the income distribution. Therefore, the higher the value of ν, the more sensitive the generalized Gini coefficient is to income changes at the bottom of the income distribution relative to the top. The conventional Gini coefficient is obtained if $\nu = 2$ (Jenkins and Van Kerm, 2009). Thus, even the conventional Gini coefficient is not free from a weighting of individuals' incomes depending on their rank in the income distribution. Due to the need of a relative inequality measure that is additive decomposable and equals the weighted sum of within-group and between-group inequality, the *generalized entropy measures* $GE_\alpha(y)$ were introduced in the empirical literature on income inequality (Cowell and Kuga, 1981a,b):

$$GE_\alpha(y) = \frac{1}{\alpha^2 - \alpha} = \int \left(\left(\frac{y}{\mu y} \right)^2 - 1 \right) f(y)\, dy\,, \tag{A.7}$$

where $\alpha \in (-\infty, +\infty)$ is a parameter that captures the sensitivity of the inequality measure to differences in the income shares in different parts of the income distribution.[111] The more negative (positive) the sensitivity parameter is, the more sensitive the inequality index is to differences in the income shares among the poorest (richest). In the empirical literature, the mean logarithmic deviation $GE_0(y)$, the Theil index $GE_1(y)$, and the half the squared coefficient of variation $GE_2(y)$ are used as prominent members of the generalized entropy measures:

$$GE_0(y) = \int \log\left(\frac{y}{\mu}\right) f(y)\, dy\,, \tag{A.8}$$

$$GE_1(y) = \int \frac{y}{\mu} \log\left(\frac{y}{\mu}\right) f(y)\, dy\,, \tag{A.9}$$

$$GE_2(y) = \frac{1}{2} \left(\frac{\sqrt{\mathrm{Var}(y)}}{\mu} \right)^2 . \tag{A.10}$$

Thus, the mean logarithmic deviation is more sensitive to differences at the bottom of

[111] Since the inequality measures are applied to income and wage, the sensitivity parameter is only defined as $[0, +\infty)$.

the income distribution, whereas the half the squared coefficient of variation is more sensitive to differences at the top of the income distribution. Depending on the part of the income distribution that experiences large income changes over time or across countries, the three inequality measures show different jumps in their levels. If the income inequality increases more strongly at the lower end of the income distribution, this is more apparent by changes in the mean logarithmic deviation, whereas strong income changes and widening incomes at the top of the income distribution can be better detected by changes in the half the squared coefficient of variation. Closely related to the generalized entropy measures are the Atkinson indexes (Atkinson, 1970). Since there is an equivalent generalized entropy measure for each Atkinson index depending on the selected value for α, the representation of the Atkinson indexes is omitted. For a good introduction to these inequality indexes and a detailed explanation, reference is made to Cowell (2000).

A.3 Decomposition of Inequality Measures

There are several decomposition techniques which target different issues of the income inequality measures. On the one hand, some decompositions can be used to measure the contribution of different income sources, such as labor income, capital income, or social benefits, to the overall income inequality (Shorrocks, 1982). On the other hand, some decompositions can reveal whether overall income inequality is more strongly influenced by a difference in or across different subgroups. The latter is explained in more detail in the following subsection. Subsequently, the decomposition of changes in income inequality into a mobility and an income growth component is presented.

A.3.1 Decomposition by Subgroups

In order to decompose the overall inequality measure by subgroups, the population is divided into M distinct non-overlapping groups of individuals, where the group identification is based on individual characteristics, such as age, educational attainment, place of residence, etc. The decomposition by subgroups identifies the contribution of inequality within each group and the contribution of inequality between groups to the overall inequality. For example, if the place of residence is the subgroup identifier, the decomposition of the overall income inequality determines whether the overall income inequality mainly reflects income differences within regions or income differences between regions. Since the Gini coefficient is not applicable for a twofold decomposition by subgroups, the generalized entropy measures, which are additively decomposable, are used in the literature (Shorrocks, 1984). Therefore, the overall income inequality is the sum of the income inequality between the weighted subgroups' average incomes and the income inequality within subgroups, where the latter is the weighted sum of income inequality within each subgroup (Jenkins and Van Kerm, 2009):

$$GE_{\alpha}(y) = GE_{\alpha}^{B}(y) + GE_{\alpha}^{W}(y) \tag{A.11}$$

with

$$GE_{\alpha}^{W} = \sum_{m=1}^{M} v_m^{\alpha} \omega_m^{1-\alpha} GE_{\alpha}(y^m) \qquad \text{and} \qquad GE_{\alpha}^{B} = \frac{\alpha}{\alpha^2 - \alpha} \cdot \sum_{m=1}^{M} v_m^{\alpha} \omega_m^{1-\alpha} - 1$$

where v_m yields the income share of group m of the total income, ω_m gives the population share of subgroup m, and $GE_{\alpha}(y^m)$ is the income inequality within the particular subgroup m. In turn, between-group inequality GE_{α}^{B} is the income inequality obtained by imputing the corresponding average income of the respective subgroup to each person of a subgroup (Cowell and Fiorio, 2011). As a quick reminder, α is the sensitivity parameter. In order to illustrate the interpretation of the decomposition by subgroups, two extreme cases can be presented. On the one hand, if the average incomes of all subgroups are equal ($GE_{\alpha}^{B} = 0$), the total income inequality is equal to the within-group inequality. Since there is no between-group inequality, the within-group inequality entirely reflects the total inequality and there is no contribution from the between-group inequality to the overall measure. On the other hand, if each individual of a subgroup earns the average income of his or her subgroup, the within-group inequality is zero ($GE_{\alpha}^{W} = 0$). Thus, the between-group inequality entirely reflects the total inequality and there is no contribution from the within-group inequality to the overall measure. Although the decomposition by subgroups is applicable to all generalized entropy measures, Shorrocks and Wan (2005) recommend the mean logarithmic deviation as the most appropriate inequality measure for two reasons. First, whereas the within-group income inequality is a weighted sum, the weights usually do not add up to one, unless if $\alpha = 0, 1$.[112] Second, due to the arbitrary sum of the weights, the within-group component of the decomposition depends on both the within-group income differences and on the between-group income differences.

A.3.2 Decomposition into Growth and Mobility

Jenkins and Van Kerm (2006) offer a method to analyze income growth and changes in income ranks between a base and a reporting year simultaneously. The authors show that the change in income inequality, measured based on the Gini coefficient, between two points in time can be decomposed into a *pro-poor income growth* or progressivitiy and a *reranking* or income mobility component. The former measures to what extent the changes in incomes benefit the low-income earners more strongly than the high-income earners of the base year, or vice versa. The latter measures the magnitude of a person's

[112]Hence, employing the Theil index, the weights correspond to the subgroup income shares.

movement along the income distribution between the base and the reporting year. Thus, the decomposition is based on the measurement of individual incomes at two points in time and derived by applying the change in the generalized Gini coefficient, which can be an alternative to Equation (A.6) expressed by

$$S_\nu = G(\nu) = 1 - \int w\,(F(y),\nu) \cdot \frac{y}{\mu(F)} f\,(y)\,dy\,,$$

where $w\,(F(y),\nu) = \nu\,(1 - F(y))^{\nu-1}$ applies, f represents the probability density of income y, μ yields the average income of the population, and ν is the sensitivity parameter of the Gini coefficient. Thus, the generalized Gini coefficient is a weighted mean of each individual's relative income, where the social weight follows a decreasing function of the individual income position within the distribution. Therefore, an individual's contribution to income inequality depends on the relative income as well as his or her income position, which classifies the generalized Gini coefficient among the linear inequality measures (Mehran, 1976). The change in income inequality between a base year $t = 0$ and a reporting year $t = 1$ can be expressed by either Lorenz curves

$$\Delta G(\nu) = G_1(\nu) - G_2(\nu) = \int_0^1 k(q,\nu) \cdot (L_0(q) - L_1(q))\,dq \tag{A.12}$$

or incomes

$$\Delta G(\nu) = \int w(F_0(y),\nu) \cdot \frac{y}{\mu(F_0)} f_0(y)\,dy - \int w(F_1(y),\nu) \cdot \frac{y}{\mu(F_1)} f_1(y)\,dy\,, \tag{A.13}$$

where the respective year is expressed in the indices. In particular, the Equation (A.13) shows that a change in income inequality is always accompanied by both a change in individual weights and a change in the relative incomes. In order to derive the decomposition, the *concentration curve* $C_1^{(0)}(q)$ of incomes in the reporting year $t = 1$ is employed, whereby the individuals are ordered based on their income rank in the base year $t = 0$:

$$C_1^{(0)}(q) = \frac{1}{\mu(F_1)} \int_{\underline{y}}^{F_0^{-1}(q)} \mathrm{E}_1(y) f_0(y)\,dy\,, \tag{A.14}$$

where $\mathrm{E}_1(y)$ represents the expected value of income in the reporting year $t = 1$ if income had a value of y in the base year $t = 0$. By adding and subtracting $C_1^{(0)}(q)$ to the Equation (A.12), the change in income inequality can be divided into two components with

$$\Delta G(\nu) = R(\nu) - P(\nu)\,, \tag{A.15}$$

where

$$P(\nu) = \int_0^1 k(q,\nu)\Big(C_1^{(0)}(q) - L_0(q)\Big)dq = G_0(\nu) - G_1^{(0)}(\nu)\,,$$
$$R(\nu) = \int_0^1 k(q,\nu)\Big(C_1^{(0)}(q) - L_1(q)\Big)dq = G_1(\nu) - G_1^{(0)}(\nu)\,,$$

and $G_1^{(0)}(\nu)$ represents the generalized concentration coefficient for the reporting year $t = 1$ with the income rank order of individuals from the base year $t = 0$. Thus, $P(\nu)$ yields the progressivity of income growth and $R(\nu)$ yields the income mobility or reranking between the two years. Furthermore, Jenkins and Van Kerm (2006) show that given $\mu_0 \neq \mu_1$,

$$P(\nu) = \frac{\pi}{1+\pi} \cdot K(\nu) \tag{A.16}$$

applies for the progressivity component, where $K(\nu)$ represents a generalized Kakwani-type index of progressivity and summarizes the proportionality of individual income growth (Kakwani, 1977). Additionally, the average income growth of the population is given by $\pi = \frac{\mu_1 - \mu_0}{\mu_0}$. Therefore, based on the value of aggregate income growth π, two distinct cases can be examined. First, the aggregate income growth is positive $\pi > 0$. Then, income growth is progressive $P(\nu) > 0$ if income growth is concentrated more among the low-income earners than among the high-income earners. This causes, ceteris paribus, income inequality to decrease over time and is referred to as *pro-poor growth*. However, if the opposite occurs, income growth will be regressive $P(\nu) < 0$, which can be referred to as *pro-rich growth*. Second, the income growth is negative $\pi > 0$. Then, income growth can be still progressive if income reductions are concentrated more among the high-income earners than among the low-income earners, which indicates that $K(\nu) < 0$ applies. In general, the progressivity component $P(\nu)$ yields the change in income inequality if there had been no reranking between the base and the reporting year $R(\nu) = 0$, i.e. the income rank order of the base year is retained in the reporting year. On the other hand, the reranking component $R(\nu)$ yields the change in income inequality if income growth had been equi-proportionate $P(\nu)$, i.e. each individual's income increased by the same percentage. Thus, income inequality can increase despite pro-poor income growth due to the overcompensating effect of reranking, which is, to an extent, counterintuitive at first glance. Since the decomposition method is based on tracking individuals' income position over time, low-income earners in the initial year might move towards middle-income jobs in the reporting year due to pro-poor growth, but they are simultaneously replaced by new low-income earners who were middle- or high-income earners in the base year. If the new set of low-income earners in the reporting year have, on average, a lower income than the previous set of low-income earners in the base year, the reranking index will exhibit the pro-poor growth index, which leads to an increase in cross-sectional income inequality. Therefore, the decomposition method measures the income changes of a fixed income group the membership of which is defined by the base year (progressivity) and adds a term that accounts for membership changes (reranking).

A.4 Measurement of Mobility

The different measures of income inequality relate to a certain point in time. Thus, they offer a snapshot of the current income distribution. Furthermore, the linkage of annual income inequality over time enables the evaluation of the overall development of the income distribution for a statistical unit. However, income inequality measures cannot provide information about changes in incomes within the income distribution or movements of individuals along the income distribution over time. Thus, measures of income mobility are the logical complement to income inequality. The theoretical and mathematical literature on the measurement of mobility has developed a large number of new measures over the last decades. Based on the particular research question, the measures target different aspects of the intragenerational mobility.

A.4.1 Categorization of Mobility Measures

In contrast to the research on income inequality, there is no consensus about the properties postulated on the measurement of income mobility in the literature. Thus, the appropriate measure is selected depending on the research question. In general, the income mobility measures can be divided into five categories with respect to their properties or interpretations, whereby particular measures fulfill the properties of more than one category (see Jenkins and Van Kerm, 2009; Jäntti and Jenkins, 2015, among others):

i) *Exchange Mobility*
Exchange mobility measures solely consider changes in income ranks between two points in time. Thus, only the movements of individuals along the income distribution are taken into account. Therefore, there is no mobility present if all individuals take the same rank in both (the base and reporting) year, regardless of income growth in the meantime.

ii) *Structural Mobility*
Structural mobility measures take changes of the entire income distribution into account. Thus, these indexes even change in value if individuals take the same rank in the base and the reporting year, but the income distribution changes with respect to particular functionals, such as the variance, the skewness, or the kurtosis.

iii) *Independence Measures*
Independence measures are based on the correlation of individual incomes between two points in time. If there is no correlation between the individuals' incomes, the incomes in the base and the reporting year are independent from one another. This, in turn, can be assessed as perfect income mobility, since each individual has the same probability in the base year to receive a particular income in the reporting year. Therefore, there is perfect immobility if there is a perfect correlation in incomes between two points in time present.

iv) *Equalizing Measure*
Equalizing measures quantify how strongly long-term income inequality can be reduced by income mobility which is measured as income changes and movements along the income distribution over time. For this purpose, the individuals' incomes are tracked over time and transformed into long-term income data (e.g. average or total income over time), which is used in order to measure long-term income inequality. Ultimately, the difference in long-term and short-term income inequality determines income mobility.

v) *Directionality*
Since mobility measures compare the incomes between at least two points in time, their values can depend on whether the incomes of the base year or the reporting year are used for normalization. If the dependency is present, the mobility measure is directional. If the opposite occurs, it is non-directional.

A.4.2 Unidimensional Measures

Below, intragenerational mobility measures, which were used in this study, are presented. There are plenty of income mobility measures the illustration and derivation of which have been omitted from this appendix, since they have not been applied in the empirical investigation of this work. A good review on the measurement of mobility is given in Burkhauser and Couch (2009), Jäntti and Jenkins (2015), and Jenkins and Van Kerm (2009), among others.

The *independence measures* are commonly used as natural starting point for measuring mobility, since they are based on the correlation between an individual's income at two points in time. In particular, in the literature on intergenerational income mobility, the Pearson correlation r between parents' and children's logarithmic income is often applied as a measure of dependence in incomes:

$$r = \beta \frac{\sigma_1}{\sigma_2} \tag{A.17}$$

where σ_1 and σ_2 yield the standard deviation of logarithmic incomes in the parents' and the kids' generations, respectively. Furthermore, the slope parameter β is obtained from a least-squares regression of kids' logarithmic incomes on parents' logarithmic incomes. Thus, employing the incomes of an individual at two points in time, the dependence of an individual's future income on his or her current income can be detected. Since r is β scaled, the Pearson correlation measures the degree of the regression to the mean in income between two points in time. Hart (1976) introduces an intuitive mobility measure which can be interpreted as an independence measure:

$$\textit{Hart Index} = 1 - r\,, \tag{A.18}$$

whereby this measure ranges between -1 and $+1$ and takes the value zero if there is complete immobility. Furthermore, the Hart index depicts structural as well as exchange mobility. If there is a perfect linear relationship between an individual's base year and reference year income, there is no mobility at all as there were no changes in the income ranking of individuals, although this could still be consistent with income growth. In this case, there is no exchange mobility, but there is structural mobility.

A related measure which can be interpreted as an independence measure is the *Gini mobility index* introduced by Yitzhaki and Wodon (2004). This index follows the intention of the Pearson correlation and defines income mobility as a lack of correlation between an individual's income at two point in time, but uses the Gini coefficient for the calculation and is based on ranks. Since the Gini correlation between the income distributions of two points in time is a directional measure, i.e. the value depends on whether the changes in income refer to the base year or the reference year, it is calculated for both directions by (Jäntti and Jenkins, 2015)

$$\Gamma_{12} = \frac{\mathrm{Cov}\left(\frac{y_1}{\mu_1}, F_2\right)}{\mathrm{Cov}\left(\frac{y_1}{\mu_1}, F_1\right)} \qquad \text{and} \qquad \Gamma_{21} = \frac{\mathrm{Cov}\left(\frac{y_2}{\mu_2}, F_1\right)}{\mathrm{Cov}\left(\frac{y_2}{\mu_2}, F_2\right)}\,, \tag{A.19}$$

where $\frac{y_1}{\mu_1}$ and $\frac{y_2}{\mu_2}$ yield the relative income of an individual in the base and reference year, respectively, i.e. the individual income divided by the mean income in the corresponding year. F_1 and F_2 give the fractional rank of an individual in the particular years. Employing the covariances, the Gini mobility index is defined as the weighted average of the two directional measures, whereby the weights are the cross-sectional Gini coefficients in the base and reference years:

$$\textit{Gini Mobility Index} = \frac{G_1\,(1-\Gamma_{12}) + G_2\,(1-\Gamma_{21})}{G_1 + G_2}\,, \tag{A.20}$$

where G_1 and G_2 are the cross-sectional Gini coefficients in the base and the reference years, respectively. If there are no positional changes of individuals between the two points in time, the Gini mobility index equals zero. Furthermore, the index takes the value 1 if there is complete origin independence and takes the value 2 if there is complete rank reversal (Yitzhaki and Wodon, 2004). Therefore, the former can be interpreted as complete mobility if mobility is defined as the lack of dependence of individual's cross-sectional incomes.

Another strand of the literature on the measurement of income mobility builds on the idea that the aim of income mobility is to reduce long-term inequality. In his pioneering work, Shorrocks (1978) points out that *"mobility causes inequality to decline as the accounting interval grows"* and introduces a measure of income rigidity, which can be easily transformed to an income mobility index, because the rigidity index is bounced to one for conventional inequality indexes. Thus, taking the average income of an individual over a particular time period smooths his or her income fluctuations out. Since these fluctuations no longer contribute to the calculation of inequality in the average incomes of the individuals, the average static income inequality over a particular time period should be higher than the inequality in individuals' average incomes. Therefore, the difference between the inequality of average incomes and average cross-sectional inequality can be used to derive a measure of mobility. Based on the rigidity index, proposed by Shorrocks (1978), the *Shorrocks mobility index* is defined by:

$$\textit{Shorrocks Mobility Index} = 1 - \frac{I(\mu_i)}{\sum\limits_{t=1}^{T} \frac{\mu^t}{\mu} I(y_{it})}, \tag{A.21}$$

where $I(\mu_i)$ and $I(y_{it})$ represent the income inequality, measured, for example, by the Gini coefficient, based on the average incomes of individuals over the whole time period T and the income inequality based on incomes of individuals in each cross-section t, respectively. Furthermore, μ^t gives the cross-sectional mean income in t and μ is the average of the mean incomes over the whole observation period T. Thus, the denominator is a weighted average of the cross-sectional income inequality, whereby the weights $\frac{\mu^t}{\mu}$ are the proportion of the economy's entire income in t and sum to unity. The Shorrocks mobility index has two crucial features which explain the widespread use in the empirical application. First, in contrast to the independence measures, the index utilizes individuals' incomes in the years within the time period in order to calculate mobility rather than applying only the base and the reference year of the time period. Thus, employing a fixed time window enables the calculation of trends in income mobility by moving the fixed time window over a period of time. Second, the expansion of the time window shows how fast the smoothing of income fluctuations occurs within a country and how fast mobility converges to its long-term value. Furthermore, this feature is of particular interest in the comparison of groups or countries with respect to their income mobility patterns. However, Fields (2010) criticizes that the denominator of the Shorrocks mobility index is an average inequality measure which is, in general, not intended as the reference point in the research of income mobility. The question is to what extent wage mobility equalizes or disequalizes long-term incomes relative to the base year rather than to an average reference. Thus, he proposes a refinement of the Shorrocks mobility index by employing the income inequality in the base year as the reference:

$$\textit{Fields Mobility Index} = 1 - \frac{I(\mu_i)}{I(y_{i1})}\,, \tag{A.22}$$

where $I(\mu_i)$ is the income inequality based on the average incomes of the individuals over the time window and $I(y_{i1})$ yields the income inequality in the base year. In turn, the interpretation of the index follows the explanations for the Shorrocks mobility index.

B
Quantile Regressions

Quantile regressions complement the common estimation techniques which measure the effect of an independent variable on the average of the dependent variable. Furthermore, they are meaningful when the focus is on the entire distribution of the dependent variable. In particular, it is worthwhile to measure the effect the covariates have on the different quantiles of the distribution when investigating the issues of individual income, wages, or human capital accumulation. Whether certain measures affect the distribution of dependent variables and, consequently, individuals differently is especially relevant for economic policy recommendations. Conditional quantile regressions and unconditional quantile regressions offer two econometric instruments of analysis to measure effects on the distribution as a whole and on particular quantiles. Both estimation approaches measure the effect of an independent variable on the dependent variable, controlled for the combined correlation with the remaining independent variables.

B.1 Conditional Quantile Regression

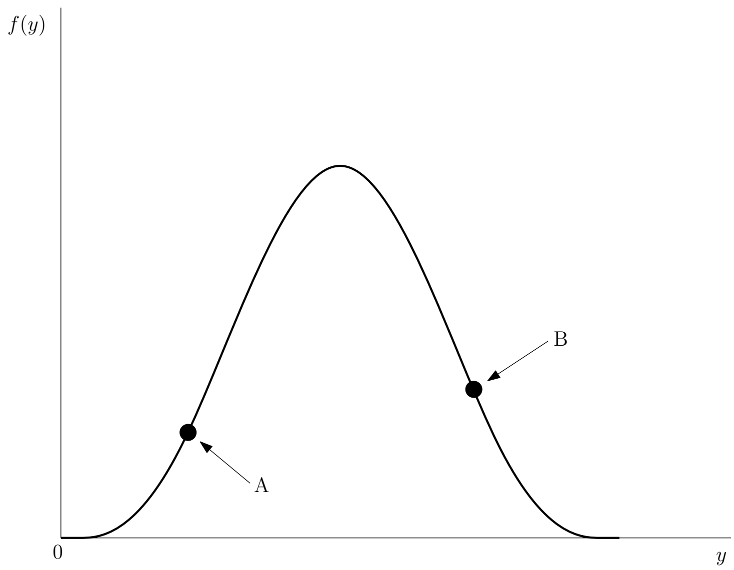
The conditional quantile regressions estimate the correlation between an independent variable and the dependent variable in different quantiles of the distribution of the dependent variables, whereby the variation of the effect of the independent variable being considered is estimated for persons whose dependent variable values differ while their values for the remaining independent variables are the same. They are used especially to evaluate the distribution of the dependent variable, as the determined effects refer to the distribution and not particular persons along the distribution (Killewald and Bearak, 2014).

Since the appropriate interpretation of the results of the conditional quantile regression are misleading, a small example will provide a remedy. Assuming that a training measure has a positive effect on wages in the first wage decile, this does not necessarily imply that the wage of a person in the first decile without training would increase if he or she participates in the training session. The effect merely means that the first decile of the wage distribution with training measures generates higher wages than the first decile of the wage distribution without training measures. The training measure only results in wage increases in the overall first wage decile if it does not lead to changes in the ranking of individuals (Angrist and Pischke, 2009).

B.1.1 Graphical Explanation

The interpretation of the results of the conditional quantile regression can be illustrated by a graphical representation of conditional distribution functions. For the purpose of simplicity, let us consider a bivariate case, wherein educational attainment is the only independent variable that has influence on wages. Three categories of educational attainment, low-skilled, medium-skilled, and high-skilled, are used for the graphical representation.[113] Additionally, two persons, a low-wage earner A and a high-wage earner B, are picked out of the unconditional wage distribution $f(y)$ (see Figure B.1). When wages are conditioned to the educational attainment categories, a conditional

Figure B.1: Unconditional wage density



wage distribution for each level of educational attainment is obtained (see Figure B.2 and Figure B.3). The black lines represent the estimated wages from the three quantile regressions at the 25th, 50th, and 75th percentiles. Both the low-wage earner and high-wage earner are in the 75th percentile. Therefore, they are relatively more successful with regard to their wages than the remaining persons in their educational attainment category. The conditioning for educational attainment results in the low-wage earner being at the top end of the conditional wage distribution, whereas he or she would

[113]The evaluation based on a continuously defined education variable, such as education years, does not differ from the discrete case, but it is less suitable for a graphical illustration

Figure B.2: Quantile regression with different slopes

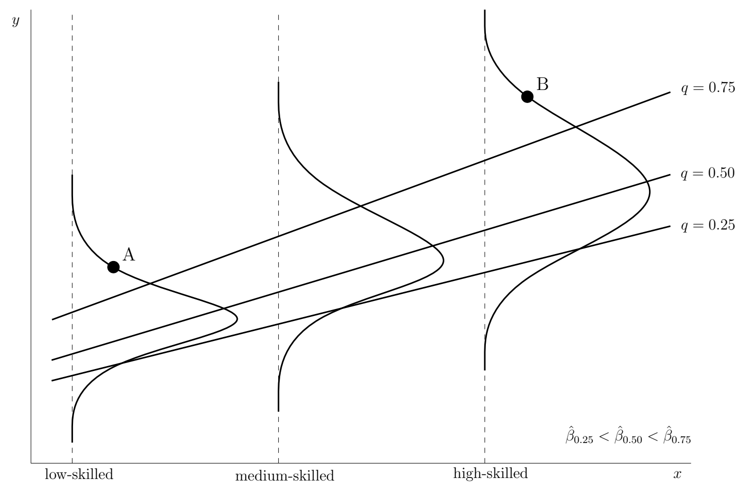
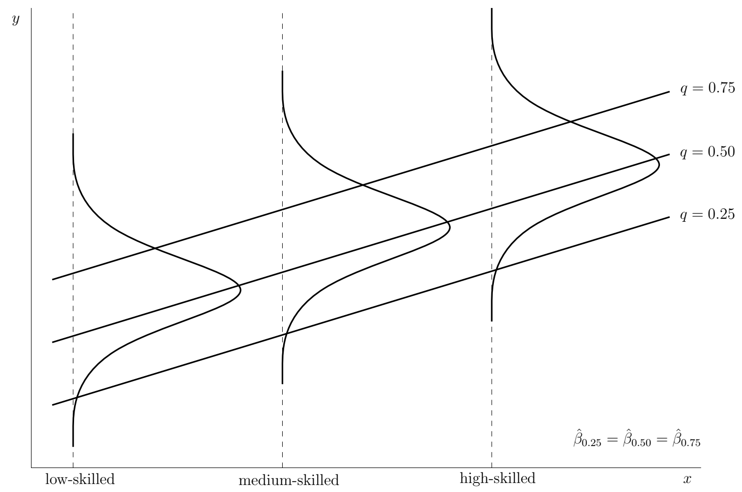


Figure B.3: Quantile regression with similar slopes



have been at the bottom end of the unconditional wage distribution. Thus, this type of regression is not able to interpret the estimated coefficients of particular covariates in relation to any particular individual among the distribution, but rather in the context of the distribution. For example, a coefficient of $\hat{\beta}_{75} = 0.2$ therefore means that a transfer to the next higher category of educational attainment at the 75th percentile of the conditional wage distribution is more likely, but it is not previously known which persons will remain in this quantile.

Applying conditional quantile regressions, information can be given about how the wage distribution has changed within a category of educational attainment. If the coefficients are relatively constant throughout all quantiles, the only effect of educational attainment on wages is a *location shift* (Hao and Naiman, 2007). Greater educational attainment increases the average wages uniformly in the remaining quantiles of the wage distribution and therefore, wage inequality within a category of educational attainment remains unchanged.[114] However, if the coefficients increase (decrease) throughout

[114]In particular, this occurs if there is homoscedasticity in the data.

the quantiles, the wage inequality within a category of educational attainment also increases (decreases). Since coefficients differ across the quantiles, there is a *location and scale shift* (Angrist and Pischke, 2009).

If further independent variables are used, the conditional quantile regression measures whether persons have higher or lower wages than expected given the manifestation of the remaining independent variables. The effect of educational attainment on the different quantiles then measures the effect on persons that pertain to the respective quantile, conditioned to the remaining independent variables.

B.1.2 Derivation of the Conditional Quantile Regression

Let $q \in (0,1)$ denote the q-th quantile of the distribution of income y given the vector of some covariates $\boldsymbol{x_i}$. Then, the conditional quantile function is defined as

$$Q_q(y_i|\boldsymbol{x_i}) = F^{-1}(y_i|\boldsymbol{x_i})\,,$$

where $F(y_i|\boldsymbol{x_i})$ is the cumulative income distribution function at y_i, conditional on $\boldsymbol{x_i}$. Thus, if $q = 0.1$, the function $Q_q(y_i|\boldsymbol{x_i})$ yields the income value of the lowest decile of y_i given $\boldsymbol{x_i}$ (Angrist and Pischke, 2009). Furthermore, the conditional quantile function is the quantile version of the conditional expectation function and solves the minimization problem

$$\boldsymbol{\beta_q} = \arg\min_{\hat{\beta}} \mathrm{E}\left[c_q(y_i - \boldsymbol{x_i'}\boldsymbol{\hat{\beta}_q})\right]\,,$$

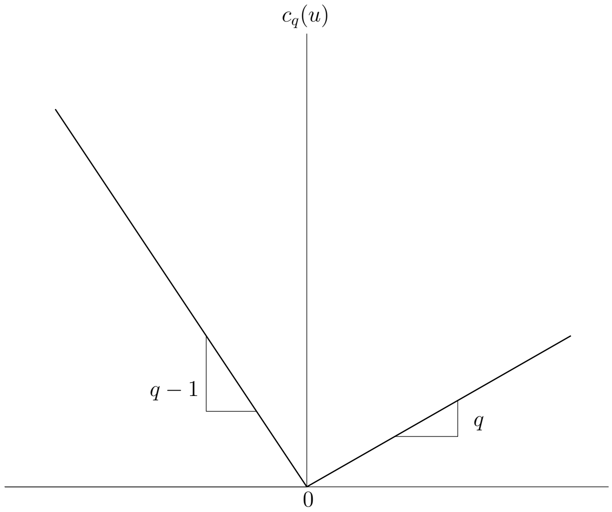
where the first element of $\boldsymbol{x_i}$ is unity and the conditional quantile regression function is obviously linear in parameters. Since the conditional quantile regression is an extremum estimator, such as the ordinary least squares regression, $c_q(\cdot)$ represents the *asymmetric absolute loss function* or *check function* , expressed by

$$c_q(u) = \Big(q \cdot \mathcal{I}[u \geq 0] + (1-q)\cdot \mathcal{I}\,[u < 0]\Big)\cdot \Big|u\Big| = \Big(q - \mathcal{I}[u<0]\Big)\cdot u$$

where $\mathcal{I}[\cdot]$ is the indicator function and u the error term (Wooldridge, 2010). If $u > 0$ is given, the slope of $c_q(u)$ is equivalent to q and if $u < 0$ is given, the slope is equivalent to $-(1-q)$. Thus, the slope is undefined for $u = 0$ (see Figure B.4). Therefore, the conditional quantile function is not differentiable at zero and can be expressed by

$$c_q(y_i - \boldsymbol{x_i'}\boldsymbol{\hat{\beta}_q}) = \begin{cases} q(y_i - \boldsymbol{x_i'}\boldsymbol{\hat{\beta}_q}) & \text{for} \quad y_i - \boldsymbol{x_i'}\boldsymbol{\beta_q} \geq 0 \\ (1-q)(y_i - \boldsymbol{x_i'}\boldsymbol{\hat{\beta}_q}) & \text{for} \quad y_i - \boldsymbol{x_i'}\boldsymbol{\beta_q} < 0 \end{cases}$$

Figure B.4: Asymmetric loss function of the conditional quantile regression



Source: own illustration, based on Koenker and Hallock (2001)

In order to obtain consistent estimators for the parameters $\hat{\boldsymbol{\beta}}_{\boldsymbol{q}}$, the sample analog is applied

$$\begin{aligned}&\min_{\beta\in\mathbb{R}^K}\sum_{i=1}^{n} c_q(y_i-\boldsymbol{x}_{\boldsymbol{i}}'\boldsymbol{\beta})\\&\min_{\beta\in\mathbb{R}^K}\sum_{i:y_i\geq\boldsymbol{x}_{\boldsymbol{i}}'\boldsymbol{\beta}}^{n} q|y_i-\boldsymbol{x}_{\boldsymbol{i}}'\boldsymbol{\beta}|+\sum_{i:y_i<\boldsymbol{x}_{\boldsymbol{i}}'\boldsymbol{\beta}}^{n}(1-q)|y_i-\boldsymbol{x}_{\boldsymbol{i}}'\boldsymbol{\beta}|\,,\end{aligned}\tag{B.1}$$

where $0<q<1$ applies and estimated coefficients $\hat{\boldsymbol{\beta}}$ depend on the chosen value at a particular quantile Q_q for estimation (Koenker and Bassett, 1978). The minimand of the conditional quantile regressions averages absolute deviations rather than squared deviations. Therefore, it is more robust towards outliers than the ordinary least squares regression.

Given that the loss function is not differentiable at zero, common gradient optimization methods are not applicable to calculate estimators for the parameters. In general, the simplex method with a finite number of simplex iterations is used as the optimization method. Moreover, the conditional quantile regression pertains to the m-estimators and $\hat{\boldsymbol{\beta}}_{\boldsymbol{q}}$ is, given general conditions, asymptotically normal (Cameron and Trivedi, 2005):

$$\sqrt{n}(\hat{\boldsymbol{\beta}}_{\boldsymbol{q}}-\boldsymbol{\beta}_{\boldsymbol{q}})\xrightarrow{d}\mathcal{N}[\boldsymbol{0},\boldsymbol{A}^{-1}\boldsymbol{B}\boldsymbol{A}^{-1}]\,,$$

where

$$\boldsymbol{A} = \text{plim}\frac{1}{n}\sum_{i=1}^{n} f_{u_q}(0|\boldsymbol{x_i})\boldsymbol{x_i}\boldsymbol{x_i'}\,,$$
$$\boldsymbol{B} = \text{plim}\frac{1}{n}\sum_{i=1}^{n} q(1-q)\boldsymbol{x_i}\boldsymbol{x_i'}\,,$$

and f_{u_q} is the conditional density of the error term $u_q = y - \boldsymbol{x}'\boldsymbol{\beta_q}$ evaluated at the value $u_q = 0$. In most applications, the variance of $\hat{\boldsymbol{\beta}}_{\boldsymbol{q}}$ is estimated by *paired bootstrapped resampling*.

In order to illustrate the difference between homoscedasticity and heteroscedasticity in the estimations, an alternative representation of the conditional quantile function is employed

$$Q_q(y_i|\boldsymbol{x_i}) = \alpha + \boldsymbol{x_i}\boldsymbol{\beta} + F_{u_i}^{-1}(q)\,,$$

where $F_{u_i}^{-1}(q)$ is the distribution of the error terms u_i. Thus, the income quantile depends on $F_{u_i}^{-1}(q)$, conditional on the set of exogenous variables $\boldsymbol{x_i}$. If there is no correlation between the distribution of the error terms and the independent variables, the errors are independently and identically distributed. Thus, there is homoscedasticity in the estimations and the variance of the conditional income distribution is constant and similar in value across the combinations of exogenous variables. Thus, considering the educational attainment of an individual as a determinant of individual income, the income distribution within each educational degree has the same variance, conditional on the remaining independent variables (see Figure B.3). Since the inverse distribution function no longer varies among the observations, the conditional quantile function can be represented by

$$Q_q(y_i|\boldsymbol{x_i}) = \left[\alpha + F_u^{-1}(q)\right] + \boldsymbol{x_i'}\boldsymbol{\beta}\,,$$

whereby $F_{u_i}^{-1}(q) = F_u^{-1}(q)$ applies. Therefore, the conditional quantile functions have the same slopes $\boldsymbol{\beta}$ at each quantile for the covariates. They solely differ in their intercepts due to the term $[\alpha + F_u^{-1}(q)]$. Ultimately, there is no need for the application of conditional quantile regression if homoscedasticity is present, since merely a location shift occurs (Cameron and Trivedi, 2010). However, if there is heteroscedasticity present in the estimations, i.e. the errors are non-independently and identically distributed, and the estimated coefficient of the conditional quantile regressions increases along the quantiles, the income distribution can be expressed by

$$y_i \sim \mathcal{N}(\boldsymbol{x_i'}\boldsymbol{\beta}, \sigma^2(\boldsymbol{x_i}))\,,$$

where the normal distribution and $\sigma^2 = (\boldsymbol{\lambda}'\boldsymbol{x_i})^2$ is used for simplicity. Furthermore, $\boldsymbol{\lambda}$ is a vector of positive coefficients, where $\boldsymbol{\lambda}'\boldsymbol{x_i} > 0$ holds, and the conditional quantile function can be expressed by

$$Q_q(y_i|\boldsymbol{x_i}) = \boldsymbol{x_i'}\boldsymbol{\beta} + (\boldsymbol{\lambda}'\boldsymbol{x_i})\Phi_u^{-1}(q)\,,$$

where $\Phi_u^{-1}(q)$ is the inverse of the standard normal cumulative distribution function. Therefore, the conditional quantile regression coefficients increase among the quantiles with $\boldsymbol{\beta_q} = \boldsymbol{\beta} + \boldsymbol{\lambda}\Phi_u^{-1}(q)$.

In comparison to the ordinary least squares regression, the conditional quantile regression has some advantages. First, it is a semi-parametric approach, since there is no assumption about the parametric distribution. Second, it can easily be applied to heteroscedastic data. Third, the effect of a covariate on the entire income distribution is investigated, instead of the average income. Fourth, the conditional quantile regression is equivariant to monotone transformations:

$$Q_q[h(y)] = h[Q_q(y)]\,,$$

where $h(\cdot)$ is a monotonic function that transforms the dependent variable y. Moreover, $Q_q[h(\cdot)]$ gives the value at the quantile q of the transformed variable and $h[Q_q(\cdot)]$ is the transformation of value at the quantile q of the dependent variable (Koenker, 2005). In particular, this equivalence property proves to be useful in the estimation of income or wage regressions, since incomes and wage are usually included as lograthmized dependent variables into estimations.

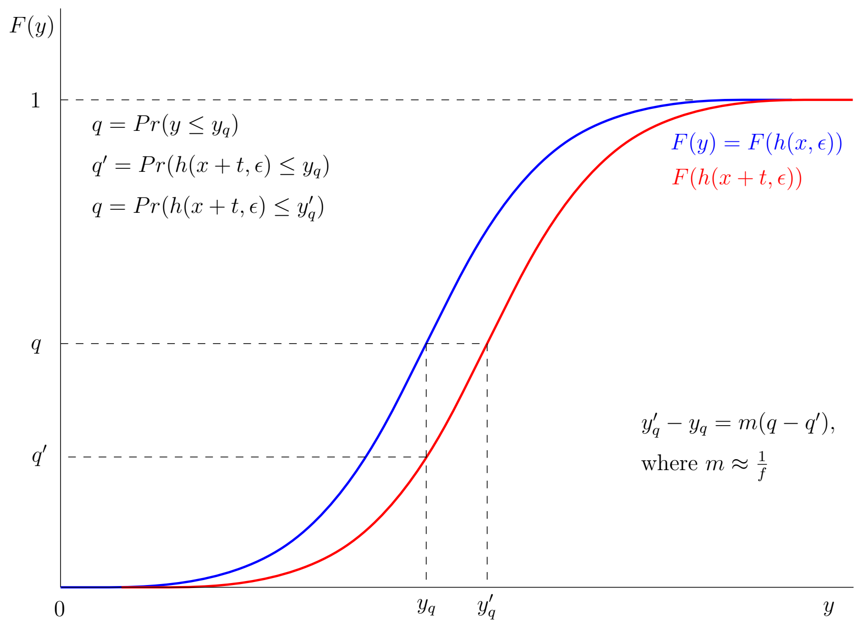
B.2 Unconditional Quantile Regression

The unconditional quantile regression has been developed due to the shortcomings of the conditional quantile regression. The RIF regression, which is an unconditional quantile regression, has been recently introduced by Firpo et al. (2009) and will be explained in more detail below. Although Chernozhukov et al. (2013) offers an alternative and a more computing-intensive method for the estimation of unconditional quantile regressions, the notation "unconditional quantile regression" always refers to the RIF regression in the following explanation. The major disadvantage of the conditional quantile regression is that the estimated coefficients account for the impact of a particular exogenous variable on a quantile of the conditional distribution and cannot be interpreted as an impact on the same quantile of the unconditional distribution. In contrast, the RIF regression defines the quantiles based on the unconditional distribution of the dependent variable before the regression is executed. Thus, the independent variables do not determine in advance which person or observation is assigned to a particular quantile (Killewald and Bearak, 2014). Therefore, the estimated coefficients of unconditional quantile regression measure the impact of a particular covariate on the marginal distribution of the dependent variable. Thus, they can be interpreted as an effect on a particular *person* within the employed quantile q. To put it more simply, the effect quantifies the change in the dependent variable of a person who is located at the particular quantile if the value of the particular covariate increases by one unit.

B.2.1 Graphical Explanation

The intuition of the unconditional quantile regression can be illustrated by the comparison of two different distributions of the same dependent variable. Indicating that years spent in education have an effect on an individual's wage, the blue line plots the cumulative distribution of wages $F(y)$ (see Figure B.5). The y-axis represents the

Figure B.5: Graphical illustration of the unconditional quantile regression



Source: own illustration, according to Fortin et al. (2011)

quantiles $q \in [0,1]$ of the wage distribution and the x-axis yields the wages at the the particular quantiles y_q. Thus, $q = 0.5$ represents the median of the wage distribution and y_q yields the median wage of the sample. Next, the educational attainment x in the population or sample is perturbed by giving everyone one additional year of schooling $x + t$. Thus, in the partial equilibrium, individuals' wages should increase along the entire wage distribution. Therefore, the former median wage y_q can now be achieved in a lower quantile q' than before. Since this relationship applies to all wages, an outward shift of the wage distribution from the blue to the red line occurs. Thus, at each quantile q, the new wage y'_q on the red line is higher than the former wage y_q on the blue line. The aim of the unconditional quantile regression is the estimation of the difference between these wages $y'_q - y_q$ in combination with the change in the educational attainment of the sample. Furthermore, if the slopes of both cumulative distribution functions $F(h(x,\epsilon))$ and $F(h(x+t,\epsilon))$ are almost comparable at a particular former wage y_q, the difference can be expressed, according to Firpo et al. (2009), by

$$y'_q - y_q = \frac{q-q'}{f(y_q)}\,,$$

which considers the density at the former wage of the particular quantile $f(y_q)$ and vividly represents the intuition of the RIF regression.

B.2.2 Derivation of the RIF Regression

The RIF regression is based on the concept of the influence functions, which measure the effect of an infinitesimal change of the sample distribution on a real-valued functional distribution or statistics $v(F)$.[115] The influence function IF of a functional v is defined as

$$\mathrm{IF}(y,v,F) = \lim_{\epsilon\to 0}\frac{v(F_{\epsilon,\Delta_y})-v(F)}{\epsilon} = \left.\frac{\partial v(F_{\epsilon,\Delta_y})}{\partial\epsilon}\right|_{\epsilon=0}\,,$$

where $F_{\epsilon,\Delta_y} = (1-\epsilon)F+\epsilon\Delta_y$ is a mixture model with a perturbation distribution Δ_y, which puts a unit mass point at any wage y. Furthermore, the expectation of the IF is equal to zero. Firpo et al. (2009) use the quantile function $Q_q(F) = y_q$ for the statistics $v(F)$ of the wage distribution in order to quantify how strongly the unconditional quantile of the wages y is modified by a small change of the distribution of the independent variables. Thus, they show that the influence function IF of the unconditional wage quantile q is expressed by

$$\mathrm{IF}(y_i,y_q,F) = \frac{q-\mathcal{I}[y_i\le y_q]}{f(y_q)}\,, \tag{B.2}$$

where $f(y_q)$ yields the density at the wage y_q that is associated with a particular quantile q. Furthermore, the indicator function $\mathcal{I}[y_i \le y_q]$ takes the value one if a person or observation has a wage less than or equal to the wage at the particular quantile. If the opposite occurs, it takes the value zero. If an individual with a wage below y_q is added to the sample, the estimation is adjusted downwards for a given quantile q. In turn, this adjustment is scaled with the density at the wage y_q, which enables the transformation of changes at the quantile into changes of wages y. In order to derive the estimation method, Firpo et al. (2009) perform a sophisticated transformation of the influence function and introduce the recentered influence function (RIF), which is the total of the

[115]Influence functions were initially introduced in econometrics by Hampel (1974) in order to develop robust estimation methods.

original functional $v(F)$ and its influence function IF

$$\mathrm{RIF}(y_i; y_q, F) = y_q + \mathrm{IF}(y_i, y_q, F) = y_q + \frac{q - \mathcal{I}[y_i \leq y_q]}{f(y_q)} \,. \tag{B.3}$$

Furthermore, the expectation value of the RIF is equivalent to the wage at the particular quantile y_q, which can easily be shown by

$$\mathrm{E}[\mathrm{RIF}(y_i; y_q, F)] = y_q + \frac{q - \mathrm{E}\Big[\mathcal{I}[y_i \leq y_q]\Big]}{f(y_q)} = y_q + \frac{q - q}{f(y_q)} = y_q \,. \tag{B.4}$$

Thus, the conditional RIF is given by

$$\mathrm{E}[\mathrm{RIF}(y_i; y_q, F)|\boldsymbol{x_i}] = \boldsymbol{x_i'}\boldsymbol{\beta_q} + \epsilon_i \,. \tag{B.5}$$

Therefore, the estimated coefficients capture the effects of the independent variables on the unconditional quantile function, which can be shown using the identity in (B.4) and the law of iterated expectations

$$y_q = \mathrm{E}[\mathrm{RIF}(y_i; y_q, F)] = \mathrm{E}\Big[\mathrm{E}[\mathrm{RIF}(y_i; y_q, F)|\boldsymbol{x_i}]\Big] = \boldsymbol{x_i'}\boldsymbol{\beta_q} \tag{B.6}$$

In order to estimate the parameters $\boldsymbol{\beta}_q$, the conditional RIF from (B.5) has to be rearranged, according to the following procedure:

$$\begin{aligned} \mathrm{E}[\mathrm{RIF}(y_i; y_q, F)|\boldsymbol{x_i}] &= y_q + \frac{q - \mathrm{E}\Big[\mathcal{I}[y_i \leq y_q]|\boldsymbol{x_i}\Big]}{f(y_q)} \\ &= y_q + \frac{q - \Big(1 - \Pr\big(y_i > y_q|\boldsymbol{x_i}\big)\Big)}{f(y_q)} \\ &= \left(y_q + \frac{q-1}{f(y_q)}\right) + \frac{1}{f(y_q)} \cdot \Pr(y_i > y_q|\boldsymbol{x_i}) \\ &= a_q + \frac{1}{f(y_q)} \cdot \Pr(y_i > y_q|\boldsymbol{x_i}) \,, \end{aligned} \tag{B.7}$$

where $a_q = y_q + \frac{q-1}{f(y_q)}$ holds. Ultimately, substituting (B.5) into (B.7) yields

$$\begin{aligned} a_q + \frac{1}{f(y_q)} \cdot \Pr(y_i > y_q|\boldsymbol{x_i}) &= \boldsymbol{x_i'}\boldsymbol{\beta_q} + \epsilon_i \\ \Pr(y_i > y_q|\boldsymbol{x_i}) &= -a_q + \boldsymbol{x_i'}\boldsymbol{\beta_q} f(y_q) + \epsilon_i \,. \end{aligned} \tag{B.8}$$

Firpo et al. (2009) offer and present three methods in order to estimate Equation (B.8): (i) ordinary least squares regression (RIF OLS), (ii) binary logit regression (RIF logit), and (iii) a non parametric regression. Since the first is used in this work, the procedure for the estimation of the RIF OLS is explained in more detail. The derivation of the estimation parameters $\hat{\boldsymbol{\beta}}_q$ of the RIF OLS is straightforward though the application of

$$\hat{\boldsymbol{\beta}}_q = (\boldsymbol{x_i'}\boldsymbol{x_i})^{-1}\boldsymbol{x_i'}\widehat{\mathrm{RIF}}(y_i, y_q, F) \tag{B.9}$$

Since the predicted $\widehat{\mathrm{RIF}}$ depends on the unconditional wage density, the unconditional wage density and the wages at the particular unconditional quantile q were estimated based on a non parametric density estimator, such as the kernel density estimator. Thus, the predicted $\widehat{\mathrm{RIF}}$ can be expressed by

$$\widehat{\mathrm{RIF}}(y_i, y_q, F) = \hat{y}_q + \frac{q - \mathcal{I}[y_i \leq \hat{y}_q]}{\hat{f}(\hat{y}_q)}\,, \tag{B.10}$$

which, in turn, can be substituted into the Equation (B.9). Thus, in order to estimate the parameters of the RIF OLS, the following steps have to be applied to the data, according to Firpo et al. (2009):

1. Generate a binary variable D_i that indicates whether a person i's wage exceed y_q or not

   $$D_i(y_i) = \begin{cases} 0 & \text{for} \quad y_i \leq y_q \\ 1 & \text{for} \quad y_i > y_q \end{cases}$$

   This is the left hand side variable in (B.8)

2. Run an ordinary least squares regression of D_i on a constant and the covariates $\boldsymbol{x_i}$

   $$D_i = \gamma_0 + \boldsymbol{x_i'}\boldsymbol{\gamma_1} + \eta_i\,,$$

   where $\boldsymbol{\gamma_1} = \boldsymbol{\beta_q} f(y_q)$ applies due to Equation (B.8) and yields the marginal effects of $\boldsymbol{x_i}$ on the fraction of outcomes above y_q

3. Generate a kernel density estimate of $f(y)$ in order to obtain the density $\hat{f}(y_q)$ at the particular quantile q

4. Divide $\boldsymbol{\gamma_1}$ by $\hat{f}(y_q)$ in order to obtain $\hat{\boldsymbol{\beta}}_{\boldsymbol{q}}$

   $$\hat{\boldsymbol{\beta}}_{\boldsymbol{q}} = \frac{1}{\hat{f}(y_q)} \cdot \boldsymbol{\gamma_1}$$

Although the RIF regression is a well-defined estimation method, it has two shortcomings. First, the estimation power as well as the size of estimation parameters depend heavily on kernel density estimation $\hat{f}(y_q)$. If the distribution of the dependent variable is symmetric, there are no concerns. However, if the distribution is strongly right-skewed or left-skewed, the kernel density estimates might be close to zero. In the event of skewness, small changes in the kernel density in absolute terms can result in stark distortions of the estimates (Lubrano and Ndoye, 2014). Second, the RIF regression merely assumes that the density function of the dependent variable is locally invertible around y_q, instead of suggesting global inversion (Fortin et al., 2011).

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