Essays on trade, inequality, and redistribution

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Zusammenfassung

Die vorliegende Dissertation beschäftigt sich mit den Auswirkungen der Globalisierung auf den Arbeitsmarkt sowie der Analyse der Determinanten staatlicher Umverteilung. Im Mittelpunkt steht dabei die empirische Auseinandersetzung mit diesen beiden Aspekten. Die in den letzten Jahrzehnten erlebte Öffnung der Märkte und die damit einhergehende steigende internationale Verflechtung wird neben dem technischen Fortschritt in der Literatur als Haupttreiber der wirtschaftlichen Entwicklung gesehen. In letzter Zeit jedoch ist die Globalisierung zunehmend in den Ruf geraten, verstärkt negative Konsequenzen mit sich zu bringen, z.B. in Form höherer Ungleichheit bzw. einer höheren Volatilität der Beschäftigung.

In diesem Zusammenhang existiert eine Reihe von Fragen, die für ein breites Ländersample empirisch bislang wenig erforscht wurden. Wie wirkt eine verstärkte Handelsverflechtung von hochentwickelten Volkswirtschaften auf die Beschäftigung, insbesondere in dem durch den Strukturwandel ohnehin anfälligen Industriesektor? Sind negative Auswirkungen möglicherweise der Fokussierung auf einzelne Länder sowie konkrete Handelsbeziehungen (z.B. mit China) geschuldet? Ist die zunehmende Umverteilung durch den Staat auf die wachsende Ungleichheit in den Ländern infolge der Globalisierung zurückzuführen? Und: Spielen kulturelle Aspekte eines Landes eine Rolle für die Höhe der Umverteilung? Dies sind zentrale Fragestellungen, mit denen sich die einzelnen Kapitel dieser Arbeit auseinandersetzen.

Die Arbeit gliedert sich in fünf Kapitel. Das erste Kapitel führt zunächst allgemein in den Forschungsbereich ein, verdeutlicht die Motivation und beschreibt ausführlich den Aufbau der Arbeit. Das zweite Kapitel untersucht die Beschäftigungswirkungen einer zunehmenden Handelsverflechtung für 12 OECD-Länder und 11 Sektoren des verarbeitenden Gewerbes für den Zeitraum 1996-2011. Aufgrund der starken Fragmentierung von Produktionsprozessen wird das Ausmaß der Handelsintensität mittels importierter Vorprodukte gemessen. Die Ergebnisse deuten auf einen insgesamt leicht positiven Beschäftigungseffekt in den 12 Ländern durch die Globalisierung hin, wobei auf eine Vielzahl weiterer Einflusskanäle, wie z.B. den technischen Fortschritt, demografi-

sche Faktoren oder die Größe des Sozialstaats, kontrolliert wird. Ein bedeutender Teil der importierten Vorprodukte weist eine komplementäre Beziehung zur Industrieproduktion in den OECD-Ländern auf. Weltweit offene Märkte erhöhen zudem die Absatz- und Beschäftigungsmöglichkeiten, wodurch die häufig dokumentierten Beschäftigungsverluste durch die Globalisierung (Autor et al., 2013; Geishecker, 2006) kompensiert werden.

Eine umfangreiche Sensitivitätsanalyse untermauert die Stabilität der Ergebnisse. Neben der Berücksichtigung zyklischer Schwankungen sowie weiterer möglicher Einflusskanäle werden potentielle Endogenitätsprobleme mittels einer Instrumentvariablenschätzung gelindert. Als Instrument werden dabei importierte Vorprodukte in andere Staaten als das betreffende Land verwendet. Durch die Nutzung eines hierarchischen Modells mit 3 Ebenen (Länder-, Sektor- und zeitliche Ebene) kann zudem ermittelt werden, auf welcher dieser Ebenen sich die Variation in den Daten befindet. Obwohl der größte Teil der Variation zwischen den einzelnen Beobachtungen innerhalb von Ländern und Sektoren auftritt, betonen verschiedene Konsistenztests den Nutzen des verwendeten Mehrebenenmodells.

Im nächsten Schritt werden die importierten Vorprodukte nach ihrer Herkunft untergliedert, wodurch die Arbeitsmarkteffekte von verstärktem Handel für verschiedene Herkunftsländer und -regionen (wie z.B. China, die BRIC-Staaten oder die neuen EU-Mitgliedsstaaten) bestimmt werden können. Die Ergebnisse zeigen, dass die Auswirkungen auf den Arbeitsmarkt sich in Abhängigkeit des Ursprungslandes der Vorprodukte unterscheiden. Importierte Vorprodukte aus China und den neuen EU-Mitgliedsstaaten erzeugen negative Beschäftigungswirkungen in den betrachteten OECD-Ländern und deuten auf eine substitutive Beziehung zwischen heimischer und ausländischer Industrieproduktion. Importe aus den anderen EU-Mitgliedsstaaten (EU-15) hingegen erhöhen das Beschäftigungswachstum. Länderspezifische Schätzungen für jede der 12 betrachteten Nationen verweisen zudem auf deutliche Unterschiede in den Arbeitsmarkteffekten. Während importierte Vorprodukte aus China das Beschäftigungswachstum in Frankreich und Spanien reduzieren, können für Deutschland und Italien keine signifikant negativen Auswirkungen beobachtet werden. Die Ergebnisse verdeutlichen, dass Globalisierung neben Gewinnern auch Verlierer produziert, die durch den Sozialstaat aufgefangen werden müssen.

Die verstärkte Nachfrage nach dem Sozialstaat stellt den Ansatzpunkt für die beiden folgenden Kapitel dar, in denen der Aspekt der Umverteilung näher beleuchtet wird. Im dritten Kapitel werden daher die Determinanten staatlicher Umverteilung analysiert. Konkret geht es dabei um die Frage, an welchen Faktoren sich der Staat orientiert, wenn er umverteilende Maßnahmen durchführt. Den Ausgangspunkt für die Untersuchungen stellt die Meltzer-Richard-Hypothese dar, die sowohl für die OECD-Staaten als auch für ein breites Ländersample empirisch bestätigt werden kann. Der Einfluss ist allerdings abhängig vom Entwicklungsstand der Länder. Während in reichen Nationen mit starken politischen Rechten der Zusammenhang zwischen Ungleichheit und Umverteilung sehr robust ist, gilt dies in weitaus geringerem Maße für ärmere Länder mit weniger entwickelten politischen Rechten. Die Ergebnisse zeigen, dass über den politischen Kanal eine höhere Ungleichheit in mehr Umverteilung umgemünzt wird. Dies gilt unabhängig vom zugrundeliegenden sozialen Sicherungssystem eines Landes.

Darüber hinaus ist auch die Form der Einkommensverteilung entscheidend für die Höhe der staatlichen Umverteilung. Während die Mittelschicht stärkere Umverteilungsmaßnahmen befürwortet, üben Top-Einkommensbezieher einen signifikant negativen Einfluss auf die Höhe der Umverteilung aus. Hohe Einkommen verfügen somit über andere Kanäle als den Wahlprozess (z.B. Kampagnenfinanzierung), um ihren Einfluss auf den politischen Betrieb geltend zu machen. Bezieher niedriger Einkommen, die die Hauptprofiteure staatlicher Transfers sind, spielen hingegen keine Rolle im Entscheidungskalkül der Politiker.

Die aktuelle Literatur verweist zudem auf die Bedeutung der subjektiv wahrgenommenen Ungleichheit für die Nachfrage nach Umverteilung. Die Ergebnisse offenbaren, dass das tatsächliche Ausmaß der Ungleichheit von den Individuen häufig falsch eingeschätzt wird, wobei jedoch die Höhe der Fehleinschätzung von Land zu Land deutlich variiert. In Ländern, in denen die Bürger sich des Ausmaßes der Einkommensungleichheit bewusst sind, führt eine höhere Ungleichheit auch zu mehr Umverteilung. In Nationen, in denen die Höhe der Ungleichheit gravierend fehleingeschätzt wird, ist die Forderung nach umverteilenden Maßnahmen gering, selbst wenn die Markteinkommen sehr ungleich verteilt sind.

Im vierten Kapitel wird der im vorangegangenen Kapitel aufgestellte Untersuchungsrahmen um kulturelle Aspekte erweitert. Hintergrund ist der in den letzten Jahren weltweit zu beobachtende Anstieg von Migrationsströmen und dessen mögliche Auswirkungen auf die Sozialstaaten in den Aufnahmeländern. Dieses Kapitel befasst sich deshalb mit der Frage der Auswirkungen von Kultur und verschiedenen Formen von gesellschaftlicher Diversität auf die Höhe der staatlichen Umverteilung für ein breites Ländersample. Dazu werden verschiedene kulturelle Dimensionen verwendet und mit regionalen sowie externen Variablen instrumentiert, um kulturelle Charakteristika von institutionellen Gegebenheiten zu trennen. Die empirischen Ergebnisse deuten auf einen signifikanten, jedoch ambivalenten Einfluss von Kultur auf die Höhe der Umverteilung. Während Länder mit einem hohen Maß an Individualismus und gegenseitigem Vertrauen sowie geringen familiären Bindungen mehr umverteilen, ist das Gegenteil für Länder mit hoher Machtdistanz und der Vorstellung, dass persönlicher Erfolg das Ergebnis harter Arbeit ist, zu beobachten.

Neben diesen direkten Effekten auf die Höhe der Umverteilung wirken kulturelle Werte jedoch auch indirekt, indem sie den von Meltzer und Richard beschriebenen Zusammenhang beeinflussen. Darüber hinaus verdeutlicht dieses Kapitel, dass eine höhere kulturelle als auch ethnische Diversität in einer Gesellschaft die Großzügigkeit des Wohlfahrtsstaates reduziert. Die Gründe hierfür liegen in unterschiedlichen Präferenzen für Umverteilung zwischen Migranten und Einheimischen sowie einer starken Gruppenloyalität, wonach die Unterstützung für Transfermaßnahmen sinkt, wenn die Begünstigten einen anderen ethnischen bzw. kulturellen Hintergrund aufweisen. Der negative Zusammenhang zwischen Umverteilung und Diversität ist jedoch nicht-linear und am stärksten, wenn es eine kulturelle oder ethnische Mehrheit in einem Land gibt, wohingegen in einer hinreichend diversen Gesellschaft dieser Zusammenhang deutlich schwächer auftritt.

Die Dissertation schließt im fünften Kapitel mit einer Zusammenfassung der wesentlichen Erkenntnisse, die im Rahmen der Arbeit gewonnen wurden. Ein Ausblick weist zudem auf noch offene Forschungsfragen sowie mögliche künftige Forschungsfelder.

Diese Dissertation trägt in ihren empirischen Teilen zur aktuellen Literatur bei, indem die genannten Fragestellungen für ein möglichst breites Ländersample untersucht werden. Dies betrifft insbesondere die Untersuchung der Auswirkungen der Globalisierung auf den Arbeitsmarkt für 12 OECD-Länder, die Ausführungen zum Meltzer-Richard-Effekt und zur Rolle der wahrgenommenen Ungleichheit sowie die Bestimmung von Kultur und deren Einfluss auf die Umverteilung für eine Vielzahl von Ländern.

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Chapter 1

Introduction

1.1 Motivation

Globalization and redistribution currently receive a lot of attention from scholars, policy makers, and society. Global trade volume has more than tripled since 1990 (World Bank, 2016). Meanwhile, the manufacturing sector has lost significant employment and output shares. According to the EU KLEMS database, manufacturing employment decreased by one third (32.7 percent) in the United States and 38.5 percent in the United Kingdom between 1995 and 2010, whereas the decline was moderate in Germany (12.4 percent) and Italy (8.7 percent) (O'Mahony and Timmer, 2009). While many people attribute rising economic prosperity to open markets and increasing trade, other parts of society hold globalization responsible for adverse structural changes and higher job volatility, boosting demand for redistributional activities of the government.

Previous research on the effects of globalization on labor market outcomes in manufacturing is inconclusive. A number of studies point to detrimental labor market effects (Autor et al., 2013; Geishecker, 2006), while other investigations identify overall employment gains due to higher trade integration (Dauth et al., 2014). The results obtained from these examinations are crucially dependent on the country of analysis, which is why it is difficult to make general statements on the impact of globalization on manufacturing employment.

In addition, market inequality and the generosity of the welfare state have increased considerably during the last decades. According to the SWIID provided by Solt (2009, 2016), inequality before taxes and transfers increased by 7.59 Gini points in Germany and 7.69 Gini points in the United States between 1980 and 2010, reaching comparable levels of about 50 Gini points in both countries in the most recent period. A mixed picture of market inequality can be observed with respect to developing economies. While inequality decreased by 2.78 Gini points in Brazil between 1980 and 2010, the increase amounted to 7.23 Gini points in India and an astonishing 21.44 Gini points in China.

The degree of governmental redistribution also increased, but with considerable differences across the countries. Effective redistribution, which is the difference between pre- and post-tax and transfer income inequality, increased by 5.36 Gini points in Germany between 1980 and 2010, while the increase was moderate in the United States (1.25 Gini points) and Brazil (1.49 Gini points). In China, redistribution has become negative in the most recent period, indicating that government intervention has made the distribution of incomes more unequal. In India, the amount of redistribution remains very low (0.53 Gini points in the 2010 period). The findings imply that the redistributive response to higher market inequality varies greatly across countries, necessitating a deeper analysis of the determinants of governmental redistribution.

Several research questions arise from these current economic trends. While previous research has mainly focused on the role of growing trade on labor markets for a single country, there is a surprising scarcity of cross-national studies on this topic. This dissertation provides a comprehensive view of the link between import penetration and manufacturing employment growth between 1996 and 2011, and includes 12 OECD countries which represent more than three quarters of total GDP in the OECD. The third chapter is concerned with the exploration of the roots of governmental redistribution, an issue where recent literature has long been confronted with limited data availability and severe measurement problems. Due to recent data advancements, it is now possible to calculate a measure of effective redistribution for a broad panel of countries. Then, special emphasis is put on the link between culture and redistribution. Culture is described as the collective mental programming of people that distinguishes members of one social group from members of another group or nation. As data on cultural traits for a large sample of countries has become available only recently, there is still a lot of uncharted territory in this research area, particularly with respect to redistribution.

The dissertation is therefore concerned with the investigation of two main issues. First, Chapter (2) provides an empirical assessment of the link between globalization and labor market outcomes in the manufacturing sector for several countries. However, as adverse structural changes due to globalization increase the demand for equalizing public policies, Chapters (3) and (4) analyze the determinants of governmental redistribution, with a special focus on the effects of culture and diversity on the welfare state.

1.2 Outline and contributions of this dissertation

This dissertation consists of five chapters. Following this introduction, Chapter (2) investigates the relationship between growing import penetration and manufacturing employment growth in 12 OECD countries between 1996 and 2011. Theoretically, globalization may have adverse effects on manufacturing employment, since foreign goods which are highly tradable internationally may substitute for domestically produced ones. However, trade liberalization may create new market opportunities for firms, boosting employment growth in manufacturing. Similarly, foreign goods may also act as complements to domestic manufacturing production, likewise fostering employment opportunities at home. Previous research has mostly investigated the globalization-employment nexus in a single country context. In an attempt to fill the gap in the empirical literature, Chapter (2) examines this relationship for a number of countries which represent more than three quarters of total GDP in the OECD.

The results of Chapter (2) emphasize a weak positive overall impact of growing trade on manufacturing employment. Due to increasing production fragmentation across borders, international trade can be proxied via the exchange of intermediate inputs rather than final goods. The application of the latest version of the World Input-Output Database (WIOD), which has only recently become available, allows measurement of the imported intermediates according to their country of origin. The WIOD includes input-output tables for 40 countries from around the world between 1995 and 2011, which allows us to quantify the impact of intermediate inputs from China, the BRIC nations (Brazil, Russia, India, China), and the EU member states on employment growth in 11 manufacturing industries. The results indicate that the intermediates' country of origin matters when examining the impact on manufacturing employment. While intermediate inputs from China and the new EU member states[1] are substitutes for manufacturing employment growth in the 12 OECD countries, imports from all other EU members tend to act as complements to domestic manufacturing production. However, the results differ considerably when looking at each country separately.

The analysis in Chapter (2) employs a three-level mixed model to adequately account for the hierarchical structure of the data. Incorporating this information is reasonable, as observations from the same country and the same industry are not independent from one another. In the next step, the chapter provides an extensive sensitivity analysis. The inclusion of several covariates and the application of various model specifications leave the main results unchanged. To eliminate cyclical fluctuations which may play a role in explaining employment prospects, we average the data and split the sample into two periods and into 4-year averages. Re-estimating the baseline regressions yields mostly insignificant results with regard to our import penetration variable.

A further empirical challenge is that imported intermediates may be correlated with unobserved shocks in product demand. To avoid potential weaknesses which may arise due to endogeneity, we use an instrumental variable strategy, where intermediate inputs to a given country are instrumented with the intermediates to other countries (jackknifed intermediate inputs). The findings suggest a mostly positive and partly significant effect of imported intermediate inputs on manufacturing employment growth. When accounting for the intermediate inputs' country of origin, the estimations via the IV-2SLS specification confirm the adverse effects of inputs from China and the new EU members on employment growth, while an employment-enhancing impact can be observed with regard to intermediates from other EU countries. The results indicate that the effect of

[1]This comprises the countries that joined the European Union in 2004/07.

globalization on manufacturing employment is quite ambiguous, offering one explanation for why demand for social security increased considerably during the last decades. The following chapters are therefore concerned with a deeper analysis of this point.

Chapter (3) examines the determinants of governmental redistribution. The analysis begins with the empirical investigation of the relationship between inequality and redistribution. According to the Meltzer and Richard (1981) model, higher market inequality increases demand for redistribution in a majority-voting framework, translating to an expansion of the welfare system. Research on this topic has been strongly limited due to restrictions in reliable and comparable measures of redistribution. Fortunately, recent advances in data availability made by the SWIID 5.0 (Solt, 2009, 2016) enable the exploration of the inequality-redistribution nexus, which is based on a substantially larger number of country-year observations. The empirical findings confirm the Meltzer-Richard hypothesis and are robust to several model specifications and various sample compositions as well as distinct measures of income inequality and different social security and pension systems. However, it turns out that the positive relationship between inequality and redistribution mainly stems from advanced economies. In early stages of development, the marginal effect of market inequality on redistribution is zero. As the economies develop, the link becomes positive and significant if economies exceed a critical income level. As an increase in the level of development typically coincides with greater democratic rights, a similar impact on redistribution can be found with respect to a higher sophistication of political rights, implying that it is through the political process that inequality translates into redistribution.

In a next step, the investigation in Chapter (3) aims to explain further determinants of governmental redistribution beyond the Meltzer-Richard effect. The analysis is thus concerned with the shape of the income distribution. In a majority-voting model, groups other than the median voter should theoretically exert only negligible influence on redistribution. In fact, the middle class is supportive of more governmental redistribution activities. The results also reveal that top incomes impede redistribution, highlighting that there are mechanisms that affect the political process beyond the median voter hypothesis. This, however, cannot be observed for individuals at the bottom of the income distribution which do not play a crucial role in determining the amount of redistribution.

Previous research emphasizes the importance of individual perceptions in the creation of demand for redistribution. While cross-country evidence on perceptions of inequality has been rather scarce, the literature suggests that individuals often hold erroneous beliefs about income inequality. The results in this chapter show that the degree of misperception differs considerably across countries. If individuals are aware of national income disparities, demand for redistribution is higher. However, in the presence of misperceptions, demand for redistribution may be low, even if market inequality is quite high. Re-estimating the inequality-redistribution nexus indicates that the Meltzer-Richard effect is even stronger when using perceived inequality measures. The results reveal that governmental redistribution is influenced by subjective perceptions rather than actual inequality.

Chapter (4) extends the framework developed in Chapter (3) by studying the role of culture and diversity. Culture is considered the collective level of human mental programming that is shared between people belonging to a certain social group, which is passed from one generation to the next (Hofstede, 2001). Due to the sharp rise in migration around the world in recent years, this chapter is concerned with the consequences of culture and diversity on welfare systems and redistribution in a broad sample of countries. The investigation uses cultural dimensions proposed by Hofstede (2001) and Alesina and Giuliano (2015) and employs regional as well as several external instruments to disentangle cultural traits from institutions. The external instruments include data on linguistic differences and on the prevalence of the pathogen Toxoplasma gondii, a parasite that has been shown to alter the behavior of its intermediate host while rarely leading to manifest disease. Another biological instrument incorporates the frequency of blood types. As parents transmit DNA to their offspring along with the transfer of cultural values, we do not assume a causal link running from genes to culture, but rather assess the correlation between genetic markers and culture.

The results in Chapter (4) show a substantial but ambiguous impact of cultural values on redistributive policies of the government. Countries with individualistic attitudes and a high prevalence of tolerance and generalized trust exhibit higher levels of redistribution, whereas the support for welfare spending is lower in nations with a high acceptance of unequally distributed power and obedience as well as strong family ties and the belief that success is the result of hard work rather than luck and connections. Several sensitivity analyses, including cross-sectional regressions, multiple imputation estimations, and the use of various external instruments, indicate that the findings are robust to alternative estimation and instrumentation strategies. As the results from Chapter (3) provide empirical support for the Meltzer-Richard model, it may also be possible that different cultural values influence the effect of inequality on redistribution. In fact, the strength of the cultural traits matters for the Meltzer-Richard effect, implying that culture explains some part of the observable differences in the redistributional response of governments to market inequality.

While the previous findings from this chapter point to the fact that culture plays a decisive role in redistributional activities of the government, the next step of the analysis is concerned with the impact of growing cultural, religious, and ethnic diversity on redistribution. To measure a country's diversity, we compute Herfindahl-Hirschman indices of the degree of ethnic and religious concentration as proposed by Alesina et al. (2003) and use data on ethnic and cultural fractionalization collected by Fearon (2003). Ethnic and cultural diversity exert a significant impact on redistribution, with higher levels of diversity resulting in less redistribution. This might be due to different preferences for redistribution between migrants and locals, as migrants' preferences for redistribution are strongly affected by preferences in their country of birth. Growing diversity may also foster racial group loyalty, emphasizing that individuals' preferences for redistribution decrease when the share of local recipients of the own ethnic group decreases. Further investigation of the relationship illustrates that diversity and redistribution are linked via a non-linear function. The negative effect of diversity on redistribution is most strongly pronounced in countries with an ethnic, religious, or cultural majority, and much less prevalent once a certain tipping point is reached.

Finally, Chapter (5) summarizes the main results of Chapters (2)–(4) and discusses some policy implications. The doctoral thesis concludes with some further research questions on manufacturing employment and redistribution which still remain open.

This dissertation provides an empirical analysis of research questions which have not yet been explored for a broad panel of countries. The following chapters study the determinants of governmental redistribution and the impact of growing trade on manufacturing employment, providing contributions in the following areas. First, the effect of globalization on manufacturing employment is analyzed for a number of OECD countries, allowing for a more comprehensive view on this topic compared to the vast number of single country studies. The second area includes the examination of the determinants of governmental redistribution for a broad panel of countries due to recent advances in data availability. This analysis comprises the empirical inquiry of the Meltzer-Richard hypothesis and other crucial factors, including perceptions. Finally, the third area of this dissertation discusses the link between culture and redistribution, a topic of which there is a surprising scarcity in the literature.

Chapter 2

Import penetration and manufacturing employment growth: Evidence from 12 OECD countries

Preliminary remarks: The globalization and the political opening of a number of countries after the fall of the Soviet Union have intensified international cooperation and exchange across the world. Among others, this development brought with it substantial effects on the labor market. Since then, a number of papers have explored the impact of growing international trade on employment, with a focus on manufacturing as goods are highly tradable across countries. While former studies suggest that globalization increases wage inequality between low-skilled and high-skilled workers and raises employment volatility (Crinò, 2009), recent empirical evidence on the role of trade liberalization on employment and wages in manufacturing is quite ambiguous (Autor et al., 2013; Dauth et al., 2014). Cross-country evidence on this topic is surprisingly scarce (Bloom et al., 2016), as previous research mostly focused on the relationship between globalization and the labor market in a single country context. To fill this gap, the chapter provides an analysis of this link for 12 OECD countries, concurrently accounting for the hierarchical structure of the data and the country of origin of the traded goods.

2.1 Introduction

In recent decades, the manufacturing sector has experienced a significant downturn in developed economies. Employment and output shares have fallen by up to two-thirds since the 1970s. Meanwhile, the role of globalization, which has boosted international trade across a growing number of countries, is highly debated. According to World Bank data, global trade volume has more than tripled since 1990, particularly in emerging countries, where a spectacular rise in the international exchange of goods and services has been observed. Whereas other factors, including skill-biased technological change (Katz and Autor, 1999; Berman et al., 1994; Machin and Van Reenen, 1998), play a prominent role in explaining labor market developments in the manufacturing sector since the 1970s, trade aspects have drawn increased attention in recent years. Although the impact of technological progress has become more skill-neutral in recent years (Autor et al., 2015), the manufacturing sector continues to become less important in terms of employment and output shares (Figure 2.1). A number of papers whose goal was to determine the role of globalization and its impact on labor market outcomes have since been published.

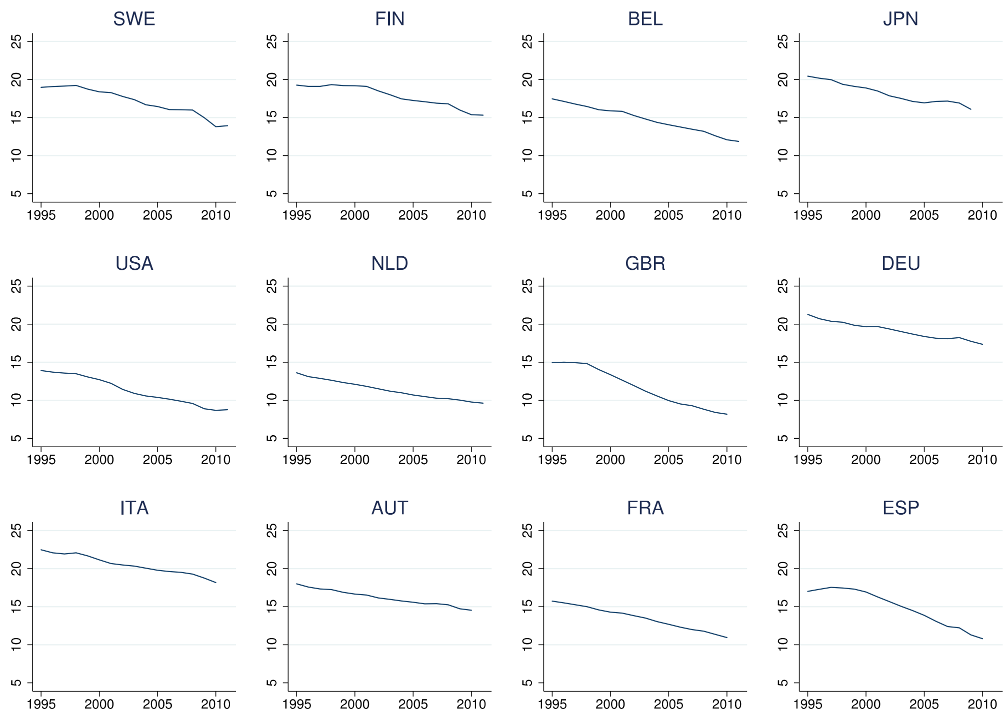

Figure 2.1 Manufacturing employment as share of total employment, in percent.

Thus far, research on the trade-employment nexus has focused on individual countries using firm-level data, whereas cross-national analyses on this topic have been rather scarce. While country-specific investigations offer an in-depth analysis of a particular case, they may say little about the overall impact of growing import penetration across multiple highly developed economies. Moreover, when employing a cross-nationally comparable dataset, instrumental variable strategies may not prove suitable to adequately account for the hierarchical structure of the data.

As production is becoming increasingly fragmented across borders, international trade mainly comprises the exchange of intermediate inputs rather than final goods (Timmer et al., 2013). Using data on the trade of final goods would therefore underestimate the true level of exchange between different countries. The World Input-Output Database (WIOD), the latest version of which has only recently become available, makes it possible to account for the trade intensity within the production process, offering comparable data on imported intermediate inputs at a two-digit level for the period from 1995 to 2011 (Timmer et al., 2015). Combining this database with several other sources produces a unique dataset which can be used to explore the effect of import penetration on manufacturing employment growth in 12 developed economies. The data also allows measurement of the impact of import competition for different countries of origin, therefore enabling more specific statements on the role of growing trade intensity.

We make use of recent advances in data availability to investigate the impact of growing import penetration on manufacturing employment growth for 12 OECD countries representing more than three quarters of total GDP in the OECD.[2] In doing so, the contribution of this chapter is threefold. First, we empirically examine the trade-employment nexus for a range of highly developed economies, thereby measuring an overall effect of increasing import competition on manufacturing employment growth across different countries. Second, the overall effect of imported intermediate inputs on employment growth is subdivided according to the country of origin. Finally, the application of a multilevel mixed model allows us to identify the influence of import penetration on employment growth at

[2]These countries are Sweden, Finland, Belgium, Japan, the United States, the Netherlands, United Kingdom, Germany, Italy, Austria, France, and Spain.

different levels.

From a theoretical perspective, growing international trade should exacerbate the situation of those workers performing tasks which are most vulnerable to offshoring (Autor et al., 2015). Following a standard Heckscher-Ohlin approach, two countries being differently endowed with capital and labor should engage in those stages of production for which the necessary factor is relatively abundant. Thus, increasing trade with emerging markets, like China, may enforce labor-abundant production in these countries while strengthening capital-intensive stages of production in rich economies.

The chapter's findings point to a positive and weakly significant link between import competition and manufacturing employment growth in the 12 OECD countries. The results are partially robust to several model specifications and alternative estimation strategies, as well as different measures of import penetration. When subdividing intermediates according to their country of origin, one can observe a negative impact of inputs from China on employment growth which is significant in a majority of the specifications. With regard to the BRIC nations (Brazil, Russia, India, China), this relationship is insignificant when controlling for exports of raw materials from those countries, indicating that the negative impact of Chinese intermediates is mitigated by trade with other countries. Meanwhile, intermediate inputs from the *new* EU members (EU-12)[3] exert a negative impact on employment growth, while the opposite is true for inputs from the European Union in general (EU-27). Apparently, intermediates from the EU-12 substitute for manufacturing production in the OECD countries, whereas imports from the *old* EU members act as a complement, increasing domestic manufacturing employment growth.

The inclusion of several covariates leaves the main results unchanged, confirming the stability of our model. We therefore control for the current account balance, the share of high-skilled workers in 1996, the strictness of employment protection legislation, and an interaction term which combines total factor productivity (TFP) and imported intermediate inputs. Additionally, the sample is split into two periods and into 4-year averages to

[3]EU-12 comprises the countries that joined the European Union in 2004/07, and includes Bulgaria, Cyprus, the Czech Republic, Estonia, Hungary, Lithuania, Latvia, Malta, Poland, Romania, Slovakia, and Slovenia.

eliminate cyclical influences. Re-estimating the baseline regressions yields mostly insignificant results. However, endogeneity might arise due to a correlation between imported intermediates and unobserved shocks in product demand. Employing an instrumental variable strategy, we observe a positive and partly significant relationship between manufacturing employment growth and different measures of import penetration, which is in line with the findings from the baseline regressions. When accounting for the origin of the imported intermediates, we find that inputs from China and the EU-12 exert a negative influence on employment prospects in rich economies, an effect which is significant in most of the specifications.

Methodologically, our unique dataset allows for the application of a three-level mixed model with random intercepts at the country and the sector level, therefore incorporating the hierarchical structure of the data. Including this information is important, as observations from the same country and the same industry are not independent from each other. To exclude the possibility that the findings are primarily driven by the selected estimation strategy, we provide an extensive sensitivity analysis, including several alterations of the baseline technique.

The chapter is structured as follows. Section (2.2) provides a short literature review and discusses some theoretical aspects. Section (2.3) offers a description of the data and outlines the underlying empirical strategy. Section (2.4) presents the main findings for various model specifications, different measures of import penetration, and alternative estimation strategies. The final section concludes.

2.2 Literature review and theoretical considerations

2.2.1 Literature review

A vigorous scientific debate on the relationship between import competition and labor market outcomes is currently in progress, with a number of studies focusing on the effects for a single country. The findings indicate a positive and mostly significant relationship between offshoring and relative labor demand of the highly skilled across different countries (Geishecker, 2006; Feenstra and Hanson, 1996; Hsieh and Woo, 2005). According to these studies, offshoring can explain 10 to 50 percent of the rise in employment and wage shares of the highly skilled, supporting the process of skill upgrading (see e.g. Berman et al., 1994; Autor et al., 1998).[4] While most investigations observe a positive relationship between offshoring and labor demand of the highly skilled, the effect is significantly negative for low-skilled workers (Bloom et al., 2016; Falk and Koebel, 2002; Morrison Paul and Siegel, 2001).

Further research focuses on production transfer within multinational enterprises and its impact on wages and relative labor demand. The relevant articles find a positive and significant effect which explains up to 15 percent of the increase in wage-bill shares of the highly skilled (Becker et al., 2013; Head and Ries, 2002). Baumgarten et al. (2013) point to the degree of interactivity and non-routine content of occupations that have an influence on the wage effects of offshoring. They observe that low-skilled workers carrying out tasks with low degrees of non-routine content experienced the greatest wage losses due to offshoring between 1991-2006.

Harrison and McMillan (2011) emphasize that in the MNE context it is the underlying motive of offshoring which determines the impact on parent employment. In firms that do significantly different tasks at home and abroad, domestic and foreign labor are complements, whereas offshoring to low-wage countries often substitutes for domestic labor. As a result, they observe a quantitatively small effect of wage changes in foreign affiliates on manufacturing employment in US-based parent companies for the 1980s and 1990s. These results are in line with the findings of Marin (2011) and Autor et al. (2015), implying that offshoring was not the primary driver of declining manufacturing employment during this period.[5] Ebenstein et al. (2014) analyze the impact of changes in trade and offshoring on

[4]The skill upgrading hypothesis originates from the discussion about the impact of technological progress on labor market outcomes, but can also be observed in the offshoring context. Spitz-Oener (2006) emphasizes that occupations require more complex skills today than they did in 1979, showing that changes in occupational content account for one third of the recent educational upgrading in employment.

[5]A recent paper by Blinder and Krueger (2013) examines the amount and the characteristics of jobs in the United States with regard to their level of offshorability. According to their findings roughly 25 percent of these jobs are potentially offshorable. They emphasize that differences in offshorability according to race, sex, age, or geographic region are minor, as is the case with respect to the routinizability of jobs as developed by Autor et al. (2003).

the wages of U.S. employees based on the location of offshoring. Again, they show that offshoring to low-wage countries substitutes for domestic employment, while offshoring to high-income countries coincides with higher employment levels in the parent company. The authors also reveal that occupational exposure to globalization exerts significant effects on wages, while industry exposure has no significant impact. Therefore, switching occupation due to trade or offshoring led to real wage losses of 12 to 17 percentage points between 1984 and 2002.

An early study by Revenga (1992) points to the negative influence of increased import competition, measured by changes in import prices between 1977-1987, on employment and wages in manufacturing industries. In a similar vein, increasing exposure to low-wage country imports negatively affects plant survival and growth, as indicated by Bernard et al. (2006). This chapter applies a measure of offshoring which defines low-wage countries as those with a per capita GDP that was less than 5 percent of U.S. per capita GDP between 1972 and 1992, including China or India.[6]

A recent strand of literature investigates the effects of growing international trade on employment outcomes in local labor markets. Autor et al. (2013) examine the impact of rising import competition from China on employment prospects in local labor markets in the U.S. and find a significantly negative relationship. With regard to local labor markets, this chapter relies on the concept of Tolbert and Sizer (1996), in which Commuting Zones (CZ) are characterized by strong commuting ties within and weak ties across their borders. The authors observe that local labor markets that are confronted with import competition from China more intensively are those that suffer most from it. They conclude that one-quarter of the aggregate decline in US manufacturing employment can be attributed to rising import competition with China, while offsetting gains in employment due to a higher demand for US exports cannot be observed. The investigation of Dauth et al. (2014) yields rather nuanced results, examining the impact of increasing trade with China and Eastern Europe on German local labor markets. Using local administrative units as local labor

[6]As per capita GDP has risen substantially in China and India (from 9 to 19 percent of the U.S. per capita GDP between 1995 and 2011 in China, and 4.3 to 8.4 percent in India), this measurement approach does not appear to be suitable for our analysis.

markets, this study does not consider commuting ties between the regions. While local labor markets that specialize in import-competing industries experience severe job losses, other regions with a focus on export-oriented industries exhibit substantial employment gains, more than offsetting the adverse employment impact of import competition. Labor market outcomes of German trade integration are mostly driven by trade with Eastern Europe, while Chinese imports only play a minor role in explaining these effects.

In a recent paper, Bloom et al. (2016) investigate the impact of import competition from China on employment and innovation for a panel of 12 European countries, suggesting that Chinese imports are associated with falling levels of manufacturing employment and reallocation of employment towards more technologically advanced firms.

2.2.2 Theoretical considerations

A standard Heckscher-Ohlin approach implies that growing trade between countries with different factor endowments would encourage both countries to specialize in the export of those commodities produced with relatively large quantities of the country's relatively abundant factor. Relatively capital- and skill-abundant countries like the United States or Germany are expected to accommodate a more capital- and skill-intensive mix of industries than are relatively labor-abundant countries like China. While this model may hold for the trade of commodities between countries of different development levels, it is not suitable for drawing conclusions on trade between countries of the same development level. Melitz (2003) provides a theoretical model explaining why large degrees of resource reallocations occur across firms in the same industry in similarly developed economies. Due to initial uncertainty regarding their productivity before entering the industry, firms with different levels of productivity coexist in an industry. In fact, only the most productive firms engage in export activities, which are costly but allow realization of gains from trade, while the least efficient firms are forced out of the industry.

Moreover, the nature of trade has changed dramatically during recent decades, illustrating subtler patterns of specialization between countries. In the past, trade was thought of as the exchange of final goods, whereas today international trade focuses on intermediates as production is increasingly fragmented across borders. Only measuring final goods trade ignores the role of intermediate inputs, and therefore underestimates the real trade intensity. Three main causes have been detected for this development, as emphasized by Kleinert (2003): outsourcing, global sourcing, and the increasing importance of the networks of multinational enterprises (MNE). According to the outsourcing hypothesis, increasing intermediate inputs are the result of firms' strategies of relocating parts of their production to foreign countries which offer comparative advantages in the production of particular products. While the outsourcing approach requires foreign direct investment (FDI) in less-developed economies, the MNE networks hypothesis focuses instead on inward FDI. In this case, the result is an increasing number of imported intermediate inputs due to growing trade between MNEs' affiliates across the world. The global sourcing approach is based on decreasing transportation costs, resulting in decreases in the prices of imported intermediates. As our sample is based on macro data, we are not interested in capturing the role of particular strategies, but rather in ascertaining the aggregate impact of growing imported intermediate inputs on employment.

There are various channels through which higher import competition affects the labor market. An increase in the number of imports may reduce domestic employment, since the foreign production, or certain stages of production, of goods makes domestic jobs redundant. In particular, this might be the case if the goods produced abroad are substitutes for those which would normally be produced domestically. On the other hand, growing trade integration creates greater market opportunities for domestic products, allowing firms to break into new markets. Furthermore, if imported goods are complements to domestically produced ones, growing trade may foster domestic production. While the first situation is employment growth reducing, the latter cases enhance employment growth. As a result, the impact of growing import penetration on manufacturing employment depends on which channel is relevant for the given situation.

In a seminal paper Grossman and Rossi-Hansberg (2008) account for the changing nature of trade through global value chains, at the same time introducing the concept of *task trade*. According to this concept, a reduction in the cost of task trade has effects which are similar to those of factor-augmenting technological progress, boosting the productivity of the factor whose tasks become easier to offshore. Apart from this productivity effect, the concept incorporates two other effects: the relative-price effect and the labor-supply effect. The relative-price effect results from changes in relative prices via a mechanism introduced by Stolper and Samuelson (1941). Since improvements in the technology generate greater cost-savings in labor-intensive industries than in skill-intensive ones, a drop in the relative price of a labor-intensive good will exert downward pressure on the wages of low-skilled workers. The labor-supply effect implies that a reduction in trade costs due to technological progress causes offshoring, which frees up domestic low-skilled labor. As these workers must be reabsorbed into the labor market, this leads to a decline in their wages. Whereas the relative-price effect and the labor-supply effect typically work to the disadvantage of low-skilled labor, the productivity effect tends to inflate their wages. Assuming that the adjustment in relative prices is not too large, all domestic parties, i.e. high-skilled as well as low-skilled labor, may benefit from offshoring, a result which contrasts with the conclusions of some traditional trade theories. Hence, the theoretical impact of offshoring on labor market outcomes is unclear a priori.

2.3 Empirical strategy

2.3.1 Data on offshoring

This analysis is particularly interested in data on international trade relations. To measure offshoring, we employ the share of imported intermediates in total non-energy input purchases for industry i and country j at time t (iii_{ijt}) as promoted by Feenstra and Hanson (1999). This can be described via a two-step procedure where

$$inp_{ijt} = \sum_{h=1}^{H} [\text{input purchases of good } h \text{ by industry } i \text{ in country } j]_t \tag{2.1}$$

$$*[\frac{\text{imports of good } h}{\text{apparent consumption of good } h}]_t.$$

In a second step, we normalize inp_{ijt} with the total purchases of non-energy intermediates in each industry i and country j at time t:

$$iii_{ijt} = \frac{inp_{ijt}}{NE_{ijt}}. \tag{2.2}$$

This measure incorporates both imports and export activities of industry i in country j at time t, the latter of which may be offsetting to some extent. Additionally, this measure permits the application of both a broad and a narrow concept of offshoring. The broad concept includes imported intermediates from all industries (III_B), whereas the narrow concept of offshoring (III_N) comprises imported intermediate inputs from the same industry. Since we conduct an aggregate analysis of the impact of offshoring on employment, we mainly focus on the broad concept of offshoring. To cross-check these findings, the results of the narrow concept are routinely reported. Furthermore, we utilize a rough measure of import penetration, denoted by III_R, which is the share of foreign intermediates in total intermediate inputs for industry i and country j at time t. This rough measure only incorporates imports and therefore ignores the role of exports and energy related aspects. While III_R serves as an initial indicator, III_B and III_N represent more sophisticated measures of offshoring.

The offshoring measures are constructed with data from the World Input-Output Database (WIOD) provided by Timmer et al. (2015), which includes input-output tables for 27 EU countries and 13 other major countries from around the world for the period from 1995-2011. Using their data, we are able to explore the effects of growing import penetration from other countries on manufacturing employment in 12 developed economies. We quantify the impact of intermediate inputs from China, the BRIC nations (Brazil, Russia, India, and China), the EU member countries (EU-27), and the new EU member states (EU-12) on employment in 11 manufacturing industries.

Table (2.1) displays the descriptive statistics for different imported intermediate inputs in total manufacturing in 2010. The share of foreign intermediates in total intermediates (III_R) varies considerably across countries, making up only 12.9 and 20.8 percent for Japan and the United States, respectively, whereas in small economies more than half of

Table 2.1 Imported intermediate inputs in total manufacturing in 2010.

Country	III_R	III_B	III_N	III_B^{CHN}	III_B^{BRIC}	III_B^{EU27}	III_B^{EU12}
SWE	.374	.615	.514	.013	.052	.313	.026
FIN	.334	.594	.413	.017	.129	.197	.019
BEL	.578	1.477	2.161	.022	.050	.818	.020
JPN	.129	.154	.073	.019	.026	.008	.000
USA	.208	.243	.148	.024	.035	.033	.001
NLD	.539	1.284	3.11	.026	.103	.491	.014
GBR	.343	.552	.541	.022	.037	.244	.018
DEU	.338	.562	.518	.027	.050	.274	.050
ITA	.251	.325	.215	.014	.044	.135	.015
AUT	.423	.858	.953	.016	.034	.525	.078
FRA	.274	.356	.293	.013	.034	.198	.012
ESP	.274	.357	.236	.009	.025	.172	.012

the intermediates in the manufacturing sector stem from abroad (Belgium: 57.8 percent, the Netherlands: 53.9 percent). The differences in imported intermediate inputs become even more distinct when employing more sophisticated measures of offshoring, ranging from .154 in Japan to 1.477 in Belgium for III_B, and from .073 in Japan to 3.11 in the Netherlands for III_N. With respect to intermediates from different countries, one can observe that intermediate inputs from China play a significant role in each of the 12 countries in the analysis, which is not the case with regard to inputs from the new EU member states. The EU-12 function as major trade partners for other EU members, whereas imported intermediate inputs from these countries hardly matter for the U.S. and the Japanese economies. This can also be recognized in Figure (2.2), which displays the development of intermediate inputs from China and the EU-12 for the period 1995-2011. The ubiquitous role of Chinese intermediates stands in stark contrast to a rather regional impact of growing trade with the new EU member states, the latter of which exert a particularly strong influence on European neighbor countries such as Austria and Germany.

Since the more sophisticated measures of offshoring include several outliers, we restrict the sample to values of III_B between -6 and 13 and values of III_N between -10 and 10. This procedure is valid, as the outliers relate to mainly small countries, where, in some sectors, the denominator of the second part of Equation (2.1) is nearly zero, resulting in an extraordinarily high or low level of imported intermediate inputs. As the observations

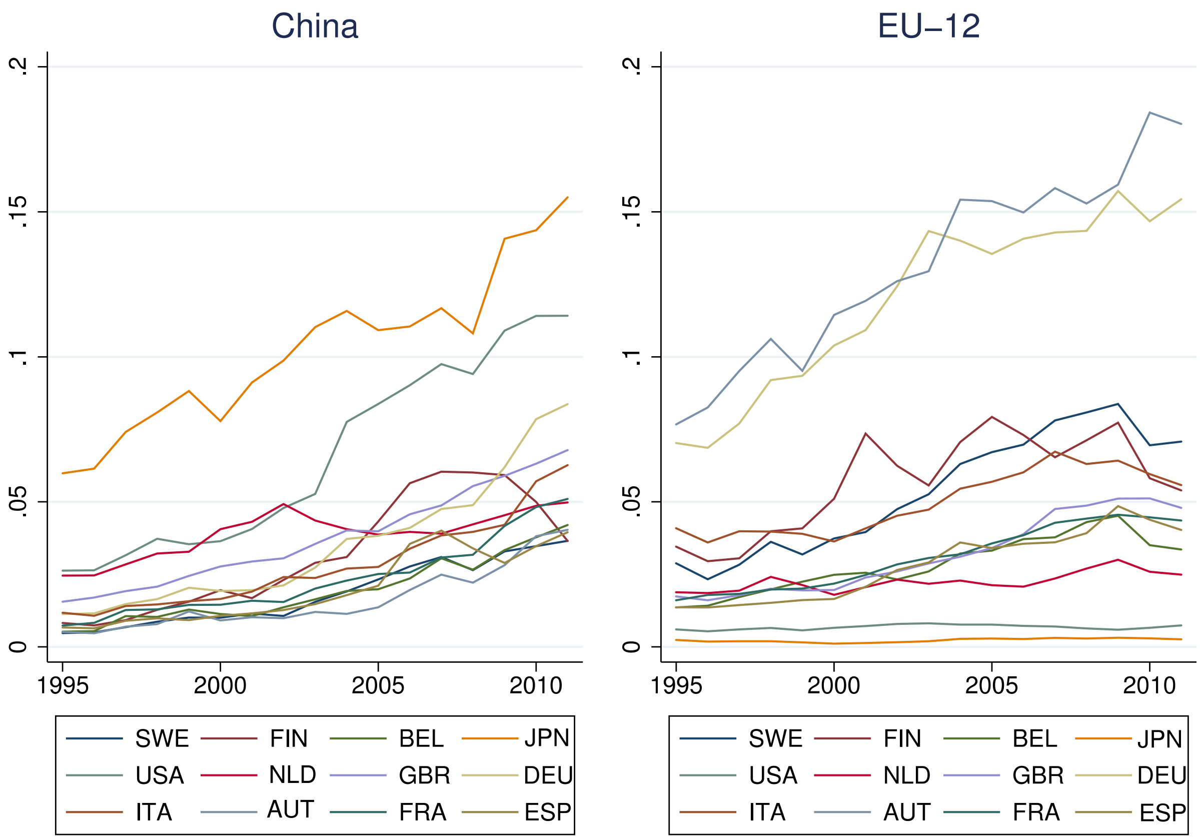

Figure 2.2 Imported intermediate inputs from China and the EU-12 as share of all foreign inputs.

excluded via application of the broad measure of offshoring are different from those excluded when using the narrow measure of offshoring, potential problems relating to choice of data are reduced. Nevertheless, to ensure that the results are not affected by data issues, we re-estimate the baseline regressions with the rough measure (III_R), which does not require any data exclusions.

2.3.2 Empirical model

To estimate the impact of import penetration on employment prospects and to achieve a deeper understanding of this relationship, we assume EMP_GR, the growth of the employment-to-working-age-population ratio, to be a function

$$EMP\_GR_{ijt} = F(IP_{ijt}, \mathbf{X}_{ijt}, \xi_t), \tag{2.3}$$

where $i = 1, \ldots, N$ denotes industries, $j = 1, \ldots, M$ denotes countries, $t = 1, \ldots, T$ is the time index, and ξ_t is a specific effect of period t. IP_{ijt} represents our import penetration measure. $\mathbf{X}_{ijt}$ captures a variety of control and environment variables and includes a number of determinants that are assumed to have an effect on manufacturing employment growth. These determinants comprise the development level of the economy, which we include via the logarithm of real per capita GDP on the expenditure side, denoted by $Log(GDP_{pc})$. We further incorporate an index of the educational level (HC) to account for differences in the qualifications of workers across different countries. The analysis also includes the fertility rate, denoted by *FERT*. Although the analysis comprises 12 highly developed economies from the OECD, there is sufficient variation in fertility rates across the countries to employ them as a covariate (mean: 1.61, std. dev.: .259, Min: 1.16, Max: 2.12). We assume the coefficient of *FERT* to be negative since a higher number of children requires more time spent on parenting, which negatively affects individual labor supply.

Governmental activities enter into the regression via the amount of public social expenditures (*PUB_SOCEXP*). We assume that a more generous welfare state hinders employment growth, since work incentives, particularly for low-skilled workers, are negatively affected by higher public social expenditures. In a further step, we include the logarithm of the employment level in 1996 (*EMP96*), which is the starting point of our analysis, as calculating growth rates leads to a loss of one observation. We apply the TFP growth rate to control for technological change, which is one of the main drivers of employment changes. Several robustness checks extend the analysis and allow for the re-estimation of the baseline model, incorporating a wide variety of covariates which serve as proxies for technological development, labor market institutions, and socio-economic circumstances. Similar to the existing literature, we utilize different measures of employment as the dependent variable. Our main dependent variable is *EMP_GR*, while further dependent variables include the logarithm of total employment, the employment-to-population ratio, and others.

Data on manufacturing employment and TFP growth is extracted from the EU KLEMS database, including information on output, employment, and growth contributions for 11 manufacturing industries in 12 OECD countries from 1970-2010 (O'Mahony and Timmer, 2009). All data on offshoring stems from the World Input-Output Tables (Timmer et al., 2015). The human capital index is taken from Barro and Lee (2013), while data on fertility, the current account balance and the share of natural resource exports is from the World Bank (2016). Data on the development level stems from the Penn World Tables 8.0 (Feenstra et al., 2015). Information on working hours of the highly skilled is extracted from the Socio-Economic Accounts of the World Input-Output Database (Timmer et al., 2015), while data on public social expenditures and employment protection legislation is taken from the OECD. Table (2.13) in the appendix provides summary statistics of the variables employed in the analysis, including their means, standard deviations, the number of observations, and their minima and maxima.

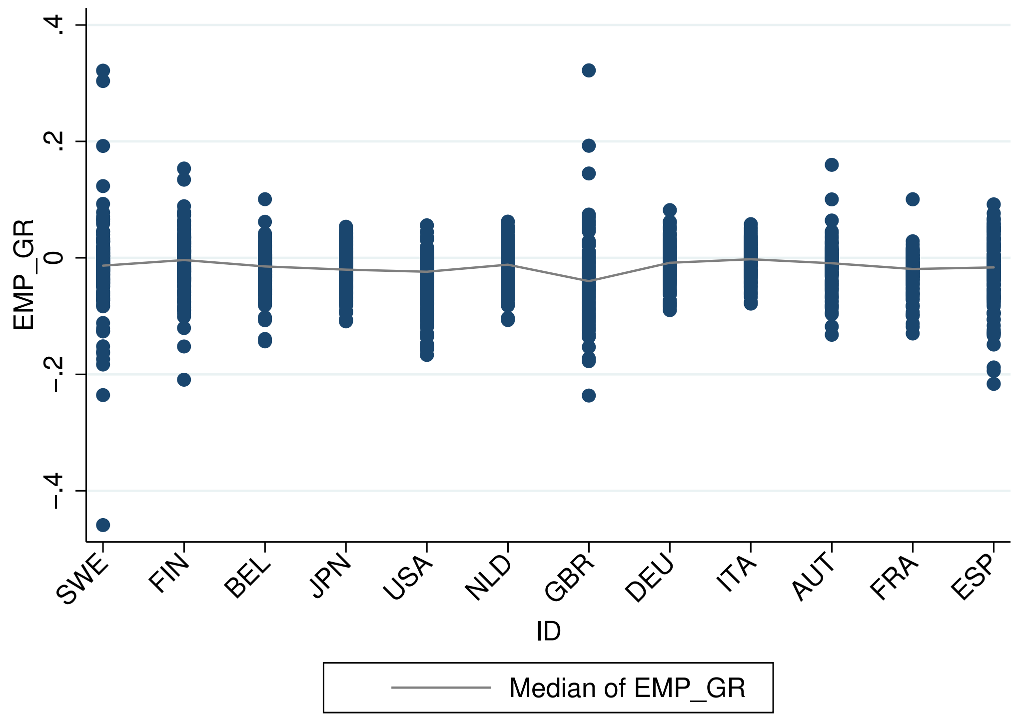

Figure 2.3 Employment growth across countries, *EMP_GR* ($N = 1,128$, skewness= 1.043, kurtosis= 2.847).

How much variation can be observed across countries and industries? The following figures illustrate employment growth across countries (Figure 2.3) and industries (Figure 2.4). The findings show negative median manufacturing employment growth in each country and display only minor variation across countries with relatively poor performance observed in Great Britain and median employment growth of around 0 for the Finnish, German, and the Italian manufacturing sectors. Similarly, we observe little variation between the industries, where the textile sector can be seen to perform more poorly relative to the others. In general, much of the variation occurs within countries or within industries. Meanwhile, there are considerable differences in terms of variation within countries, e.g. Japan vs. the United Kingdom, as well as within industries. While there is only minor variation in employment growth in the food sector, it is much higher in other industries, such as coke and refined petroleum products, or transportation equipment.

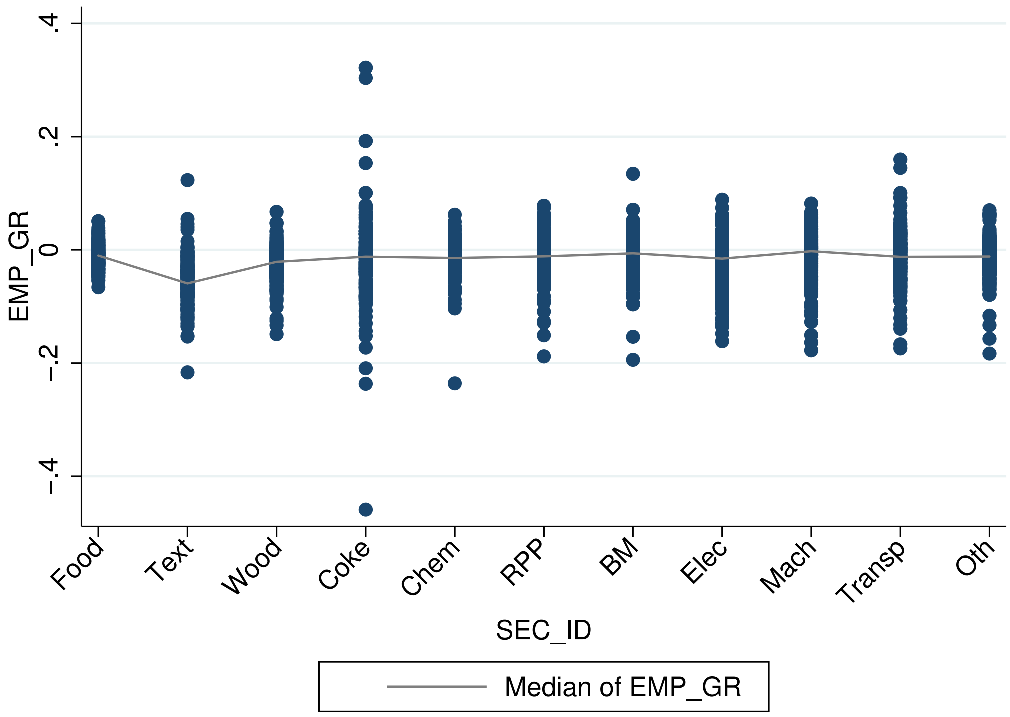

Figure 2.4 Employment growth across industries, *EMP_GR* ($N = 1,128$, skewness= 1.043, kurtosis= 2.847).

2.3.3 Estimation technique

A common and widely-used approach to investigate the trade-employment nexus is the two-stage least squares (2SLS) estimator (Autor et al., 2013; Dauth et al., 2014; Bloom et al., 2016). Consider a linear model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_K x_K + u \tag{2.4}$$

where x_K might be correlated with u. In this case, imported intermediate inputs are not independent from unobserved shocks in product demand, ans thus the true impact of imported intermediates on employment growth is misestimated. The basic concept of the 2SLS estimator involves, in the first stage, regression of endogenous covariates on the exogenous regressors and the instruments, through which we obtain the fitted values $\hat{x}_K$:

$$\hat{x}_K = \delta_0 + \delta_1 x_1 + ... + \delta_{K-1} x_{K-1} + \theta_1 z_1 + ... + \theta_M z_M + r_K. \tag{2.5}$$

By definition, r_K has zero mean and is uncorrelated with the right-hand-side variables, so that any linear combination of $\mathbf{z}$ is uncorrelated with u. Additionally, $\mathbf{z}$ must be correlated with x_K. In the second stage, regressing y on $1, x_1, ..., x_{K-1}, \hat{x}_K$ yields:

$$y = \beta_0 + \beta_1 x_1 + ... + \beta_{K-1} x_{K-1} + \beta_K \hat{x}_K + v \tag{2.6}$$

where v is a composite error term that is uncorrelated with x_1,..., x_{K-1}, and $\hat{x}_K$.

While the 2SLS approach allows for endogeneity issues, it does not sufficiently address the hierarchical structure of the data stemming from 12 countries and 11 manufacturing industries. An appropriate approach should thus differ from that of previous research, which focused on the relationship between trade and employment in a single country context. Hence, our approach employs a linear three-level model which provides the opportunity to adequately account for the hierarchical structure of the data. For any observation in country j and industry i at time t, we consider a three-level random-intercept model, with the variables to be linked additively, yielding

$$EMP\_GR_{ijt} = \beta_1 + \beta_2 \mathbf{X}_{ijt} + \beta_3 \mathbf{X}_{ij} + \beta_4 \mathbf{X}_j + \zeta_j^{(3)} + \zeta_{ij}^{(2)} + \epsilon_{ijt}, \tag{2.7}$$

where $\beta_1 + \beta_2 \mathbf{X}_{ijt} + \beta_3 \mathbf{X}_{ij} + \beta_4 \mathbf{X}_j$ is the fixed part of the model and $\zeta_j^{(3)} + \zeta_{ij}^{(2)} + \epsilon_{ijt}$ is the random part of the model. While the fixed part of the model specifies the overall

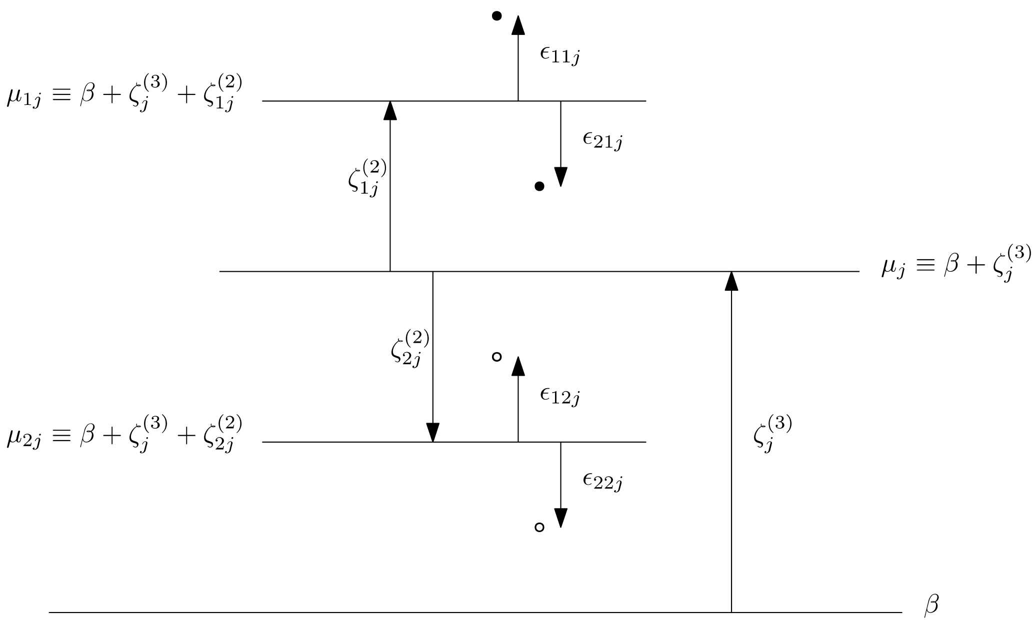

Figure 2.5 Illustration of error components of a three-level variance-components model (Rabe-Hesketh and Skrondal, 2012)

mean relationship between the dependent variable and the covariates, the random part of the model specifies how country and sector-specific relationships differ from the overall mean relationship. In the fixed part of the model, $\mathbf{X}_{ijt}$ is a set of controls at level 1 with slope coefficient β_2, $\mathbf{X}_{ij}$ is a set of covariates at the sector level (level 2) with slope coefficient β_3, and $\mathbf{X}_j$ is a set of control variables at the country level (level 3) with slope coefficient β_4.

The random part consists of a country-level random intercept $\zeta_j^{(3)}$ with zero mean and variance $\psi^{(3)}$, given the covariates $\mathbf{X}_j$, $\mathbf{X}_{ij}$, and $\mathbf{X}_{ijt}$, which represents the combined effects of omitted country characteristics. $\zeta_{ij}^{(2)}$ is a sector-level random intercept with zero mean and variance $\psi^{(2)}$, given $\zeta_j^{(3)}$, $\mathbf{X}_j$, $\mathbf{X}_{ij}$, and $\mathbf{X}_{ijt}$, representing unobserved heterogeneity at the sector level. The level-1 error term ϵ_{ijt} has zero mean and variance θ, given $\zeta_j^{(3)}$, $\zeta_{ij}^{(2)}$, $\mathbf{X}_j$, $\mathbf{X}_{ij}$, and $\mathbf{X}_{ijt}$, and varies between different points in time t as well as countries j and sectors i. The $\zeta_j^{(3)}$ are uncorrelated across countries, the $\zeta_{ij}^{(2)}$ are uncorrelated across countries and sectors, the ϵ_{ijt} are uncorrelated across countries, sectors, and observations in time, and the three error components are uncorrelated with each other (Rabe-Hesketh and Skrondal, 2012).

Figure (2.5) illustrates the error components for a three-level variance-components model. It can be observed that the error term is a composed error with $\zeta_j^{(3)}$ shared between observations of the same country, $\zeta_{ij}^{(2)}$ shared between observations of the same country and the same sector, and ϵ_{ijt} unique for each observation in time. While β represents the overall mean, the mean employment growth of country j is equal to $\mu_j \equiv E(y_{ijt}|\zeta_j^{(3)}) = \beta + \zeta_j^{(3)}$. In the second stage, a sector-specific random intercept $\zeta_{1j}^{(2)}$ produces a sector-specific mean employment growth for country j which is equal to $\mu_{1j} \equiv E(y_{ijt}|\zeta_j^{(3)}, \zeta_{1j}^{(2)}) = \beta + \zeta_j^{(3)} + \zeta_{1j}^{(2)}$. Finally, residuals ϵ_{11j} and ϵ_{21j} are drawn from a distribution with zero mean and variance θ.

Maximum Likelihood (ML) appears to be an appropriate estimation strategy, one which takes the hierarchical structure of the data into account. ML estimation yields the parameters of a statistical model, given a set of data, by finding the parameter values that maximize the likelihood of obtaining that particular set of data given the chosen probability distribution model. The probability density function *f(y*|θ) identifies the data-generating process that underlies an observed sample of data and provides a mathematical description of the data that the process will produce. The joint density of n independent and identically distributed observations from the process is the likelihood function

$$f(y_1, ..., y_n|\theta) = \prod_{i=1}^{n} f(y_i|\theta) = L(\theta|\mathbf{y}), \tag{2.8}$$

which is defined as a function of the unknown parameter vector, θ, where $\mathbf{y}$ is used to indicate the collection of sample data. For reasons of lucidity, the log of the likelihood function is employed:

$$\ln L(\theta|\mathbf{y}) = \sum_{i=1}^{n} \ln f(\mathrm{y}_i|\theta). \tag{2.9}$$

When maximizing the log-likelihood function, Maximum-Likelihood estimators have very desirable large sample properties. If the density is correctly specified, the ML estimator is consistent for θ and asymptotically more efficient than other estimators, meaning that no other estimator has a smaller asymptotic variance-covariance matrix (Greene, 2012; Wooldridge, 2010).

The literature features two major estimation methods for determining statistical parameters, assuming that the random part of the model is normally distributed: Maximum-Likelihood or restricted Maximum-Likelihood (REML). The expectation-maximization (EM) algorithm treats the random effects as missing data and allows determination of the ML or REML estimates via an iterative process, in which a provisional estimate converges to the ML or REML estimate. Both methods differ little with regard to the regression coefficients, but they vary substantially with respect to the variance components. When estimating the variance components, REML takes into account the loss of degrees of freedom which results from the estimation of the regression parameters, while ML does not. As a result, ML estimators of the variance components have a downward bias, which is why the REML method is preferable for estimation of the variance parameters. Additionally, in cases where the sample size at the highest level is small, REML produces more reliable standard errors (Snijders and Bosker, 2012). As our sample consists of 12 countries, we apply the REML method. However, REML does not allow for heteroskedasticity-robust standard errors. A Breusch-Pagan test indicates that heteroskedasticity is in fact an issue, which is why we re-estimate the baseline specification via ML and include robust standard errors as a robustness check.

2.4 Results

2.4.1 Baseline results

Table (2.2) displays the results of the baseline estimation. Column (1) presents a model which only incorporates the effect of TFP growth, the employment level at the start of our observation period, and our broad measure of import penetration. We observe a positive and weakly significant effect of import penetration on manufacturing employment growth, indicating a positive contribution of increased trade to employment prospects in the 12 OECD countries. The results support the findings of Dauth et al. (2014), pointing to job losses due to growing imports, which are meanwhile more than offset by increasing export prospects and the complementarity of the imported intermediates. Additionally, we find a negative and significant impact of TFP growth on *EMP_GR*, indicating an employment growth reducing impact of technological change in the manufacturing sector. The coefficient of the employment level in 1996 is not significant, implying that initial employment does not play a crucial role in determining future employment prospects.

Column (2) introduces the level of development, fertility, and the level of human capital into the model. The import penetration variable remains positive and significant, supporting previous findings of an overall employment enhancing impact of intermediate inputs on manufacturing employment growth in the OECD countries. The effect of *TFP* remains negative and significant, while the coefficient of the initial employment level becomes positive, but remains insignificant. The development level itself is negatively related to our dependent variable, indicating that growing prosperity negatively affects employment growth in the manufacturing sector. The reason for this is that demand for manufacturing products is saturated and therefore steadily decreasing in developed economies relative to the demand for services. As goods are internationally tradable, manufacturing firms have to pass along technological improvements and lower prices to the consumer, resulting in a constantly declining market share of the manufacturing sector. Fertility exerts a significantly negative impact on employment growth, as rearing children negatively affects the employment probability of women in particular. As expected, the sign of the coefficient of the human capital index is positive. However, the impact is not significant, since human capital operates on a long-term basis and thus the coefficient is insignificant in a year-to-year context.

Column (3) includes public social expenditures in order to factor in the generosity of the social security system and possible implications for the labor supply. The results reveal a robust negative relationship between public social expenditures and employment growth, indicating that more generous welfare states negatively affect the individual's decision to work. Additionally incorporated is the variable *RES_EXP*, which is the share of exports of raw materials out of all merchandise exports from a country or region of origin. This covariate accounts for the exports of raw materials, which often have a positive impact on employment growth due to the fact that they serve as a prerequisite for

Table 2.2 The effect of trade on manufacturing employment growth, baseline results. Dependent variable is employment growth *EMP_GR*.

	(1)	(2)	(3)	(4)	(5)
TFP	-0.0178**	-0.0176**	-0.0168**	-0.0171**	-0.0163**
	(0.00746)	(0.00742)	(0.00740)	(0.00736)	(0.00749)
EMP96	-0.00202	0.00217	0.00191	0.00362	0.00253
	(0.00188)	(0.00287)	(0.00292)	(0.00306)	(0.00297)
III_B	0.00196*	0.00183*	0.00191*		
	(0.00108)	(0.00108)	(0.00109)		
$\text{Log}(\text{GDP}_{pc})$		-0.00820**	-0.0181***	-0.0182***	-0.0170***
		(0.00346)	(0.00516)	(0.00529)	(0.00485)
FERT		-0.0398***	-0.0616***	-0.0611***	-0.0556***
		(0.00877)	(0.0127)	(0.0128)	(0.0122)
HC		0.0164	0.0130	0.00954	0.0133
		(0.0102)	(0.0148)	(0.0149)	(0.0144)
PUB_SOCEXP			-0.00261***	-0.00274***	-0.00228***
			(0.000777)	(0.000778)	(0.000759)
RES_EXP			0.489***	0.476***	0.497***
			(0.126)	(0.126)	(0.128)
III_R				0.0377**	
				(0.0150)	
III_N					-0.0000213
					(0.000817)
N	1905	1905	1905	1925	1903
Time Dummies	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

manufacturing production in highly developed economies. As we are interested in the link between employment prospects and imported intermediate inputs other than the export of raw materials, inclusion of *RES_EXP* is highly advantageous. All other regressors remain unchanged, confirming the stability of the baseline model. All specifications include time and sector dummies, as our observation period includes a variety of shocks, such as the dot-com bubble or the Great Recession, as well as such diverse sectors as, for example, food and beverages, textiles, or machinery equipment.

In Columns (4)—(5), we replace III_B with a rough (III_R) and a narrow (III_N) measure of import penetration and re-estimate our preferred baseline specification from (Column 3). Although the rough measure omits export activities as well as energy aspects, the estimated coefficient points to a positive and significant impact on manufacturing employment growth in 12 OECD countries, supporting the findings of our preferred measure III_B. Obviously, a majority of foreign intermediate inputs serve as a complement to domestic production in manufacturing, fostering employment growth rather than impeding it. Applying a narrow measure of globalization (III_N), one cannot observe a significant influence of the import variable. This might be due to the construction of the indicator that measures imported intermediate inputs from the same industry, whose impact is comparatively small in some cases. The coefficient of *TFP* remains negative and robust in all specifications, indicating that changing the import penetration measure does not change the ascertained influence of technological progress on employment growth in manufacturing.

Furthermore, we re-estimate our baseline model, altering the model fit from REML to ML, which allows for the application of heteroskedasticity-robust standard errors. Table (2.14) in the appendix displays the results. In line with the findings of our baseline regression, imported intermediate inputs are positively related to employment growth, while technological progress is not. Though the signs of the coefficients remain stable, both effects become insignificant, emphasizing the different effects of growing trade on manufacturing employment that offset each other.

Our mixed model includes random intercepts at the country and sector level, as the impact of our import penetration measure on employment growth may vary between countries and sectors. A likelihood-ratio test rejects the null hypothesis that random intercepts at the country level and at the sector level are 0. Thus, country-specific and sector-specific random intercepts are added to the population mean. Meanwhile, the null hypothesis of a random slope at the country and the sector level cannot be rejected.

2.4.2 Sensitivity analysis

Though we are convinced of the appropriateness of our baseline estimation technique for analyzing the impact of imported intermediate inputs on manufacturing employment growth, it is essential to explore whether the results are robust to alternative estimation techniques and additional variables. The first step in doing so is to include several exogenous variables which we think may additionally influence employment outcomes.

Table (2.3) replicates the baseline model of Column (3) in Table (2.2) and presents the results of the impact of the additional exogenous variables. Column (1) adds an interaction term $TFP \times III_B$, as we assume the import penetration measure to differ in terms of the intensity with which it affects employment growth, conditional upon the total factor productivity. The results indicate that TFP still exerts a negative and significant influence on employment growth for an import penetration of 0, while the coefficient of III_B remains positive but insignificant when TFP is 0. The coefficient of the interaction term reveals a positive and significant relationship, implying that the positive effect of import penetration on manufacturing employment growth is stronger for higher TFP growth rates. These findings highlight that the more productive country-sector combinations benefit most from increasing import penetration. The remaining covariates do not differ across the different model specifications, underlining the stability of the baseline results.

Column (2) incorporates a country's one-period lagged current account balance in the estimation ($CAS_{(t-1)}$). The results indicate that countries which had a current account deficit in the previous period have a lower manufacturing employment growth in the current period than those which had a surplus. As the majority of goods are highly tradable

Table 2.3 The effect of trade on manufacturing employment, sensitivity analysis, additional exogenous variables. Dependent variable is employment growth *EMP_GR*.

	(1)	(2)	(3)	(4)	(5)	(6)
TFP	-0.0185**	-0.0171**	-0.0169**	-0.0172**	-0.0167**	-0.0169**
	(0.00742)	(0.00781)	(0.00739)	(0.00738)	(0.00739)	(0.00739)
EMP96	0.00199	0.00153	0.00159	0.00130	0.00176	0.00153
	(0.00291)	(0.00290)	(0.00291)	(0.00293)	(0.00293)	(0.00293)
III_B	0.00141	0.00184	0.00198*	0.00188*	0.00187*	-0.00763
	(0.00110)	(0.00122)	(0.00109)	(0.00108)	(0.00109)	(0.00567)
$\text{Log}(\text{GDP}_{pc})$	-0.0176***	-0.00270	-0.0185***	-0.0279***	-0.0247***	-0.0170***
	(0.00504)	(0.00410)	(0.00522)	(0.00643)	(0.00633)	(0.00506)
FERT	-0.0602***	-0.0329***	-0.0631***	-0.0678***	-0.0700***	-0.0616***
	(0.0125)	(0.00902)	(0.0128)	(0.0140)	(0.0138)	(0.0125)
HC	0.0123	-0.00134	0.0121	0.00685	0.0104	0.0154
	(0.0146)	(0.0110)	(0.0149)	(0.0162)	(0.0159)	(0.0147)
PUB_SOCEXP	-0.00252***	-0.000197	-0.00264***	-0.00267***	-0.00301***	-0.00244***
	(0.000769)	(0.000606)	(0.000781)	(0.000847)	(0.000816)	(0.000771)
RES_EXP	0.482***	0.435***	0.495***	0.498***	0.512***	0.421***
	(0.126)	(0.125)	(0.127)	(0.130)	(0.129)	(0.131)
$\text{TFP}\times III_B$	0.0358**					
	(0.0151)					
$\text{CAS}_{(t-1)}$		0.00227***				
		(0.000473)				
HS96			0.0433			
			(0.0304)			
EPL				-0.0224***		
				(0.00826)		
MANUF96					-0.249	
					(0.215)	
$\text{RES\_EXP}\times III_B$						0.0606*
						(0.0354)
N	1905	1712	1905	1905	1905	1905
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

across the world, current account deficits can be interpreted as a lack of competitiveness, resulting in worse manufacturing employment prospects for those countries. Column (3) includes the share of hours worked by high-skilled workers in 1996 (*HS96*) to account for skill differences between the country-sector combinations. We obtain a positive but slightly insignificant relationship ($p = 0.14$), supporting the theoretical prediction that the availability of high-skilled workers increases labor demand. While the technology variable (*TFP*) remains robust across all specifications, the import penetration measure (III_B) is positive and weakly significant in 3 out of 5 cases.

Column (4) incorporates the employment protection legislation index for regular workers (*EPL*) from the OECD database as proposed by Crinò (2009), which serves as a proxy for the rigidity of the labor market. Controlling for our standard covariates, the results reveal that manufacturing employment growth is higher for country-sector combinations with a lower degree of employment protection legislation. The reason is that more extensive employment protection legislation impedes firms' willingness to hire new workers, a situation which adversely influences job creation in times of economic recovery.

In the following step, we reassess whether there is evidence for an *inevitable* structural change from the industry sector to the service sector (Column 5). In concrete terms, we employ the share in manufacturing value added in percent of GDP in 1996 (*MANUF96*) to examine whether countries with a strong manufacturing sector in 1996 are more intensively exposed to manufacturing employment decline than countries where manufacturing plays only a minor role. The former economies are expected to undergo serious transformations with adverse employment effects as they have not yet experienced this structural change. The results indicate that countries with a broad industrial base have not been subject to stronger manufacturing employment decline between 1996 and 2011 than countries with a smaller industrial sector. As our observation period comprises only one and a half decades, we cannot conclusively answer this question since such development generally occurs over a longer time span.

Column (6) of Table (2.3) includes the interaction term $RES\_EXP \times III_B$ in the estimation, as we expect the imported intermediate inputs to affect employment growth dependent on the extent of exports of raw materials. We assume a greater impact of imported intermediates on manufacturing employment growth when the share of exports of raw materials is larger. As exports of raw materials are a prerequisite of manufacturing production in highly developed economies, we assume the interaction term to be positive. The results confirm the theoretical predictions, with a positive and significant coefficient for $\mathit{RES\_EXP} \times III_B$. The coefficient of III_B itself is insignificant, indicating that imported intermediates exert no significant influence on manufacturing employment when the export share of raw materials is 0. However, with an increasing share of exports of raw materials the influence of imported intermediate inputs on employment growth becomes positive and significant. All other variables remain unchanged.

The analysis up to this point assumed an immediate effect of the covariates on manufacturing employment growth. Yet it may take some time for the variables to come into effect in the labor market. With regard to the baseline specification, this may apply to fertility, human capital, and import penetration. Fertility qualifies for this procedure since individuals enter the labor market one and a half to two decades after birth. We therefore use fertility rates in 1996 (*FERT96*), the start of our observation period, to account for fertility differentials between the countries. Changes in human capital endowment only gradually influence labor demand, thus we include one-period lagged human capital ($HC_{(t-1)}$). Similarly, growing import penetration might not have an immediate impact on employment growth since its consequences for employment may be temporarily prevented via public funds. Employing one-period lagged imported intermediate inputs and other lagged covariates, Table (2.15) in the appendix re-estimates the baseline specifications. The results remain relatively stable, with a significantly negative effect of *FERT96* and a positive but insignificant impact of human capital. While $III_{B(t-1)}$ becomes insignificant, this is not the case for the rough measure of import penetration ($III_{R(t-1)}$).

In a further step, we test whether the baseline results are robust to different measures of employment. Table (2.16) in the appendix displays the findings of the preferred baseline specification for different dependent variables and indicates high robustness of the results. The impact of *TFP*, *Log*(GDP_{pc}), and *PUB_SOCEXP* on employment remains negative and significant in most of the cases, while a positive and slightly significant effect of the import penetration measure can be observed for all specifications. The coefficient of HC is positive and highly significant only when using employment levels as dependent variables, whereas it is positive, albeit insignificant, for employment growth. The share of exports of raw materials out of all merchandise exports is significantly positive when utilizing employment growth as the dependent variable, whereas a significant and negative relationship can be observed when using employment levels as the endogenous variable. The latter could be due to the fact that the extraction of raw materials is highly mechanized, creating relatively few jobs compared to other sectors.

Thus far, the analysis has focused on the aggregate impact of increasing import competition on manufacturing employment growth. Now, the baseline specification is applied to imports from specific countries in order to quantify the extent to which the effects of imported intermediates on employment growth differ by country of origin. Additionally, RES_EXP is calculated separately for the different countries or regions of origin. Column (1) of Table (2.4) replicates the preferred model specification from Column (3) of Table (2.2) and serves as a reference category. All other columns in Table (2.4) use a similar model specification.

Column (2) investigates the specific impact of intermediates from China on employment prospects in the 12 OECD countries. The results point to a negative though insignificant effect, leaving other covariates unchanged. The findings suggest that Chinese intermediate inputs act mainly as substitutes for domestic production in the highly developed economies. III_B^{CHN} also includes export activities from OECD countries to China which may mitigate the negative impact on manufacturing employment growth. While a higher share of exports of raw materials generally fosters manufacturing employment growth, this cannot be observed with regard to exports from China. In fact, China is the only country in the analysis where the share of exports of raw materials has been declining during the observation period. The rise of manufacturing production in China has dramatically changed the structure of exports, with an increasing relevance of goods exports.

Table 2.4 The effect of trade on manufacturing employment, sensitivity analysis, import penetration measures from different countries of origin. Dependent variable is employment growth *EMP_GR*.

	(1)	(2)	(3)	(4)	(5)
TFP	-0.0168**	-0.0166**	-0.0171**	-0.0166**	-0.0165**
	(0.00740)	(0.00740)	(0.00742)	(0.00740)	(0.00741)
Log(GDP$_{pc}$)	-0.0181***	-0.0180***	-0.0178***	-0.0185***	-0.0192***
	(0.00516)	(0.00514)	(0.00514)	(0.00519)	(0.00538)
FERT	-0.0616***	-0.0616***	-0.0615***	-0.0618***	-0.0630***
	(0.0127)	(0.0127)	(0.0126)	(0.0127)	(0.0129)
HC	0.0130	0.0130	0.0132	0.0124	0.0125
	(0.0148)	(0.0148)	(0.0147)	(0.0149)	(0.0151)
PUB_SOCEXP	-0.00261***	-0.00263***	-0.00257***	-0.00266***	-0.00275***
	(0.000777)	(0.000775)	(0.000773)	(0.000778)	(0.000795)
EMP96	0.00191	0.00143	0.00152	0.00164	0.00159
	(0.00292)	(0.00294)	(0.00298)	(0.00293)	(0.00293)
RES_EXP	0.489***				
	(0.126)				
III$_B$	0.00191*				
	(0.00109)				
RES_EXP^{CHN}		-1.353***			
		(0.335)			
III$_B^{CHN}$		-0.0824			
		(0.115)			
RES_EXP^{BRIC}			0.239***		
			(0.0629)		
III$_B^{BRIC}$			0.0222		
			(0.0209)		
RES_EXP^{EU27}				0.750***	
				(0.188)	
III$_B^{EU27}$				0.000378	
				(0.00282)	
RES_EXP^{EU12}					0.401***
					(0.100)
III$_B^{EU12}$					-0.0252
					(0.110)
N	1905	1905	1905	1905	1905
Time Dummies	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Column (3) examines the influence of imported intermediate inputs from the BRIC countries on manufacturing employment growth, where a positive but insignificant relationship can be observed. It appears that imported intermediates from Brazil or Russia tend to complement manufacturing production in the developed economies, which contrasts with the effect of Chinese imports and results in an insignificant overall effect. While imports from Brazil and Russia comprise a large number of raw materials, a positive and significant impact can be observed with respect to RES_EXP^{BRIC}. It is therefore crucial to distinguish between imports of raw materials which serve as prerequisites for manufacturing production and those that substitute for domestic production, the latter of which is the case for most of the Chinese imports.

The analysis particularly focuses on European nations, with 10 of the 12 countries analyzed being members of the European Union. For this reason, we investigate the role of the single European Market on employment prospects in the member countries. The results are shown in Column (4) and indicate a positive but insignificant relationship between intermediate inputs from the EU-27 and employment growth in the OECD countries. The findings point to a positive influence of deeper economic integration in the EU. Additionally, we separately account for the role of the new EU member states (EU-12). As can be seen from Figure (2.2) and as noted by Dauth et al. (2014), the EU-12 are highly relevant for some of the countries in the analysis, such as Austria and Germany, where a substantial share of foreign inputs originate from Eastern Europe. Column (5) displays a negative but insignificant impact of intermediates from the EU-12, which do not foster employment growth in the OECD countries. Higher export shares of raw materials in the EU-12 as well as in the EU-27 positively contribute to manufacturing employment growth. All other covariates remain robust across all specifications.

Thus far, the analysis describes the impact of imported intermediate inputs on employment growth for 12 OECD countries. Meanwhile, Table (2.17) in the appendix indicates that the effects may differ across countries and provides mixed evidence of the influence of intermediates from China and the EU-12 on employment prospects in Germany, France, Spain, and Italy. While German and Italian manufacturing employment is not negatively

Table 2.5 The effect of trade on manufacturing employment, sensitivity analysis, 4-year averages and 2 periods (1996-2003, 2004-2011), import penetration measures from different countries of origin. Dependent variable is employment growth EMP_GR.

	4-year averages			2 periods		
	(1)	(2)	(3)	(4)	(5)	(6)
III_B	0.000792			0.000207		
	(0.000915)			(0.000857)		
III_B^{CHN}		0.0302			-0.00647	
		(0.115)			(0.130)	
III_B^{EU12}			-0.0930			-0.213**
			(0.0746)			(0.0942)
N	523	523	523	262	262	262
Time Dummies	Yes	Yes	Yes	No	No	No
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

affected by intermediate inputs from China or the EU-12, adverse effects can be observed for France and Spain. The findings imply that in the latter countries neither exports to China and the EU-12 nor a higher share of exports of raw materials can compensate for the employment losses.

The previous findings are estimated on a year-to-year basis, ignoring cyclical influences which may play a role for employment prospects. Thus, we now create 4-year averages, resulting in four observations for each country-sector combination, which cover the following time periods: 1996-1999, 2000-2003, 2004-2007, and 2008-2011. Columns (1)—(3) of Table (2.5) display the results, which suggest an insignificant relationship between imported intermediates and employment growth when accounting for time and sector dummies. For reasons of lucidity, we only report the results of the import penetration variable, as the other covariates remain unchanged. In Columns (4)—(6) of Table (2.5) the time interval between 1996 and 2011 is split into two periods, 1996 to 2003 and 2004 to 2011. The main variable of interest (III_B) remains insignificant, indicating that imported intermediate inputs do not impede employment growth in the 12 OECD countries. When accounting for the intermediate inputs' country of origin, a negative, though insignificant, coefficient is obtained for inputs from China, while the relationship is significantly negative for intermediates from the EU-12. The results imply that the impact of imported intermediate inputs on manufacturing employment growth depends on the country of origin of the inputs.

2.4.3 Endogeneity

The robustness checks from Section (2.4.2) discard cyclical fluctuations and include several additional covariates in the estimation which we think may play a role in explaining employment prospects in manufacturing. In general, we observe a slightly positive and partly significant impact of imported intermediate inputs on manufacturing employment growth which is fairly robust across the different specifications. The results are more nuanced when accounting for the intermediates' country of origin. However, a major empirical challenge in determining the causal effect of trade on employment is that imported intermediates may be correlated with unobserved shocks in product demand, thus raising issues of endogeneity (Autor et al., 2013; Dauth et al., 2014; Bloom et al., 2016). In this situation, the true impact of imported intermediate inputs on employment growth may be misestimated.

To avoid potential weaknesses which may arise due to endogeneity, we employ an instrumental variable (IV) strategy, alleviating the problem of correlation between the two variables. We apply two instruments for the the import penetration measure which we assume to be endogenous. In the first case, imported intermediate inputs to a given country are instrumented with the intermediates to all other 11 OECD countries in the analysis (jack-knifed intermediate inputs). This procedure is in line with the approach of Autor et al. (2013), where Chinese imports to the United States are instrumented with Chinese imports to eight other developed economies. However, this may not ultimately solve issues of endogeneity since supply and demand shocks in neighboring countries, as well as other member states of the European Monetary Union, are likely to be correlated with those in the country of analysis (Dauth et al., 2014). Additionally, in highly integrated regions trade shocks which change trade flows between China or the EU-12 and neighboring countries may directly affect regional performance in the country of analysis,

Table 2.6 The effect of trade on manufacturing employment, regression with alternative estimation methods, instrumentation according to Dauth et al. (2014). Dependent variable is employment growth *EMP_GR*.

	OLS			IV-2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
III_R	-0.00156			0.319***		
	(0.0129)			(0.111)		
III_B		0.000551			0.207	
		(0.000649)			(0.320)	
III_N			-0.000530			0.0201
			(0.000542)			(0.102)
N	1925	1905	1903	1925	1905	1903
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

therefore violating the exclusion restriction. As the sample includes 12 OECD countries, 10 of which are located in Europe, and the underlying database (WIOD) provides data on imported intermediate inputs for 40 countries, the instrument group which allows for the correlation and the exclusion restriction consists only of Australia. While trade flows of Australia with China or the BRIC nations are relevant instruments for assessing the trade exposure of the 12 OECD countries, caution is advised with regard to Australia's trade flows with the new EU member states.

Table (2.6) reports the results of two modifications of the baseline estimations for the three preferred import penetration measures. Columns (1)—(3) provide evidence from the OLS estimation, which is often seen as a reference estimation strategy in the literature. The OLS results display an insignificant relationship between import penetration and manufacturing employment growth. However, caution is recommended when interpreting the results, as OLS does not account for the hierarchical structure of the data, ignoring the correlation of two observations of the same country-sector combination. Hence, OLS discards the information at the country and the sector level. Additionally, potential endogeneity may cause biased estimates, which is why Columns (4)—(6) display the findings of the IV estimation, where the instrumentation follows the concept of Dauth et al.

(2014). The IV strategy also does not adequately control for the hierarchical structure of the data. The results confirm the findings of the baseline regressions in Table (2.2), indicating a mostly positive and partly significant impact of imported intermediate inputs on manufacturing employment growth. A Durbin-Wu-Hausman test and a Wooldridge (2010) test reject the null hypothesis of exogeneity in most cases, which is why we rely on the IV results rather than the OLS estimates.

Moreover, we test whether additional covariates are endogenous and re-estimate the IV specification by instrumentation of further variables. We instrument the development level and public social expenditures with a one-period lag, obtaining $Log(GDP_{pc})_{(t-1)}$ and $PUB\_SOCEXP_{(t-1)}$, respectively. The results do not change considerably, supporting the robustness of the baseline results. In a subsequent step, we split our endogenous variables into a cluster mean for a specific country-sector combination ($MN\_^{*}$) and the deviation from this cluster mean ($DEV\_^{*}$), and employ these variables as covariates in the estimation. The cluster mean variable represents the between effect of different country-sector combinations, whereas the deviation depicts the within effect, comparing two observations of the same country-sector combination. While all the cluster mean variables are insignificant, the deviations from the cluster mean are significantly different from zero for $DEV\_Log(GDP_{pc})$ and DEV_PUB_SOCEXP, implying that country-sector combinations with a higher development level or higher levels of public social expenditures experience lower employment growth given the other covariates. The results also illustrate that most of the variation lies within a country-sector combination rather than between different countries and sectors.

Additionally, we account for the origin of the intermediate inputs and re-estimate the IV-2SLS specifications. Column (1) of Table (2.7) is an exact replication of Column (5) from Table (2.6) and serves as a reference category. The results suggest different effects of import penetration on manufacturing employment growth depending on the country of origin. Chinese intermediates impede employment growth, supporting the idea that inputs from China are substitutes for manufacturing production in the 12 OECD countries as supported by Autor et al. (2013). This pattern cannot be observed for in-

Table 2.7 The effect of trade on manufacturing employment, IV-2SLS results for import penetration measures from different countries of origin, instrumentation according to Dauth et al. (2014). Dependent variable is employment growth *EMP_GR*.

	(1)	(2)	(3)	(4)	(5)
III_B	0.207				
	(0.320)				
III_B^{CHN}		-0.664*			
		(0.347)			
III_B^{BRIC}			-1.164		
			(1.285)		
III_B^{EU27}				0.203*	
				(0.114)	
III_B^{EU12}					-0.966*
					(0.561)
N	1905	1905	1905	1905	1905
Time Dummies	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

termediates from the BRIC countries. Imports from nations other than China partially compensate for the employment losses which can be seen in Column (2), with the result that the overall effect is insignificant. Column (5) indicates that higher import penetration from the EU-12 hampers manufacturing employment growth in the highly developed economies. In contrast, intermediate inputs from the EU-27 have a positive influence on employment growth in manufacturing. These findings illustrate that trade with the old members of the European Union (EU-15)[7] more than compensates for the negative employment impact from trade with the new member states (EU-12). Accordingly, while inputs from the EU-15 act as complements to manufacturing production, thereby increasing domestic manufacturing employment growth, intermediates from the EU-12 tend to act as substitutes for employment growth. The results are in line with those from Table (2.4), indicating a negative impact of inputs from China and the EU-12, while a slightly positive influence can be observed for intermediates from the EU-27.

[7]The EU-15 comprises all members of the European Union which joined before the enlargement of the EU in 2004.

Table 2.8 The effect of trade on manufacturing employment, IV-2SLS regressions, 4-year averages and 2 periods (1996-2003, 2004-2011), import penetration measures from different countries of origin. Dependent variable is employment growth EMP_GR.

	4-year averages			2 periods		
	(1)	(2)	(3)	(4)	(5)	(6)
III_B	-0.00315			-0.0289		
	(0.0471)			(0.0899)		
III_B^{CHN}		-0.697**			-0.491	
		(0.306)			(0.299)	
III_B^{EU12}			-1.296*			-1.084
			(0.710)			(0.826)
N	523	523	523	262	262	262
Time Dummies	Yes	Yes	Yes	No	No	No
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Finally, we allow for cyclical fluctuations which may play a role in explaining employment prospects. Table (2.8) replicates the estimations from Table (2.5), now applying an IV strategy which accounts for endogeneity. Columns (1)—(3) use 4-year averages as described in Section (2.4.2), while Columns (4)—(6) split the sample into two periods, resulting in a strong reduction in the number of observations. The findings display an insignificant impact of III_B on manufacturing employment growth. However, a negative and significant relationship between intermediates and employment growth can be observed for inputs from China and the EU-12. The results are in line with those in Table (2.7), pointing to a substitutive impact of intermediates from these countries on domestic manufacturing production. In Columns (4)—(6) the coefficients remain negative, though slightly insignificant.

2.4.4 Residual diagnostics

In the following section some residual diagnostics are employed to assess the model fit and the stability of our results. First, we want to address the question of whether there is sufficient variation at the higher levels to justify the application of a multilevel mixed approach. Although likelihood-ratio tests support the appropriateness of including random intercepts at the country and the industry level, we partition the variance into its components to assess the level at which the variation occurs. A variance-components model indicates that only 4 percent of the variation in manufacturing employment growth stems from differences between countries. Another 9.3 percent of the variation occurs at the sector level, while most of the variation, 86.7 percent, is explained by differences between observations within a country-sector combination. These results challenge the application of a three-level hierarchical model, as the variation at the country level is below the rule of thumb of about 10 percent. The intraclass correlation of the model, which is the correlation between two observations t and t' from the same country j and the same industry i, is about 13.3 percent, implying that only this share of the variation of *EMP_GR* can be attributed to country and sector-specific characteristics. However, as likelihood-ratio tests argue in favor of the three-level hierarchical model we retain this specification.

The inclusion of a random intercept (ζ_j) at the country and the sector level enables determination of the random intercepts for each country and sector, respectively. Maximum-Likelihood estimation and empirical Bayes prediction provide two techniques for doing so. While Maximum-Likelihood estimation treats ζ_j as a fixed parameter, it is treated as a random variable in the empirical Bayes prediction. Moreover, ML estimation uses the responses y_{ijt} for country j as the only information about ζ_j by maximizing the likelihood of observing these particular values (Rabe-Hesketh and Skrondal, 2012):

$$\text{Likelihood}(y_{i1t}, ..., y_{i12t}|\zeta_j). \tag{2.10}$$

Empirical Bayes prediction also uses the prior distribution of ζ_j as additional information for predicting values of ζ_j before having seen the data. The prior distribution assumes a normal distribution for the random intercept with zero mean and estimated variance $\widehat{\psi}$. Given the observed responses y_{i1t},...,y_{i12t}, we can then combine the prior distribution with the likelihood to obtain the posterior distribution of ζ_j, leading to

$$\text{Posterior}(\zeta_j|y_{i1t}, ..., y_{i12t}) \propto \text{Prior}(\zeta_j) \times \text{Likelihood}(y_{i1t}, ..., y_{i12t}|\zeta_j) \tag{2.11}$$

where the posterior distribution of ζ_j represents the updated knowledge of the random intercept after having seen the data.

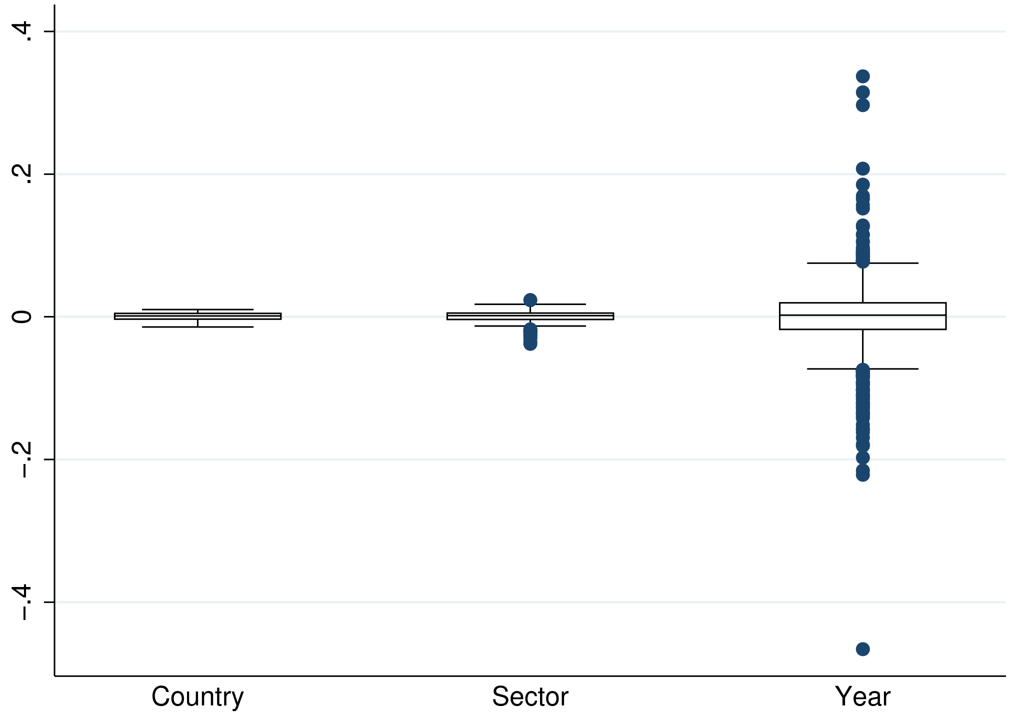

Figure 2.6 Box plots of empirical Bayes predictions for random intercepts at the country and the sector level, and level-1 residuals at the time level.

Figure (2.6) plots empirical Bayes predictions for random intercepts at the country and the sector level as well as the level-1 residuals at the time level. As the random intercepts at the different levels and the level-1 residuals are all on the same scale, one can observe that there is much more variability within countries and sectors than between them, challenging the three-level hierarchical model. As emphasized by Rabe-Hesketh and Skrondal (2012), the prediction error of the empirical Bayes prediction has zero mean over repeated samples of ζ_j and ϵ_{ijt} when model parameters are treated as fixed and known. Moreover, empirical Bayes predictions also have the smallest possible variance for given model parameters, making them the best linear unbiased predictor (BLUP) in linear models.

Table (2.9) displays the empirical Bayes predictions for the country-specific ($\zeta_j^{(3)}$) and the sector-specific ($\zeta_{ij}^{(2)}$) random effects for a generic subset of our sample, including 5 countries and 4 sectors. Column ($\zeta_j^{(3)}$) depicts the country-specific differences in man-

Table 2.9 Empirical Bayes predictions for random intercepts at the country ($\zeta_j^{(3)}$) and sector ($\zeta_{ij}^{(2)}$) level for selected countries and sectors.

Country	Sector	$\zeta_j^{(3)}$	$\zeta_{ij}^{(2)}$
JPN	Food products, beverages and tobacco	-.0003729	.0091451
JPN	Textiles, wearing apparel, leather and related prodcuts	-.0003729	-.0270934
JPN	Machinery and equipment n.e.c.	-.0003729	.0098785
JPN	Transport equipment	-.0003729	.0162428
USA	Food products, beverages and tobacco	-.0126817	.0105832
USA	Textiles, wearing apparel, leather and related prodcuts	-.0126817	-.0349687
USA	Machinery and equipment n.e.c.	-.0126817	.0005279
USA	Transport equipment	-.0126817	.000204
GBR	Food products, beverages and tobacco	-.0143465	.0093932
GBR	Textiles, wearing apparel, leather and related prodcuts	-.0143465	-.0378379
GBR	Machinery and equipment n.e.c.	-.0143465	-.0120717
GBR	Transport equipment	-.0143465	.0080854
DEU	Food products, beverages and tobacco	.005646	.0128722
DEU	Textiles, wearing apparel, leather and related prodcuts	.005646	-.0225406
DEU	Machinery and equipment n.e.c.	.005646	.0088118
DEU	Transport equipment	.005646	.0112581
ESP	Food products, beverages and tobacco	.0006859	.0035219
ESP	Textiles, wearing apparel, leather and related prodcuts	.0006859	-.0198551
ESP	Machinery and equipment n.e.c.	.0006859	.0053966
ESP	Transport equipment	.0006859	-.0053132

ufacturing employment growth. While the United States and Great Britain exhibit a country-specific downward deviation of the population mean, the opposite can be observed for Germany. However, the country-specific deviations from the population mean are moderate, ranging from -.014 for Great Britain to .010 for Italy. The differences with regard to the sector-specific random effects are somewhat larger, ranging from -.038 in the British textiles sector to .023 in the Swedish coke and refined petroleum products sector. Employment growth generally underperforms in the textiles sector, resulting in a negative sector-specific random intercept in each country of the analysis. Some sectors, e.g. food, beverages and tobacco or machinery and equipment, usually outperform other sectors with regard to the sector-specific random intercept.

Figure (2.7) illustrates the empirical Bayes predictions for the random effects at the country (level-3) and the sector (level-2) level as well as the predicted level-1 residuals. Each figure features the assumption of a normal sampling distribution in linear mixed models. The distribution of the predicted level-1 residuals (ϵ_{ijt}) seems to be leptokurtic,

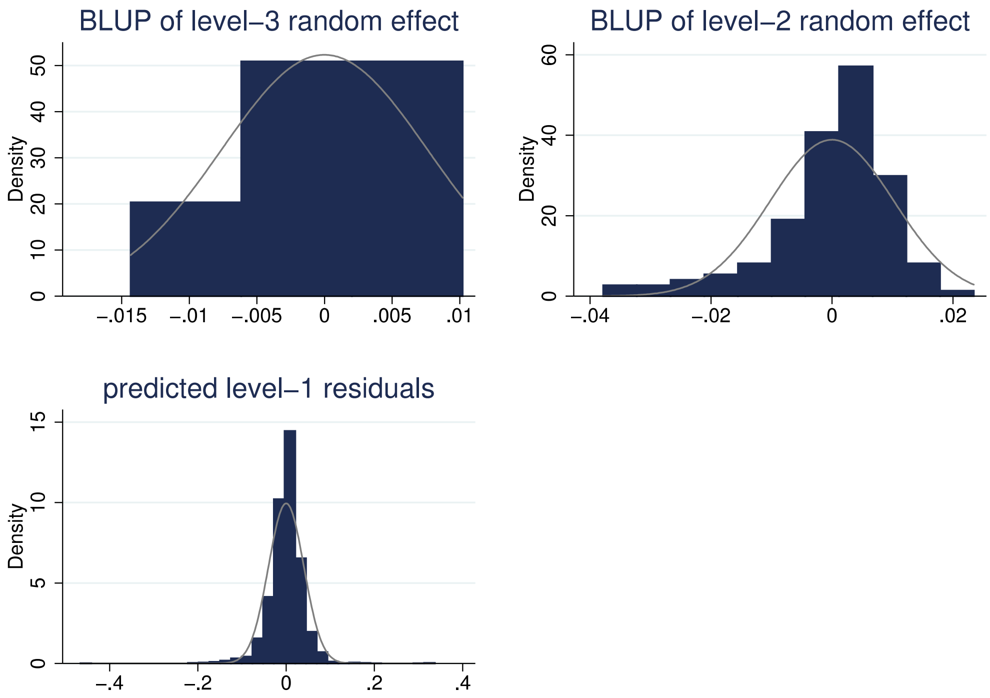

Figure 2.7 Best linear unbiased predictions for random intercepts at the country and the sector level, and level-1 residuals at the time level.

since the peak of the distribution is higher than expected for a normal distribution. The distribution of the predicted level-2 random intercepts ($\zeta_{ij}^{(2)}$) shows signs of left skewness, while a Jarque-Bera test rejects the null of normality. The predicted country-level random effects ($\zeta_{j}^{(3)}$) do not follow a normal distribution either, although a Jarque-Bera test does not reject the null hypothesis. However, this may be due to the low number of 12 observations at the country level, as the test is only valid asymptotically and relies on a large sample size. As normality cannot generally be assured, it may be useful to employ robust standard errors that do not rely on the model being correctly specified. While REML is not supported with robust variance estimation, ML estimations allow for robust standard errors (see Table (2.14) in the appendix).

In a further robustness check, we re-estimate the baseline specification without a country-level random intercept because only a small part of the variation of *EMP_GR* stems from this level. The subsequent model consists of two hierarchical levels with observation periods as level-1 and industries as level-2, using country dummies to account for differences between countries. Column (1) of Table (2.10) provides results indicating

Table 2.10 The effect of trade on manufacturing employment, two-level mixed estimations. Dependent variable is employment growth *EMP_GR*.

	(1)	(2)	(3)	(4)
level-2 random intercept:	SECTOR	COUSEC	SECTOR	COUSEC
TFP	-0.0172**	-0.0164**	-0.0172***	-0.0165
	(0.00735)	(0.00749)	(0.00626)	(0.0126)
$\text{Log}(\text{GDP}_{pc})$	-0.0658***	-0.0658***	-0.0658***	-0.0658***
	(0.0120)	(0.0119)	(0.0116)	(0.0186)
FERT	-0.0849***	-0.0850***	-0.0849***	-0.0850***
	(0.0159)	(0.0157)	(0.0165)	(0.0209)
HC	-0.0195	-0.0193	-0.0195*	-0.0193
	(0.0190)	(0.0188)	(0.0100)	(0.0229)
PUB_SOCEXP	-0.00388***	-0.00388***	-0.00388***	-0.00388***
	(0.000903)	(0.000893)	(0.000608)	(0.00115)
III_B	0.00185*	0.00183	0.00185**	0.00185**
	(0.00104)	(0.00116)	(0.000845)	(0.000757)
RES_EXP	0.548***	0.547***	0.548***	0.547***
	(0.138)	(0.136)	(0.196)	(0.207)
EMP96	-0.000676	-0.000268	-0.000666	-0.000268
	(0.00225)	(0.00163)	(0.00261)	(0.00167)
N	1905	1905	1905	1905
Time Dummies	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. Columns (3) and (4) include robust standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

that the main findings remain unchanged. While imported intermediate inputs foster manufacturing employment growth in the 12 OECD countries, the technology variable (*TFP*) exerts a significantly negative influence on employment prospects. Column (2) alters the level-2 random intercept of the hierarchical model, employing a newly created variable which groups the country and the sector level (*COUSEC*). The results remain robust, though III_B becomes slightly insignificant. However, the grouped country-sector variable does not account for the correlation between country-sector combinations, as different industries from one country are treated as independent from one another. This assumption is unrealistic since, for example, the Swedish textiles sector is not uncorrelated with the Swedish transportation equipment sector, as they share the same country.

Columns (3)—(4) of Table (2.10) do not use REML, but rather apply a ML estimation to the two-level hierarchical model, including robust standard errors. Column (3) employs the same specification as Column (1), while Column (4) employs *COUSEC* as a level-2 random intercept. The findings are similar to those of Columns (1)—(2) and the baseline results, indicating a positive and weakly significant link between import penetration and manufacturing employment growth. Yet, the underlying problems concerning the two-level approaches and the fact that the likelihood-ratio tests favor a three-level hierarchical model support the choice of the model specification as in the baseline estimation.

2.5 Concluding remarks

A vigorous political debate about the role of globalization in labor market outcomes is currently in progress. The present chapter investigates the link between growing import penetration and manufacturing employment growth in 12 OECD countries between 1996 and 2011. Based on a variety of macroeconomic indicators from multiple recently collected datasets, the findings point to a positive and weakly significant impact of imported intermediate inputs on employment growth in the manufacturing sector which is robust to various model specifications, different import penetration measures, and alternative estimation strategies.

Additionally, we disaggregate the imported intermediates according to their country of origin and determine the impact of trade with particular countries on manufacturing employment growth. The results support previous findings that increasing import penetration from China exerts a significantly negative influence on employment growth in most specifications. A similar pattern can be observed for inputs from the new EU member states (EU-12), encouraging the notion that imports from China and the EU-12 substitute for domestic manufacturing production. In contrast, intermediates from the EU-27 appear to act as complements, thereby fostering employment growth in highly developed nations. Thus, whether imported intermediate inputs are conducive or detrimental to manufacturing employment growth in the OECD countries depends on the country of origin.

Employing a three-level mixed model allows us to ascertain the specific impact of the country and the sector level. While variation at both levels is rather low, a likelihood-ratio test rejects the null that a random intercept at the country and the sector level is 0. When determining the random part of the model, differences in the country and sector-specific random intercepts are moderate, with employment growth being relatively weak in the United Kingdom and the United States, as well as in the textiles sector. Otherwise, employment growth performs better in the food products, beverages and tobacco sector, as well as in Germany and Italy. Accounting for potential endogeneity leaves the results mainly unchanged, underlining the stability of the baseline findings.

This chapter offers a cross-nationally comparable analysis of the effect of growing import penetration on manufacturing employment growth in 12 OECD countries. The results indicate that there are different channels through which trade affects manufacturing employment, highlighting individuals' diverse attitudes toward globalization. To acquire a broader view of the trade-employment nexus from a macroeconomic perspective, future research should focus on enlarging the sample. Prospective studies may also extend this research question to the services sector, which is becoming increasingly more strongly connected with manufacturing and whose products are increasingly tradable. This may enable a comprehensive assessment of how countries adjust to growing international trade.

Appendix

Table 2.11 Country labels

ID	Country	Country Label
1	Sweden	SWE
2	Finland	FIN
3	Belgium	BEL
4	Japan	JPN
5	United States	USA
6	Netherlands	NLD
7	United Kingdom	GBR
8	Germany	DEU
9	Italy	ITA
10	Austria	AUT
11	France	FRA
12	Spain	ESP

Table 2.12 Sector labels

SEC_ID	Sector	Sector Label
5	Food products, beverages and tobacco	Food
6	Textiles, wearing apparel, leather and related products	Text
7	Wood and paper products; printing and reproduction of recorded media	Wood
8	Coke and refined petroleum products	Coke
9	Chemicals and chemical products	Chem
10	Rubber and plastics products, and other non-metallic mineral products	RPP
11	Basic metals and fabricated metal products, except machinery and equipment	BM
12	Electrical and optical equipment	Elec
13	Machinery and equipment n.e.c.	Mach
14	Transport equipment	Transp
15	Other manufacturing; repair and installation of machinery and equipment	Oth
40	Total manufacturing	Total

Table 2.13 Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	Obs.
EMP_GR	-0.018	0.044	-0.459	0.322	2024
TFP	0.019	0.121	-0.857	2.042	2057
Log(GDP$_{pc}$)	13.754	1.253	11.717	16.412	2244
FERT	1.606	0.259	1.16	2.12	2244
HC	2.993	0.251	2.597	3.619	2244
PUB_SOCEXP	24.103	4.592	14.077	32.391	2233
III$_B$	0.654	0.995	-5.176	12.229	2222
RES_EXP	0.152	0.026	0.11	0.194	2244
EMP96	5.15	1.559	1.053	7.997	2244
III$_R$	0.315	0.18	0.022	0.981	2244
III$_N$	0.223	1.076	-9.027	9.842	2219
TFP$\times$III$_B$	0.008	0.17	-3.456	5.676	2244
CAS$_{(t-1)}$	1.225	3.893	-9.676	9.343	1914
HS96	0.143	0.065	0.033	0.402	2244
EPL	2.122	0.74	0.26	2.88	2244
III$_B^{CHN}$	0.011	0.014	0	0.111	2244
III$_B^{BRIC}$	0.035	0.063	0.003	0.723	2244
III$_B^{EU27}$	0.329	0.708	-23.799	8.73	2244
III$_B^{EU12}$	0.016	0.024	0	0.595	2244
MANUF96	0.201	0.037	0.15	0.289	2244
RES_EXP$\times$III$_B$	0.129	1.231	-23.803	47.285	2244
RES_EXP^{CHN}	0.044	0.009	0.029	0.059	2244
RES_EXP^{BRIC}	0.244	0.049	0.178	0.318	2112
RES_EXP^{EU27}	0.068	0.016	0.048	0.101	2244
RES_EXP^{EU12}	0.103	0.024	0.071	0.168	2244

Table 2.14 The effect of trade on manufacturing employment, baseline regressions with robust standard errors. Dependent variable is employment growth *EMP_GR*.

	(1)	(2)	(3)	(4)	(5)
TFP	-0.0179	-0.0179	-0.0173	-0.0175	-0.0172
	(0.0166)	(0.0165)	(0.0163)	(0.0166)	(0.0163)
EMP96	-0.00206	0.00201	0.00195	0.00342	0.00211
	(0.00209)	(0.00340)	(0.00358)	(0.00384)	(0.00356)
III_B	0.00194	0.00173	0.00187		
	(0.00147)	(0.00145)	(0.00140)		
Log(GDP_{pc})		-0.00746*	-0.0115**	-0.0121**	-0.0105**
		(0.00418)	(0.00497)	(0.00562)	(0.00460)
FERT		-0.0368***	-0.0454***	-0.0472***	-0.0395***
		(0.00917)	(0.0154)	(0.0170)	(0.0128)
HC		0.0145	0.0152	0.0130	0.0144
		(0.0142)	(0.0190)	(0.0208)	(0.0169)
PUB_SOCEXP			-0.00138	-0.00167	-0.000931
			(0.00114)	(0.00120)	(0.000978)
RES_EXP			0.430	0.427	0.426
			(0.333)	(0.323)	(0.349)
III_R				0.0322	
				(0.0286)	
III_N					-0.000104
					(0.000447)
N	1905	1905	1905	1925	1903
Time Dummies	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.15 The effect of trade on manufacturing employment, baseline regressions with lagged covariates. Dependent variable is employment growth *EMP_GR*.

	(1)	(2)	(3)	(4)	(5)
TFP	-0.0176**	-0.0178**	-0.0175**	-0.0171**	-0.0174**
	(0.00746)	(0.00746)	(0.00745)	(0.00740)	(0.00745)
EMP96	-0.00251	0.00291	0.00280	0.00469	0.00314
	(0.00184)	(0.00285)	(0.00289)	(0.00303)	(0.00289)
$\text{III}_{B(t-1)}$	-0.0000272	-0.0000194	-0.0000194		
	(0.000193)	(0.000193)	(0.000192)		
Log(GDP_{pc})		-0.00857***	-0.0109***	-0.0115***	-0.0108***
		(0.00329)	(0.00376)	(0.00408)	(0.00369)
FERT96		-0.0297***	-0.0297**	-0.0283*	-0.0293**
		(0.00985)	(0.0123)	(0.0148)	(0.0118)
$\text{HC}_{(t-1)}$		0.0125	0.0118	0.00949	0.0118
		(0.00931)	(0.0110)	(0.0123)	(0.0107)
PUB_SOCEXP			-0.000846	-0.00115*	-0.000740
			(0.000593)	(0.000646)	(0.000578)
RES_EXP			0.313***	0.293**	0.315***
			(0.118)	(0.118)	(0.118)
$\text{III}_{R(t-1)}$				0.0353**	
				(0.0145)	
$\text{III}_{N(t-1)}$					0.00000362
					(0.0000304)
N	1905	1905	1905	1925	1903
Time Dummies	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.16 The effect of trade on manufacturing employment, baseline regressions, different dependent variables.

	(1)	(2)	(3)	(4)	(5)	(6)
TFP	-0.0168**	-0.0171**	-0.0174**	-0.0302	-0.000314**	-0.000471**
	(0.00740)	(0.00740)	(0.00723)	(0.0211)	(0.000128)	(0.000194)
$\text{Log}(\text{GDP}_{pc})$	-0.0181***	-0.0146***	-0.0124***	-0.0763**	-0.000621***	-0.00141***
	(0.00516)	(0.00449)	(0.00384)	(0.0303)	(0.000162)	(0.000247)
FERT	-0.0616***	-0.0360***	-0.0350***	0.0800**	-0.0000737	-0.000772**
	(0.0127)	(0.0114)	(0.00939)	(0.0406)	(0.000243)	(0.000369)
HC	0.0130	0.00729	0.0194*	0.137***	0.000839***	0.00194***
	(0.0148)	(0.0134)	(0.0109)	(0.0484)	(0.000286)	(0.000435)
PUB_SOCEXP	-0.00261***	-0.00223***	-0.000481	-0.0138***	-0.000119***	-0.000148***
	(0.000777)	(0.000717)	(0.000577)	(0.00213)	(0.0000128)	(0.0000195)
III_B	0.00191*	0.00199*	0.00190*	0.00614*	0.0000510**	0.0000722**
	(0.00109)	(0.00109)	(0.00104)	(0.00343)	(0.0000208)	(0.0000316)
EMP96	0.00191	0.00208	0.00329			
	(0.00292)	(0.00292)	(0.00286)			
RES_EXP	0.489***	0.446***	0.164*	-2.947***	-0.0209***	-0.0328***
	(0.126)	(0.123)	(0.0960)	(0.291)	(0.00175)	(0.00267)
N	1905	1905	2015	2037	2037	2037
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses. The dependent variables are as follows: *EMP_GR* in Column (1), growth of total employment in Column (2), growth of the employment-to-population ratio in Column (3), the logarithm of total employment in Column (4), the employment-to-population ratio in Column (5), and the employment-to-working-age-population ratio in Column (6). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.17 The effect of trade on manufacturing employment, sensitivity analysis for single countries, different import penetration measures. Dependent variable is employment growth *EMP_GR*.

	DEU	FRA	ESP	ITA	DEU	FRA	ESP	ITA
III_B^{CHN}	0.217	-1.427***	-1.722***	-0.630				
	(0.207)	(0.538)	(0.583)	(0.724)				
III_B^{EU12}					-0.0798	-1.692**	-1.276*	0.216
					(0.243)	(0.799)	(0.657)	(0.661)
N	154	154	154	154	154	154	154	154

Notes: Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Chapter 3

Determinants of governmental redistribution: Income distribution, development levels, and the role of perceptions

Preliminary remarks:[8] The previous chapter showed that an increase in imported intermediate inputs fosters employment growth in the manufacturing sector. The reason for that is that globalization increases market opportunities in advanced economies with higher job growth that compensates for employment losses through trade and offshoring. Furthermore, a majority of imported intermediates tend to be complementary to domestic production, which is why an increasing number of foreign inputs enhances manufacturing employment growth in highly developed countries. The results also indicate that the labor market effects depend on the intermediate inputs' country of origin. Thus, globalization produces winners and losers, increasing the demand for social security and redistribution.

This chapter analyzes the determinants of governmental redistribution, thereby examining the role of inequality, income distribution, development levels, and perceptions. The investigation opens with the hypothesis developed by Meltzer and Richard (1981),

[8]This chapter is based on joint work with Klaus Gründler and has been published as Gründler and Köllner (2016).

assuming a political economy channel to be the driver of the inequality-redistribution nexus. At first glance, the size of the welfare state has heavily increased in advanced economies with higher sophistication of political rights during the last decades, while the amount of redistribution has remained comparatively low in most parts of Asia, Africa, and Latin America, which all exhibit lower levels of political rights. The findings of this chapter imply that it is through the political channel that higher inequality translates into higher redistributional activities of the government.

3.1 Introduction

What determines the extent of redistribution? The well-known Meltzer and Richard (1981) model applies the median voter theorem, originally developed by Downs (1957) and Hotelling (1929), to the field of inequality and redistribution. In a majority-voting framework, the Meltzer-Richard hypothesis predicts that a higher level of inequality leads to greater demand for redistribution that translates to an expansion of the welfare system. Although the theoretical basis of the Meltzer-Richard model is profound and broadly accepted, the empirical findings are far from consistent. A significant and positive relationship between inequality and redistribution is found by Milanovic (2000) and Scervini (2012), while other studies observe a negative link (Georgiadis and Manning, 2007), no significant relationship (Kenworthy and McCall, 2008; Gouveia and Masia, 1998), or multiple steady states (Bénabou, 2000).

So far, two main problems have impeded research on the inequality-redistribution nexus. First, earlier studies often rely on rough measures of redistribution. However, the extent to which specific fiscal policy instruments are actually redistributive often remains unclear. Second, truly comparable cross-national data on income inequality has long been rather scarce.

Although comparability and quality of the LIS Cross-National Data Center are unparalleled among cross-national inequality data, the calculations which use a uniform set of assumptions and definitions on the basis of harmonized micro data result in a limited data coverage of only 232 country-years for which net inequality is available. While this limitation hampers research on inequality based on a broad panel of countries, the incorporation of a larger set of observations typically comes at the cost of sacrificing the benefits of comparability. Fortunately, some major progress has been made in cross-national inequality datasets in recent years, particularly with regard to the World Income Inequality Database (WIID) and the Standardized World Income Inequality Database (SWIID). The latest update of the SWIID to version 5.0 now includes 174 countries from 1960 to present, enabling acquisition of roughly 4,600 country-year observations that are comparable to those obtained by the LIS. Unlike previous data collections, the clear distinction between inequality before and after taxes and transfers allows for computation of a direct measure of redistribution via the "pre-post" approach. The large data coverage also permits inclusion of developing countries in the empirical analysis. However, as data quality in the SWIID varies across different country groups and periods, such analyses require careful treatment of the data. To account for the uncertainty in the SWIID data, we compare our baseline results with regressions based on multiple imputations and estimates that rely on the WIID data. For additional robustness checks, we employ further proxies for redistribution, including parameters of structural tax progressivity and transfer payments.

We make use of recent advances in data availability by examining the Meltzer-Richard hypothesis on a broad basis. In doing so, the contribution of this chapter is threefold. First, we empirically investigate the redistribution-inequality nexus for a cross-nationally comparable dataset built entirely on national micro data. The analysis also includes the effect of different shapes of income distributions. The intuition of this strategy is that inequality may be driven by top or bottom income earners, yielding varying effects on redistribution due to different political influence of these groups. Second, we enlarge the sample and analyze the Meltzer-Richard effect in a broad panel of countries, thereby accounting for different development levels and varying sophistication of political rights. Finally, we elucidate the role of perceptions, illustrating that it is not the actual, but rather the subjective level of inequality that determines demand for redistribution.

In a majority-voting model, groups other than the median voter should exert only negligible influence on redistribution. In practice, however, top incomes may be reluctant to support redistribution while the bottom decile of the income distribution typically benefits from a more expansive welfare system. To lower the financial burden through redistribution, top incomes might engage in rent-seeking behavior. Some studies (Scervini, 2012; Bassett et al., 1999) state that de facto political power may be above the median, as higher income levels devote additional resources towards campaign contributions. Additionally, Rosenstone and Hansen (1993) show that political participation increases with income and education. This may also explain why rationally-acting politicians have an incentive to refrain from focusing on bottom-income voters (Blais, 2000; Norris, 2002). In contrast, redistribution via the unemployment system may benefit the lowest incomes disproportionately if labor market conditions affect redistributional activities of policymakers (Scervini, 2012).

In democracies, the relationship between market income inequality and redistribution is stronger than in authoritarian regimes (Perotti, 1996). As gaining votes does not play a significant role in policy making in non-democratic regimes, governments can ignore preferences of poorer voters (Milanovic, 2000). Empirical evidence regarding the impact of democracy on redistribution is, however, somewhat inconclusive. While Persson and Tabellini (1994) emphasize the importance of democratic institutions, Scervini (2012) confirms the findings of Alesina and Rodrik (1994) and Perotti (1996) indicating that democracy does not have a significant influence on redistribution. Acemoglu et al. (2015) refer to the fact that different institutional regimes have varying effects on redistribution depending, inter alia, on the stage of development.

Recent investigations further emphasize that individuals often hold erroneous beliefs about income inequality. Previous research focused on biased perceptions of inequality within a country or in the cross-section. Cruces et al. (2013) explore the perceptions of individuals in a micro study from Argentina and observe systematic biases in individuals' perceptions of their own relative position in the income distribution. Likewise, Norton and Ariely (2011) and Chambers et al. (2014) show that perceptions on the level of income and wealth inequality in the United States are heavily distorted. Fernández-Albertos and Kuo (2016) employ data from a web-based survey in Spain and find that only 14 percent of the participants correctly assigned themselves to the decile in the income distribution to which they actually belong. Further studies (Niehues, 2014; Engelhardt and Wagener, 2014; Gimpelson and Treisman, 2015) use data from the International Social Survey Programme (ISSP) on self-assessment by individuals concerning their position on the income scale to compare actual and perceived inequality across countries. They provide some evidence that the Meltzer-Richard effect may be less pronounced when examining actual inequality, but may increase if perceived inequality measures are analyzed, implying that it may be the perception of the electorate rather than objective data that drives the demand for redistribution. In this chapter, we follow earlier approaches, compiling subjective inequality measures based on the ISSP and the World Value Survey (WVS). Owing to recent advancements in data availability, our study provides a first attempt to explore the effect of perceptions on redistribution in a panel context.

Our findings point to a positive and significant link between market inequality and redistribution in the OECD countries. The results are robust to several model specifications and various sample compositions as well as distinct measures of income inequality and different social security and pension systems. Whereas the baseline estimations study the effect of officially reported market inequality, perceived inequality measures highlight an even larger impact. If citizen-voters consider the income distribution to be highly unequal, there may be strong demand for redistribution, even if "real" market inequality is moderate or low. Conversely, if voters are not aware of the "true" extent of inequality, demand for redistribution may be lower than that induced by the actual distribution of incomes.

Moreover, the chapter provides robust evidence that the shape of the income distribution is highly relevant for redistributional issues of the government. While the middle class exerts a significant influence on the amount of redistribution, we do not find any such impact for individuals at the bottom of the income distribution. Rather, our results reveal that top incomes in a society impede redistribution. These findings indicate that it is not the poor, but rather the rich, who play a crucial role in redistributional activities of the government.

It turns out that the Meltzer-Richard effect—while prevalent in the whole sample estimations—cannot be observed in developing countries. In fact, the robust positive effect of market inequality on redistribution stems mainly from advanced economies. This implies that market inequality hardly influences redistributional issues when democratic structures have not yet evolved. An increase in the level of development typically coincides with greater democratic rights, leading to a significant impact of market inequality on redistribution. As a consequence, the Meltzer-Richard effect becomes incrementally important with an increasing development level.

A growing body of the political economy literature points to further channels beyond Meltzer and Richard (1981), in particular focusing on the insurance motive (Varian, 1980; Moene and Wallerstein, 2001, 2003). While wielding influence on redistribution, this motive is more than canceled out by the effect of inequality.

The chapter is structured as follows. Section (3.2) offers a description of the data and discusses the underlying empirical strategy. Section (3.3) outlines the main results for various sample compositions and extends the analysis for different development levels and perceptions. The final section concludes.

3.2 Empirical strategy

3.2.1 Data on redistribution

For our analysis, we are particularly interested in data concerning inequality and redistribution. To measure inequality, we use the Gini coefficient, which gauges personal income inequality between households. Depending on the income concept used to build this measure, we can distinguish between the Gini of incomes before ("market Gini") and after ("net Gini") taxes and transfers. Differences between these variables are the result of governmental interventions. Thus, redistribution can be measured as the difference between market and net inequality, i.e.

$$\mathrm{REDIST}_{it} = \mathrm{GINI(M)}_{it} - \mathrm{GINI(N)}_{it} \tag{3.1}$$

where GINI(M) and GINI(N) denote market and net Ginis, and REDIST is the amount of redistribution in country $i = 1, \ldots, N$ at time $t = 1, \ldots, T$. This measure is often referred to as the "pre-post-approach" (see Lupu and Pontusson, 2011; Van den Bosch and Cantillon, 2008 for a detailed discussion). A related measure that reflects assessment of the *relative* reduction in market inequality can be computed via

$$\mathrm{REDIST}_{it}^{\mathrm{rel}} = \frac{\mathrm{GINI(M)}_{it} - \mathrm{GINI(N)}_{it}}{\mathrm{GINI(M)}_{it}}. \tag{3.2}$$

Unlike other macroeconomic statistics where researchers may be reasonably confident that series are constructed consistently across national statistical offices, the definitions and assumptions used for compilation of inequality series often vary substantially across countries (Atkinson and Brandolini, 2001). Owing to inadequate official statistics of inequality, researchers and international institutions have compiled a number of secondary datasets that seek to provide comparable country-year estimates of summary measures of income distributions. The gold standard of these collections is the database of the LIS Cross-National Data Center.[9] While comparability and quality of the LIS data are unparalleled, the calculation of inequality measures based on harmonized micro data including a uniform set of assumptions and definitions restricts data availability. The net inequality series in the LIS currently covers 232 country-year-combinations with data from 41 countries, seven of which are each represented by only one observation. This limitation makes cross-country analysis based on a broad panel an impossible task and is also an impediment to implication of dynamic panel data techniques, which require a sufficient lag structure. The incorporation of a larger number of country-years, however, typically comes at the cost of sacrificing the benefits of comparability and harmonization. Atkinson and Brandolini (2001) review the pitfalls encountered in the utilization of secondary datasets, concluding that simple adjustments for the differences in definitions are often not sufficient to ensure comparability.

Two data collections have been particularly successful in providing cross-national data

[9] Even the LIS has recently been subject to some criticism (see the dispute between Ravallion, 2015 and Gornick et al., 2015).

with global coverage for relatively long time spans. These are the “World Income Inequality Database” (WIID) provided by UNU-WIDER (2014) and the “Standardized World Income Inequality Database” (SWIID) compiled by Solt (2009, 2016). An intense discussion has arisen on whether to use the WIID or the SWIID for cross-country analyses on inequality. As Jenkins (2015) argues, any researcher employing cross-national income inequality data needs to acknowledge the benefit-cost trade-off and has to ensure that any analytical conclusions drawn are in accordance with the underlying data concept. In our case, there are some strong arguments advocating for the utilization of the SWIID. First, in light of the divergence of the inequality datasets at hand, the data used must be appropriate for the underlying research topic (see Solt, 2015; Atkinson and Brandolini, 2009). The provision of both gross and net Gini indices based on comparable welfare definitions enables calculation of redistribution according to Equation (3.1) that is consistent across countries. Second, while the revised version 3.0 A of the WIID from 2014 brings about a substantial expansion in the coverage of Gini indices—therefore enabling calculation of effective redistribution for some country-years—it does so with significantly reduced scope compared to the SWIID. This particularly applies to developing economies, where only a few country-years include market *and* net Ginis.

As with any cross-national inequality dataset, the SWIID represents a particular choice in the balance between comparability and coverage. While it may not be the most appropriate choice for all research on income inequality—especially if researchers are interested in changes in inequality over time in a single country—, the maximization of comparability for the broadest possible coverage of country-years makes the SWIID an advantageous choice for redistribution studies based on broad panel estimation (see Acemoglu et al., 2015).

Our analysis relies on data on market and net inequality from the SWIID 5.0, made available in October 2014. The SWIID seeks to maximize comparability by using the LIS series as baselines and filling in the missing observations via generation of model-based multiple imputation estimates derived from source data. Altogether, the SWIID provides 100 multiple imputation estimates for each country-year, which can be used to form point estimates of inequality by averaging the individual estimates or can be employed in MI regression models. Whereas earlier versions of the SWIID are entirely based on the WIID, version 5.0 utilizes over ten thousand Gini coefficients from national statistical offices, scholarly articles, Eurostat, the OECD, SEDLAC, Deininger and Squire (1996), as well as Milanovic (2014). Some concerns have been raised with regard to the multiple imputation procedure of version 4.0 of the SWIID (Jenkins, 2015). However, version 5.0 has addressed many of these issues.[10] Both the coverage and comparability of the SWIID exceed those of alternative inequality data collections.[11] Since its introduction in 2008, the SWIID has expanded considerably over time. In version 5.0 it covers 174 countries from 1960 to 2013 with estimates of net income inequality comparable to those obtained from the LIS Key Figures for 4,631 country-years, and estimates of market income inequality for 4,629 country-years. The standardization process of the SWIID is described in Solt (2016).

We calculate REDIST as the difference between market and net Ginis as they appear in the SWIID. While utilization of all possible information in the SWIID allows for acquisition of a large set of country-years, caution is advised when interpreting this measure. The SWIID algorithm uses estimates for some of the data on gross or net income inequality, which is why in some cases the difference between both measures contains little information about country specific redistribution.[12] To address this problem, the SWIID reports a subsample of redistribution data which only consists of country-years for which micro data on net and gross inequality is available. This sample further discards observations from low-income countries before 1985 and from high-income countries be-

[10]This particularly applies for the sorting of the source data into several categories, defined by the combination of welfare definition and equivalence scale used in their calculation. In addition, as Solt (2015) emphasizes, most of the remaining arguments are hardly tenable with respect to version 5.0 of the SWIID.

[11]"All the Ginis" from Milanovic (2014) and the WIID 3.0 A cover less country-year observations than the SWIID, particularly with regard to the distinction between net and gross Gini indices. In addition, Milanovic (2014) stresses the incomparability of the observations included in his dataset and provides a series of dummy variables to account for the underlying income and household concept in order to calculate the Gini indices.

[12]Note, however, that the SWIID 5.0 avoids global fixed adjustments, as Atkinson and Brandolini (2001) highlight that differences between welfare definitions vary across countries and over time. Rather, the adjustments utilized in the SWIID vary over time and space as much as possible given the underlying data. A precise description of the multiple imputation procedure and a detailed documentation of the number of countries for which adjustments vary can be found in Solt (2015, 2016).

fore 1975. Coverage of this subsample—which we denote as REDIST(S)—includes 2,030 country-years. Whenever feasible, we rely on the high-quality observations included in REDIST(S). As a consistency check of our results, we also run a sensitivity analysis based on the WIID data.

While computation of redistribution in accordance with the pre-post approach has only recently found its way into the field of economics, it is very common in the sociological and public policy literature.[13] The huge advantage of the method is that it yields a measurement of *effective* redistribution, highlighting the *results* of redistributional activities by the government rather than the *effort* by which the result has been achieved. Owing to the limited availability of net and market Ginis in the past, some previous studies have employed indirect measures to proxy redistribution, such as average or marginal tax rates and different types of social spending. Yet such measures provide only a rough estimate of the extent of redistribution, as it remains unclear to what extent such fiscal policy instruments are actually redistributive. Figure (3.12) in the appendix shows the relationship between REDIST and social transfer payments. Both variables are positively correlated, indicating that a higher level of REDIST coincides with a more expansive social security system. However, the R-squared of a bivariate regression of transfer payments on REDIST is only .33, which underscores our argument that social spending alone is insufficient to properly model redistribution.

Three methodological notes shall be made: First, as a measure of effective redistribution via taxes and transfers, REDIST does not include in-kind provision of public goods. Like most inequality databases, the SWIID is based on surveys covering household disposable income, which do not capture individual consumption of public goods. Second, the pre-post approach does not cover public attempts to equalize market inequality, neither by the promotion of equal opportunities nor by state intervention in private wage agreements. Third, a potential weakness of the pre-post approach is that the level of gross inequality is not necessarily independent of the extent of public redistribution (see Bergh, 2005). On the upper end, taxes may reduce the labor supply of high-income earners, thus

[13] Van den Bosch and Cantillon (2008) provide an overview of the role of the pre-post approach in measuring the redistributive impact of taxes and transfers.

mitigating gross inequality. On the lower end, however, a generous welfare system may provide incentives for the poor to withdraw from the labor market and to live on transfers rather than relying on labor incomes. In line with Ostry et al. (2014), we suggest that the influence of redistribution on market inequality may be not essential, as both effects are—to some extent—offsetting. One way to mitigate the problems arising from potential second-order effects is application of relative redistribution measures. By division of REDIST by the pre-tax pre-transfer distribution of market income, $\mathrm{REDIST}^{\mathrm{rel}}$ also captures feedback effects of redistributive policies. To assess stability of the results, we also report the outcomes based on $\mathrm{REDIST}^{\mathrm{rel}}$ routinely for each estimation.

3.2.2 Redistribution and inequality across countries

How much redistribution can be observed in the countries available in the SWIID? Figure (3.1) illustrates the histogram and the kernel density of REDIST(S) and $\mathrm{REDIST(S)}^{rel}$ using 5-year averages. In fact, inequality turns out to be very persistent in the data, where the variation between countries is more than twice as high as the variation within countries. In addition, averaging the data is necessary in the subsequent empirical analysis to eliminate cyclical fluctuations in some of the covariates and to estimate long-term rather than short-term effects.

The mean difference between the market and the net Gini in the sample is 9.65. However, the standard deviation of REDIST(S) is high (7.35), pointing to substantial variations in the amount of redistribution across countries. Some nations with a generous social security system redistribute more than 20 Gini points, while redistributive efforts in other countries are considerably less pronounced. D'Agostino's K-squared test rejects the assumption of a normal distribution.[14] Rather, the kernel density suggests a bimodal distribution, where the largest part of the data is located around a moderate redistribution level, and a second mode refers to a substantially higher level of REDIST(S). A similar pattern can be observed with respect to our relative redistribution measure.

The data also reveals that countries tend to redistribute more if the average income

[14]We apply the version of D'Agostino's K-squared test published in D'Agostino et al. (1990) which corrects standard errors by the sample size.

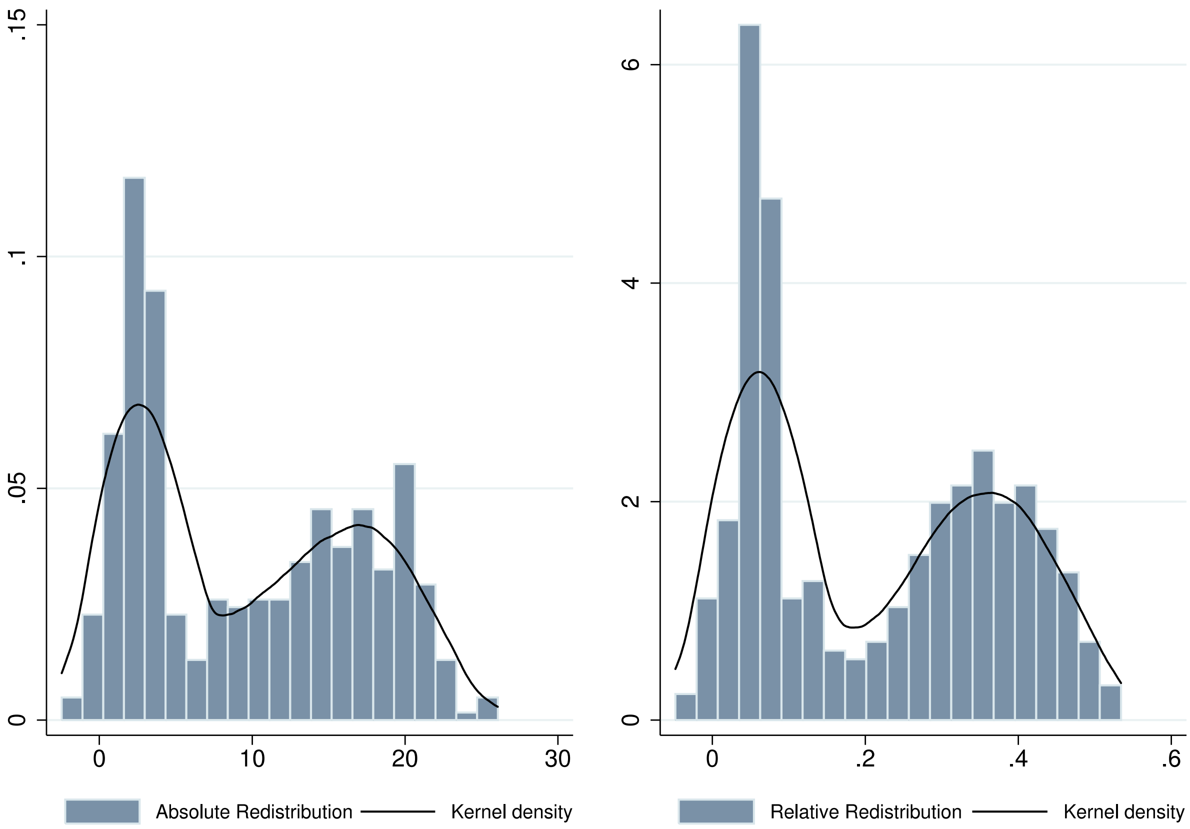

Figure 3.1 The distribution of the amount of absolute (REDIST(S), left panel) and relative (REDIST(S)^{rel}, right panel) redistribution across countries. Kernel is Epanechnikov.

level is higher. When classifying the countries according to the World Bank, the mean value of redistribution in advanced economies is 14.53 Gini points, which substantially exceeds the mean redistribution level of developing countries (4.28 with regard to REDIST(S) and 3.62 in the broader sample REDIST). Similar differences occur when considering relative redistribution (32.5 percent in high-income countries and 9.3 percent in the developing world). In addition, we observe a significantly higher amount of redistribution in democracies (14.61 Gini reduction) compared to countries with a non-democratic form of government (3.27).

Figure (3.2) illustrates the kernel density of the Gini coefficients before and after taxes and transfers, when all data from the broad sample of the SWIID is used. The mean value of the market Gini is 43.94 and is reduced to 38.91 after redistribution. However, the standard deviation of inequality after taxes and transfers is higher (11.14)

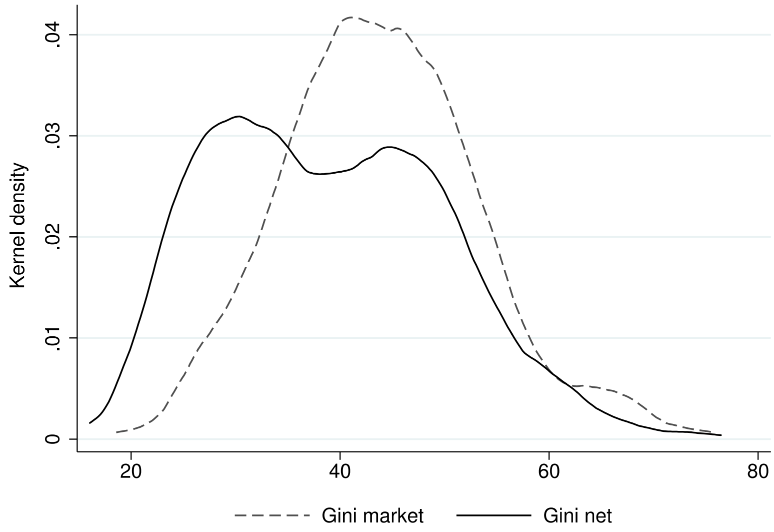

Figure 3.2 Kernel density of Gini coefficients before and after taxes and transfers, whole sample period. Kernels are Epanechnikov.

than before the redistributive intervention of the government (9.46). D'Agostino's K-squared test rejects the hypothesis that the net Gini is normally distributed, but it does not reject the null of normality of the market Gini. Redistribution policies apparently differ substantially across countries, transforming the unimodal distribution of the market Gini into a bimodal distribution with respect to the net Gini. Notably, whereas there are substantial deviations in net inequality between democracies and non-democracies, a similar pattern cannot be observed with regard to market inequality. In fact, the Gini coefficients of democracies (43.92) and non-democracies (43.22) are nearly equal. However, market inequality differs substantially with regard to the level of development, where low-income countries (46.03) are faced with a much higher level of inequality than advanced economies (39.97).

Figure (3.3) graphs the extent of redistribution for the United States, Germany, Sweden, and Italy, as well as the OECD average (dashed line). The extent of market inequality has developed quite similarly during the past 30 years, even though the design and scope of social security models differ considerably between these countries (Sapir, 2006).[15] What is

[15]Note, however, that market inequality is not independent from the social security system in place as emphasized by Gornick and Milanovic (2015). They point to the fact that excluding households above the age of 60 results in different levels of market inequality, since the share of older people in the labor force varies significantly between countries. Unfortunately, data on market inequality by age is not available for a broad cross-country sample.

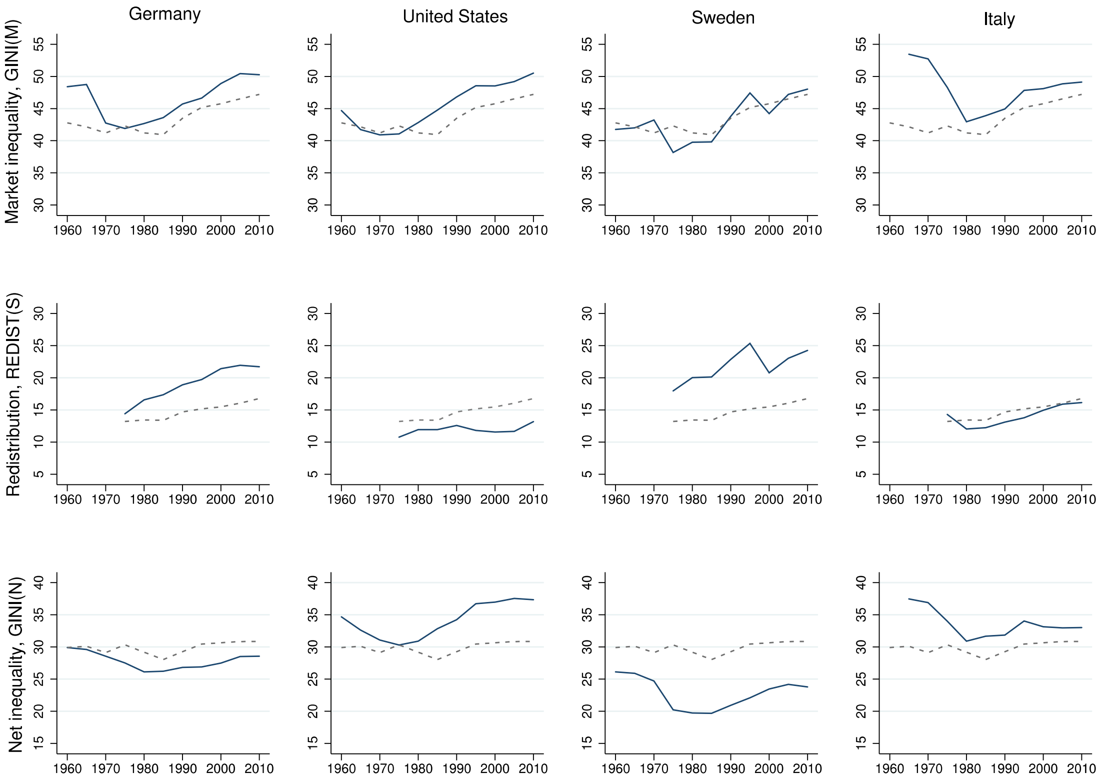

Figure 3.3 The development of market and net inequality and the level of redistribution in the United States, Germany, Sweden, and Italy. The graph uses REDIST(S), the sample for which micro data on net and market inequality is available. The dashed lines represent the OECD average.

striking about this development is the sharp increase in market inequality that has begun in the early 1980s and that affected each of the countries in an equal manner. Moreover, a similar increase is visible if we take into consideration the average of all OECD countries. These findings suggest that market inequality is to some extent driven by multinational trends such as technological progress and globalization (see, e.g., Autor et al., 2015).

The redistributional response to the increase in market inequality, however, differs substantially between the countries depicted in Figure (3.3). Government-induced inequality reduction is particularly strong in Sweden (24.25 Gini points in the post-2010 period) and Germany (21.72), where a stark increase is to be observed during the past decades. This increase is considerably above the average of the OECD nations. Both Germany and Sweden possess expansive social security systems, which is why we would expect REDIST(S) to assume relatively high values. The picture changes if we look at the United States and Italy, two countries with average income levels comparable to those of Germany and

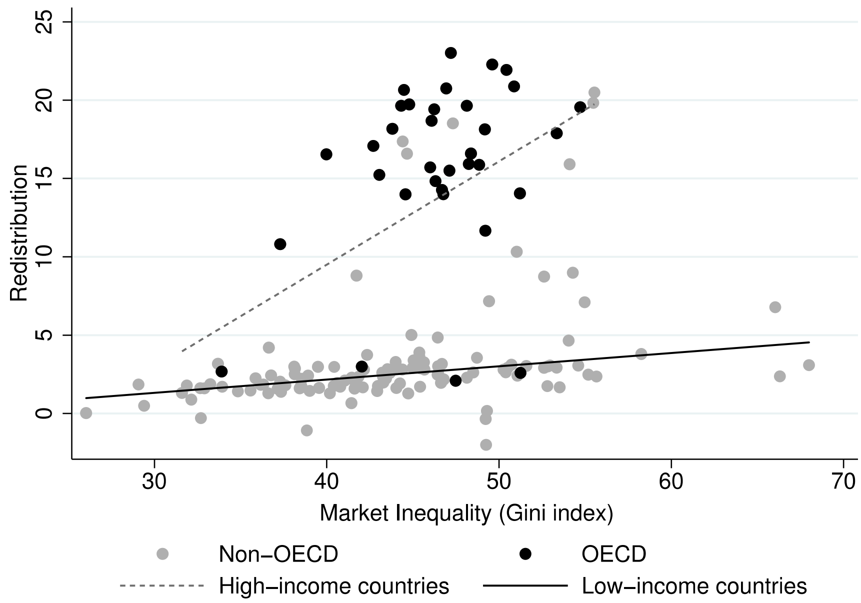

Figure 3.4 The relationship between market inequality and redistribution, period 2010-2013. "High-income countries" and "Low-income countries" illustrate the regression lines between market inequality and redistribution in the subsamples of advanced and developing economies, respectively. Country classification refers to the World Bank. OECD member states are labeled with "OECD".

Sweden. Due to their less generous public health and unemployment insurance systems, the observable redistributive efforts are substantially lower. This exemplifies the large deviations among the OECD member states: While the average level of redistribution in the post-2010 period (16.77 Gini points) was significantly above the world average (8.17), the standard deviation was only slightly smaller (5.53 Gini points in the OECD and 7.74 in the world).

At first glance, a bivariate analysis of the link between the market Gini and the amount of redistribution reveals no robust relationship (see Figure 3.4). When taking the level of economic development into account, however, the analysis points to a positive relationship between market inequality and redistribution in both the sample of low-income countries (correlation: 55.22 percent) and the sample of advanced economies (39.87). What distinguishes these groups from one another is that high levels of market inequality in developing economies are accompanied by a much lower degree of redistribution compared to advanced countries. This underlines that the relationship between inequality and redistribution has to be examined while holding constant some crucial variables that distinguish the countries. In particular, Figure (3.4) emphasizes that political institutions crucially affect the Meltzer-Richard hypothesis: Most of the OECD countries with sophisticated institutions and comparatively high levels of political rights tend to redistribute considerably more than non-OECD nations. Exceptions from that general rule are Chile, Mexico, Turkey and the Republic of Korea.

3.2.3 Empirical model and estimation technique

To estimate the determinants of redistribution and to achieve a deeper understanding of the relationship between inequality and redistribution, we assume REDIST to be a function

$$\mathrm{REDIST}_{it} = F(\mathrm{REDIST}_{it-1}, \mathrm{GINI(M)}_{it}, \mathbf{X}_{it}, \eta_i, \xi_t), \tag{3.3}$$

where $i = 1, \ldots, N$ denotes countries, $t = 1, \ldots, T$ is the time index with t and $t-1$ five years apart, ξ_t is a specific effect of period t, and η_i is a country-specific effect which accounts for unobserved heterogeneity. Equation (3.3) specifies that redistribution in t depends on its level in $t-1$, incorporating path dependencies in the model. The idea is that institutions, once established, are typically difficult to reform in the short to medium term (Acemoglu et al., 2015). The high degree of persistency of REDIST(S) observable in Figure (3.3) provides support for this view. $\mathbf{X}_{it}$ captures a variety of control and environment variables and includes a number of determinants that we assume to have an effect on the level of redistribution. These determinants comprise the development level of the economy, which we include via the logarithmic value of real per capita GDP, denoted by $\log(\mathrm{GDP}_{pc})$. We further incorporate an index of political rights (POLRIGHT) to account for the differences in redistribution between democracies and non-democracies. The analysis also includes the logarithm of the fertility rate, denoted by log(FERT). With the income level held constant, higher fertility rates imply a more binding budget constraint for the household, which may influence the redistributional efforts of the government. The labor market enters into the regression using the unemployment rate (UNEMP). In a subsequent step, we analyze the impact of different socio-economic groups on the extent of redistribution, dependent upon their income level. This includes the income shares of the richest 1 percent (TOP-1), the lowest decile of the income distribution (BOTTOM-10), and the middle class. We model the middle class by employing two different concepts: the first (broader) concept MIDDLECLASS sums the income shares of the lower middle, middle, and upper middle quintiles of the income distribution, whereas the second (narrower) concept QUINT_3 only incorporates the middle quintile. The role of the public pension system in the redistribution process is analyzed by inclusion of AGE, the age dependency ratio of the population older than 64 to the working age population. Additionally, we enlarge the basic system in later sections by utilizing measures of perceived inequality.

Data concerning the development level, fertility, unemployment, age dependency, and the quintiles and deciles of the income distribution are extracted from World Bank (2016), POLRIGHT stems from Freedom House (2014), and TOP-1 is taken from SWIID 4.0, which is the latest version covering data on the income share of the top 1 percent. Due to potential concerns about the data quality of version 4.0 of the SWIID, we analyze robustness of our results using data on top incomes from the World Wealth and Income Database (WID), compiled by Alvaredo et al. (2015). In addition, as data regarding the shape of the income distribution is partly from World Bank and partly stems from the SWIID, Figure (3.13) in the appendix conducts a consistency check between inequality measures of both sources. This test highlights a high degree of comparability between the data.

Table (3.9) in the appendix provides descriptive statistics of the variables used in the empirical analysis, including their means, standard deviations, the number of observations, as well as their minima and maxima. The data implies a positive correlation between redistribution and the initial income level (61 percent), democracy (52 percent), market inequality (26 percent), and both measures of the middle class (49 percent in each case). In contrast, the top income share (-12 percent) is negatively related to REDIST and REDIST(S).

To more profoundly study the empirical determinants of redistribution, we consider the variables to be linked additively and transform Equation (3.3) into a 5-year panel data model to capture the long-term determinants of redistribution, which yields

$$\text{REDIST}_{it} = \vartheta \text{REDIST}_{it-1} + \alpha \text{GINI(M)}_{it} + \boldsymbol{\delta' } \mathbf{X}_{it} + (\eta_i + \xi_t + v_{it}), \tag{3.4}$$

where $v_{it} \equiv u_{it} - \xi_t - \eta_i$ is the idiosyncratic error term of the estimation and u_{it} is the error including time- and country-specific effects.

Using Within Group (WG) or Random effects (RE) estimations to account for unobserved heterogeneity in Equation (3.4) would yield a bias in the estimates, as RE requires by construction that $\text{Cov}[\eta_i, \text{REDIST}_{it-1}] = 0$ and $\text{Cov}[\eta_i, \mathbf{X}_{it-1}] = 0$, while the application of WG would lead to a correlation of the transformed error term and the time-demeaning transformation of REDIST_{it-1} (Nickell, 1981). In order to circumvent these problems, the econometric literature has developed more reliable estimators which introduce a lagged dependent variable.

A common and widely-used approach to account for both unobserved heterogeneity and endogeneity is the estimator proposed by Arellano and Bond (1991). Introduce for reasons of lucidity $\Delta k \equiv (k_{it} - k_{it-1})$ and $\Delta_2 k \equiv (k_{it-1} - k_{it-2})$, the basic idea of this approach is to adjust Equation (3.4) to

$$\Delta \text{REDIST} = \vartheta \Delta_2 \text{REDIST} + \alpha \Delta \text{GINI(M)} + \boldsymbol{\delta' } \Delta \mathbf{X} + \Delta \xi + \Delta v \tag{3.5}$$

and to use sufficiently lagged values of REDIST, GINI(M), and $\mathbf{X}$ as instruments for Δk and Δ_2REDIST. These instruments are valid provided that the error term is serially uncorrelated. However, first differencing Equation (3.4) discards the information in the equation in levels. This drawback is particularly severe with regard to the purpose of this chapter, as most of the variation in our data stems from the cross-section rather than the time-dimension. Blundell and Bond (1998) and Bond et al. (2001) show that the standard first-difference GMM estimator can be poorly behaved if time-series are persistent or if the relative variance of the fixed effects η_i is high. The reason is that lagged levels in these cases provide only weak instruments for subsequent first-differences, resulting in a large finite sample bias.

System GMM proposed by Arellano and Bover (1995) and Blundell and Bond (1998) provides a tool to circumvent this bias if one is willing to assume a mild stationary restriction on the initial conditions of the underlying data generating process.[16] In this case, additional orthogonality conditions for the level equation in Equation (3.4) can be exploited, using lagged values of Δk and $\Delta_2 k$ as instruments. In doing so, system GMM maintains some of the cross-sectional information in levels and exploits the information in the data more efficiently. Satisfying the Arellano and Bover (1995) conditions, system GMM has proven to have better finite sample properties (see Blundell et al., 2000). To detect possible violations of these assumptions, we conduct Difference-in-Hansen tests for each of the system GMM regressions.[17]

Define the vectors $\tilde{\mathbf{X}}'_{it} \equiv [\text{GINI(M)}_{it}\ \mathbf{X}'_{it}]$ and $\mathbf{A}'_{it} \equiv [\text{REDIST}_{it}\ \tilde{\mathbf{X}}'_{it}]$. The moment conditions used in the estimation of the first-difference GMM method considered in this chapter can then be expressed as

$$\mathrm{E}\{(v_{it} - v_{it-1})\mathbf{A}_{it-2}\} = 0 \text{ for } t \geq 3, \tag{3.6}$$

implying that the set of instruments is restricted to lag 2. Such a restriction is necessary, as otherwise the problem of "instrument proliferation" may lead to severe biases (Roodman, 2009b). System GMM additionally uses moment conditions based on the regression equation in levels, which in our case are

$$\mathrm{E}\{(v_{it} + \eta_i)(\mathbf{A}_{it-1} - \mathbf{A}_{it-2})\} = 0 \text{ for } t \geq 3. \tag{3.7}$$

In principle, the equations can be estimated using one-step or two-step GMM. Whereas one-step GMM estimators use weight matrices independent of estimated parameters, the two-step variant weights the moment conditions by a consistent estimate of their covariance matrix. Bond et al. (2001) show that the two-step estimation is asymptotically more efficient. Yet it is well known that standard errors of two-step GMM are severely down-

[16] The assumption regarding the initial condition is $\mathrm{E}(\eta_i \Delta \text{REDIST}_{i2}) = 0$, which holds when the process is mean stationary, i.e. $\text{REDIST}_{i1} = \eta_i/(1-\vartheta) + v_i$ with $\mathrm{E}(v_i) = \mathrm{E}(v_i \eta_i) = 0$.

[17] A more detailed description of the estimator in the context of the empirical application can be found in Bond et al. (2001) and Roodman (2009b).

ward biased in small samples. We therefore rely on the Windmeijer (2005) finite sample corrected estimate of the variance, which yields a more accurate inference.

3.3 Results

3.3.1 Baseline results: Redistribution in the OECD countries

Table (3.1) reports the results of our baseline estimates. The specifications use REDIST(S), the subsample of observations available in the SWIID that is entirely built on national micro data. In addition, we start our analysis by examining only the OECD countries, where social security systems have reached a comparable level of sophistication. To avoid overfitting problems which might potentially arise due to the small number of cross-sections included in the panel, we collapse the instrument matrix as suggested by Roodman (2009b). The analysis in Table (3.1) is split into three parts: Panel A reports the results of the estimations that use the point estimates of inequality and redistribution, Panel B is based on all imputations of GINI(M) and REDIST(S) available in the SWIID, and Panel C applies the relative measure of redistribution REDIST(S)$^{\text{rel}}$. For each panel, we report five different specifications, which are labeled as Columns (1a)–(5).

Columns (1a) and (1b) present a reduced model which only incorporates the effect of market inequality, the development level, and the lagged dependent variable. The estimation in Column (1a) is built on 33 OECD member states for which inequality data is available. In the subsequent model specifications, limited availability of data concerning the top income share necessitates exclusion of South Korea, Luxembourg, New Zealand, and Portugal, resulting in a total of 29 OECD countries included in the estimation. In order to facilitate direct comparison of the reduced models with the subsequent specifications, Column (1b) re-estimates the reduced model based on the reduced sample of Columns (2)–(5). As hypothesized by Meltzer and Richard (1981), Columns (1a) and (1b) highlight a positive and highly significant impact of market inequality on the extent of redistribution, confirming that a poorer median voter has a higher demand for redistribution. Additionally, we observe that richer economies on average tend to redistribute more. Meanwhile, the lagged endogenous variable points to persistency of redistribution over time, implying that there are few changes in the composition of social security systems in the medium term.

Column (2) introduces several variables that distinguish the countries and that may affect the level of governmental redistribution. These predictors include unemployment, the degree of democratization, and the fertility rate in the model. We may expect that governments that attend to the support of the indigent redistribute more if unemployment is prevalent. Likewise, there may be a close entanglement between fertility and redistribution, as higher fertility rates may generate higher demand for social transfers, e.g. via child allowance or maternity leave programs. Finally, a higher degree of democratization theoretically assures that demand for redistribution translates into real policy actions. The results of Column (2), however, imply that neither of these variables is decisive in the OECD countries. With the exception of a positive contribution of the level of democratization in the last column, the additional variables are insignificant irrespective of the alternate model specifications depicted in the subsequent columns. Yet this result does not necessarily mean that redistribution is entirely unaffected by unemployment or democracy, as the OECD countries are highly comparable with respect to these additional variables. Intuitively, if each country in the sample possesses a similarly high level of democratization, then it is impossible to detect a potential impact of less sophisticated political rights. We will come back to this issue in Section (3.3.3).

Columns (2)–(4) further account for the shape of the income distribution by incorporation of the income share held by the middle class, the top 1 percent, and the bottom 10 percent. The reason for the inclusion of these variables is that different shapes of income distributions can result in similar Gini indices. However, inequality can be driven by numerous factors, e.g. by a large share of top income earners or by a large fraction of the population with low incomes. Whereas these different shapes yield comparable Gini indices, their influence on the level of redistribution may differ substantially, as different income groups deviate in their ability to exert political power. The estimated parameter of MIDDLECLASS is positive and highly significant, suggesting that the middle class

Table 3.1 Baseline regressions, determinants of redistribution in the OECD countries. Dependent variables are absolute redistribution, REDIST(S), in Panels A-B and relative redistribution, REDIST(S)$^{\text{rel}}$, in Panel C.

	(1a)	(1b)	(2)	(3)	(4)	(5)
	Panel A: Absolute redistribution, REDIST(S)					
GINI(M)	0.430***	0.277**	0.567***	0.570***	0.598***	0.573***
	(0.118)	(0.124)	(0.175)	(0.159)	(0.140)	(0.208)
Log(GDP$_{pc}$)	1.482	1.834*	-0.744	1.328	0.963	-0.671
	(2.052)	(1.044)	(1.683)	(0.903)	(1.403)	(1.535)
REDIST $(t-1)$	0.577***	0.886***	0.219*	0.262*	0.199**	0.184
	(0.114)	(0.127)	(0.119)	(0.147)	(0.0915)	(0.130)
UNEMP			-0.0630	-0.0282	-0.0473	-0.0391
			(0.144)	(0.102)	(0.102)	(0.130)
POLRIGHT			1.008	-0.224	-0.238	1.850*
			(1.635)	(1.551)	(1.401)	(1.113)
Log(FERT)			1.260	-3.053	-0.634	-0.856
			(2.014)	(3.042)	(2.716)	(3.163)
MIDDLECLASS			0.861***		0.741***	0.840***
			(0.192)		(0.183)	(0.195)
TOP-1			-0.305	-0.503***	-0.287**	-0.333
			(0.206)	(0.167)	(0.138)	(0.215)
QUINT$_3$				1.705***		
				(0.412)		
BOTTOM-10					0.901	
					(0.591)	
AGE						0.133
						(0.0959)
	Panel B: Absolute redistribution with multiple imputations, REDIST(S)$_{\text{MI}}$					
GINI(M)$_{\text{MI}}$	0.419***	0.221**	0.581***	0.405**	0.595***	0.661***
	(0.141)	(0.106)	(0.214)	(0.182)	(0.176)	(0.216)
	Panel C: Relative redistribution, REDIST(S)$^{\text{rel}}$					
GINI(M)	0.00888**	0.00352*	0.00680*	0.00178	0.00577	0.00886**
	(0.00366)	(0.00203)	(0.00385)	(0.00261)	(0.00450)	(0.00391)
Observations	202	111	111	111	111	111
Countries	33	29	29	29	29	29
Hansen p-val	0.932	0.482	0.941	0.981	0.977	0.973
Diff-Hansen	0.613	0.999	1.000	1.000	1.000	1.000
AR(1) p-val	0.0992	0.041	0.830	0.433	0.840	0.461
AR(2) p-val	0.214	0.183	0.234	0.544	0.172	0.482
Instruments	48	19	39	39	42	42
Collapsed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the Arellano and Bover (1995) conditions. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2 and collapsed to prevent instrument proliferation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

plays a decisive role in redistributional issues. Column (3) features the same regression as Column (2) but replaces MIDDLECLASS with QUINT_3, the income share held by the third quintile, more distinctively capturing the influence of the median income. As in the case of MIDDLECLASS, we can observe a significantly positive impact on redistribution. Since there is little difference in the results when comparing MIDDLECLASS and QUINT_3, we subsequently apply the broader definition MIDDLECLASS, commonly used in other studies (e.g. Atkinson and Brandolini, 2011; Grabka and Frick, 2008).

Unlike the effect of the middle class, the estimated coefficient of TOP-1 is negative and significant in most specifications, fostering notions of their engagement in rent-seeking behaviour and cronyism. As high-income earners are typically net-payers of redistributive policies, they tend to reject expansions of the welfare system. The significant impact of top-earners underscores that there are mechanisms that influence the political process beyond the median voter hypothesis. These mechanisms, however, do not include political power of the poor, which in fact seems to be considerably weaker. Column (4) captures the effect of the income share held by the lowest decile of the distribution, denoted by BOTTOM-10. The estimated parameter is positive, but insignificant. This result strongly resembles the effect of the unemployment rate, implying that the poor exert little influence on the level of redistribution. This points to two possible explanations: Governmental redistribution is either not affected by the interests of the bottom incomes, or redistributional activities are weakly targeted.

Finally, the last column of Table (3.1) incorporates the age dependency ratio (AGE), i.e. the ratio of people older than 64 to the working-age population. Inclusion of AGE allows us to investigate the extent to which redistribution is composed of pension payments. The results suggest that a higher age dependency ratio is generally associated with more redistribution. Yet this effect is not significant at the commonly used levels ($p = 0.29$).

Panel A uses point estimates of inequality to assess its effect on redistribution, as is common in the recent literature (see, e.g., Ostry et al., 2014; Acemoglu et al., 2015). The SWIID 5.0 contains 100 multiply-imputed values for each of the inequality measures, allowing for multiple imputation (MI) estimation of the empirical models. Using MI yields larger standard errors on coefficients, as it takes into account the imputation variability (for a detailed discussion with a focus on the SWIID, see Jenkins, 2015). To estimate the impact of the uncertainty introduced by the MI procedure on estimation precision, Panel B reports the results when estimating the model specifications of Panel A based on multiply-imputed market inequality and redistribution. The outcomes underscore a high degree of robustness of the findings in Panel A, as the impact of multiply-imputed market inequality is strongly significant and very similar in size compared with Panel A. These results are encouraging, as they emphasize that neglect of the imputation variability does not produce notable changes in the standard errors. Nevertheless, to ensure that the results are not affected by the uncertainty of the SWIID estimates, we routinely report the outcome of the equivalent MI estimation for each of the empirical models in the subsequent tables. In addition, we discuss the MI results more in detail in the sensitivity analysis of Section (3.3.4).

Panel C documents the effect of market inequality on governmental redistribution when redistribution is measured in relative terms ($\text{REDIST(S)}^{\text{rel}}$). Similar as in the results reported in Panels A and B, a higher level of market inequality is positively related to redistribution. However, in the case of relative redistribution, the effect is slightly less pronounced, which indicates that second-order effects to some extent may play a role. The model specifications are identical to the previous panels, where little change in the effects of the remaining variables can be observed.

Regarding the validity of our results, we refer to the test statistics given in the lower part of the baseline table. The Hansen test of overidentifying restrictions indicates validity of the instruments in each of the regressions. Similarly, the Difference-in-Hansen test emphasizes the validity of the additional orthogonality conditions of system GMM, which suggests a potential loss in efficiency when estimating the baseline regression via first-difference GMM. In addition, the AR(2) p-value implies absence of second-order serial correlation in the residuals.

3.3.2 Insurance motives, different social models, and taxes

In the next step, we want to analyze our findings concerning the origin of redistribution in OECD countries in greater detail. More specifically, we are interested in three particular questions: (1) can we observe the Meltzer-Richard effect when we use specific fiscal policy measures rather than effective redistribution, (2) are there transmission channels other than the Meltzer-Richard effect that explain how market inequality translates into redistribution, and (3) does the effect of market inequality depend upon different social models?

Table (3.2) is concerned with the first two of these questions. First, we explicitly account for the redistributive design of the tax and transfer system employing different variables on structural tax progressivity and social transfers as dependent variables. Tax data are from the World Tax Indicators database (WTI, 2016), which offers structural parameters on tax progressivity for many countries. Additionally, social transfer payments are gathered from World Bank (2016). To measure tax progressivity, we use two different approaches. The average tax rate progression (ARP) provides information on the structural progressivity of national tax schedules with respect to changes in average tax rates along the income distribution. We take this variable directly from the WTI. In addition, we follow Arnold (2008) and Attinasi et al. (2011), computing an index of tax progressivity (TAP) via

$$\text{TAP} = 1 - \frac{100 - \text{marginal tax rate}}{100 - \text{average tax rate}}, \tag{3.8}$$

where average and marginal tax rates are evaluated at the average production worker wage with higher values of TAP implying higher progressivity.[18] Finally, we analyze the effect of market inequality on subsidies and other transfer payments (SOT).

Table (3.2) reports two model specifications identical for each of the variables. The first variant refers to the reduced model of the baseline table, while the second specification

[18] To assess stability of the results, we compute TAP for several parts of the income distribution, employing average and marginal tax rates for incomes eqivalent to higher shares of a country's per capita GDP in local currency. It turns out that the results are stable across these definitions, which is why the table focuses on the original variable TAP.

Table 3.2 Determinants of redistribution in the OECD countries, alternative redistribution measures. Dependent variables are average rate progression, tax progression, and social transfers.

	Av. Rate Prog. (ARP)		Tax Prog. (TAP)		Social Transf. (SOT)		Incloss (INC)	
	(1)	(4)	(1)	(4)	(1)	(4)	(1)	(4)
	Panel A: Market inequality GINI(M)							
GINI(M)	0.000609*	0.00150**	0.00592*	0.00674*	0.247*	0.524	-0.0715**	0.00900
	(0.000356)	(0.000730)	(0.00334)	(0.00384)	(0.129)	(0.517)	(0.0299)	(0.131)
$\text{Log}(\text{GDP}_{pc})$	0.0160***	0.0198***	-0.00669	0.0774*	1.032	6.980	0.805**	-0.184
	(0.00574)	(0.00691)	(0.0475)	(0.0461)	(1.176)	(7.595)	(0.400)	(1.372)
UNEMP		0.00117**		0.00331		-0.471		-0.0807
		(0.000461)		(0.00519)		(0.518)		(0.116)
POLRIGHT		-0.00275		-0.0462		-5.794*		0.136
		(0.00733)		(0.0326)		(3.458)		(1.042)
Log(FERT)		0.0205		0.109		-15.05		1.492
		(0.0155)		(0.0958)		(16.83)		(1.811)
TOP-1		-0.00318***		-0.0140*		-0.408		-0.459*
		(0.00121)		(0.00818)		(1.571)		(0.270)
MIDDLECLASS		0.00100		0.0106		0.00637		0.200
		(0.00110)		(0.00684)		(0.723)		(0.169)
BOTTOM-10		0.00194		-0.0379		3.301		-1.369**
		(0.00347)		(0.0333)		(3.629)		(0.587)
$\text{ARP}(t-1)$	0.307*	0.417***						
	(0.183)	(0.161)						
$\text{TAP}(t-1)$			0.0628	0.0356				
			(0.166)	(0.183)				
$\text{SOT}(t-1)$					0.896***	0.827***		
					(0.0472)	(0.212)		
$\text{INC}(t-1)$							0.824***	0.569***
							(0.0675)	(0.191)
	Panel B: Market inequality with multiple imputations, $\text{GINI(M)}_{\text{MI}}$							
$\text{GINI(M)}_{\text{MI}}$	0.000571**	0.00134**	0.00436***	0.00506*	0.243**	0.305	-0.0639*	-0.0472
	(0.000273)	(0.000554)	(0.00119)	(0.00281)	(0.113)	(0.384)	(0.0340)	(0.165)
Observations	125	87	125	87	91	67	103	103
Countries	34	30	34	30	33	27	29	29
Hansen p-val	0.257	0.986	0.00827	0.609	0.195	0.353	0.255	0.844
Diff-Hansen	0.766	1.000	0.173	0.935	0.343	0.902	1.000	1.000
AR(1) p-val	0.747	0.885	0.123	0.0659	0.303	0.333	0.0106	0.214
AR(2) p-val	0.200	0.860	0.726	0.977	0.203	0.967	0.137	0.507
Instruments	27	44	29	42	36	34	36	42

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. Labeling of columns refers to the model specification of the baseline results reported in Table (3.1). All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the Arellano and Bover (1995) conditions. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2 and collapsed to prevent instrument proliferation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

replicates the comprehensive model reported in Column (4) of Table (3.1). Again, Panel A is based on GINI(M), while Panel B reports the results when using multiply-imputed market inequality. As the models in Table (3.2) are based on a number of different datasets which deviate considerably in their availability of different country-years, we are unable to built our estimates on exactly the same sample as in the baseline table. To maximize comparability, each of the regressions draws on the maximum of available observations for the OECD countries.

Overall, the results of Table (3.2) support our baseline findings with respect to effective redistribution. Regardless of the model structure, gross inequality is positively associated with the progressivity of the tax system. In principle, more unequally distributed market incomes also tend to be positively related to higher transfer payments. However, this effect is only significant in the reduced specification. While this result at first sight may argue against the Meltzer-Richard hypothesis, it bears underscoring that it is unclear beforehand to what extent transfer payments are actually redistributive (see Section 3.2.1). With respect to the control variables, we observe similar effects as in our baseline estimates. Whereas a broader middle class positively influence redistributive efforts, top incomes again turn out to be impediments to such policies. The results are very robust when using the MI procedure in Panel B.

While the positive effect of market inequality on redistributive policies detected in the previous estimations puts a strong emphasis on the Meltzer-Richard hypothesis, the political science literature has brought forward some additional theories on how these variables may be linked, most notably the insurance hypothesis (Varian, 1980; Moene and Wallerstein, 2001, 2003). This line of reasoning is based on the insurance motive of self-interested voters, understanding welfare policy as the public provision of protection against risks. Assuming that insurance is a normal good and holding risk constant, they emphasize that greater inequality, hence a lower median-voter income, leads to declining support for spending on social insurance. These findings show that support on redistribution depends on the underlying motive being unknown ex ante. To evaluate their hypothesis, we replicate the measures utilized by Moene and Wallerstein (2001), henceforth referred to as *Incloss* (INC). Data on this subject stems from the OECD and sums government and mandated private expenditures in following categories: disability cash benefits, occupational injury and disease, sickness benefits, services for the disabled and elderly, survivors' benefits, active labor market programs, and unemployment insurance. Health care spending and old age cash benefits as substantial social security programs are not included since governmental spending on health care is mostly provided to all individuals within a society, which runs counter the insurance motive. The loss of income upon old age is excluded as it is an expected event in a way that losses due to disability, sickness, or unemployment are not.

The last two columns of Table (3.2) report the results when INC is used as dependent variable. To maximize comparability to the baseline results of Table (3.1), we replicate the sample composition as closely as possible with the available data. In the reduced model specification (1), a higher level of market inequality contributes significantly negative to public spending on insurance against income losses. Once we account for the shape of the income distribution, this effect turns insignificant. The shape parameters tell us why: Apparently, both the individuals at the bottom *and* the individuals at the top possess negative preferences against insurance policies. While the first provides support of Moene and Wallerstein (2001), the latter implies that the top 1 percent has a higher preference for private rather than public insurance. This suggests that the insurance motive, though having an effect on redistribution, is outweighed by the Meltzer-Richard effect.

The differentiation between private and public insurance is indeed crucial in the assessment of the effect of market inequality, particularly with respect to pension spending. In fact, the substantial variation in redistribution across countries may well be the result of different social models. In aging societies, large extents of redistribution may predominantly be due to the generosity of the public pensions system, whereas other social security systems may put a stronger focus on pro-poor redistribution. To account for these deviating motives, we calculate the ratio of private to total pension spending using data from the OECD. In countries with a high share of private pension spending, we assume public pension funds to be mainly targeted to those in need, while other countries with

Table 3.3 Determinants of redistribution in the OECD countries, the effect of different social models. Dependent variables are absolute redistribution, REDIST(S), in Panels A-B and relative redistribution, REDIST(S)$^{\text{rel}}$, in Panel C.

	Social models		Social models and AGE		Social models and GINI(M)	
	(1)	(5)	(1)	(5)	(1)	(5)
	Panel A: Absolute redistribution, REDIST(S)					
GINI(M)	0.646***	0.528*	0.370***	0.680**	0.590***	0.604***
	(0.176)	(0.272)	(0.163)	(0.142)	(0.227)	(0.220)
Log(GDP$_{pc}$)	3.181	0.0274	7.565***	1.301	5.252*	0.00507
	(4.175)	(2.127)	(2.808)	(2.594)	(3.304)	(1.902)
REDIST($t-1$)	0.185	0.182		0.172	0.488*	0.186*
	(0.152)	(0.128)		(0.144)	(0.252)	(0.108)
PRO-POOR	-6.391	-0.883			-4.491	-6.060
	(6.194)	(2.359)			(8.642)	(7.921)
AGE		0.101	0.0745	0.164*		0.0168
		(0.0802)	(0.160)	(0.0865)		(0.0827)
PRO-POOR×AGE			-0.139*	-0.0958*		
			(0.0769)	(0.0551)		
PRO-POOR×GINI(M)					0.00121	0.177
					(0.243)	(0.132)
	Panel B: Absolute redistribution with multiple imputations, REDIST(S)$_{\text{MI}}$					
GINI(M)$_{\text{MI}}$	0.429**	0.897**	0.417**	0.417**	0.204*	0.576*
	(0.183)	(0.455)	(0.200)	(0.190)	(0.116)	(0.318)
	Panel C: Relative redistribution, REDIST(S)$^{\text{rel}}$					
GINI(M)	0.00689**	0.00555*	0.00673***	0.00362	0.00689***	0.00768**
	(0.00305)	(0.00319)	(0.00249)	(0.00267)	(0.00250)	(0.00339)
Observations	111	111	111	111	111	111
Countries	29	29	29	29	29	29
Hansen p-val	0.00211	0.775	0.0111	0.796	0.00106	0.938
Diff-Hansen	0.997	0.999	0.996	0.999	0.996	1.000
AR(1) p-val	0.963	0.543	0.338	0.842	0.442	0.934
AR(2) p-val	0.317	0.409	0.192	0.151	0.237	0.153
Instruments	18	43	20	45	21	44
Collapsed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. Labeling of columns refers to the model specification of the baseline results reported in Table (3.1). All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the Arellano and Bover (1995) conditions. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2 and collapsed to prevent instrument proliferation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

virtually no private pension spending combine insurance based motives as well as pro-poor ones. These considerations in mind, we create a dummy PRO-POOR, which is 1 if the private share on total pension spending exceeds 0.10—the median in our sample—, and 0 otherwise. As pension systems reflect social preferences that only gradually changes, we assign the computed value of PRO-POOR for country i to each country-year (i, t) to enlarge the time dimension exploitable in the empirical analysis.[19]

Table (3.3) uses PRO-POOR to investigate the role of different social models in greater detail. This analysis proceeds in three steps: First, we analyze the effect of PRO-POOR in the reduced model (1) and the comprehensive model (5) that incorporates the age dependency ratio. Second, we assess the effect of the age dependency ratio contingent upon the social models of the countries. Finally, we study potential differences in the Meltzer-Richard effect depending on the motive of the redistribution system. The labeling of the Columns refer to the model specifications used in Table (3.1). As there are virtually no changes in the controls, the table focuses on the variables of interest.

When introducing our social security system dummy in the baseline specification, we observe that the influence of market inequality on redistribution increases. PRO-POOR itself possesses a negative sign, implying that social systems that mainly focus on the indigent tend to redistribute less. However, this effect is not significant. In the next step, we compute an interaction term between the age dependency ratio and the social security system dummy, denoted with PRO-POOR$\times$AGE. We include this interaction and the original age dependency ratio in the model specifications (1) and (5). When accounting for the motive of the social security system, the age dependency ratio contributes positively to redistribution. This effect is particularly pronounced in the comprehensive model. In addition, the interaction term has a negative sign, suggesting that the age dependency ratio is of less importance in pro-poor targeted social security systems. This explains the overall insignificant effect of AGE in Table (3.1), where the two opposing effects cancel out. Finally, we are interested whether the Meltzer-Richard effect differs between different

[19]In fact, we observe that there are virtually no alterations in PRO-POOR across the time periods for which data is available. The only exception in the sample of OECD countries is Mexico, where the indicator changes from 0 to 1 between the periods 2000-2004 and 2005-2009.

social models. In accordance with the findings of Table (3.2) that suggest a negative effect of market inequality on public spending on income losses, we find that market inequality tends to be more important for redistributive issues in countries where redistribution is mainly pro-poor targeted. Yet this effect is far from being significant.

As in the baseline table, Panels B and C report the results when REDIST(S) is replaced by multiple imputations and relative redistribution, respectively. Again, the results remain stable when accounting for both imputation variability and relative inequality reduction.

3.3.3 Redistribution in a broad sample of countries

While the restriction of the sample to advanced economies for which micro data on gross and net Ginis are available ensures the highest possible degree of comparability, it is accompanied by two distinct disadvantages. First and most obvious, the number of observations included in the sample is low, which is why the results should be interpreted with caution. Second, reliance on the sample of highly developed countries may not be sufficient to reveal the deeper institutional determinants of redistribution. As political rights have reached sophisticated levels in each OECD member state, the estimations provide no information on the Meltzer-Richard channel in countries with less democratization or authoritarian governments. In addition, the low extent of variation with respect to political rights in the OECD countries inhibits investigation of the role of institutions in the redistribution process. For these reasons, it is not guaranteed that it is the *political* channel through which market inequality translates to more redistribution. One way to cope with both disadvantages is to compare the results of Table (3.1) to identical specifications on the basis of a broader sample that also includes developing economies with less developed political rights.

Such estimations, however, present the challenge of accounting for specific effects arising from different countries and development levels. To allow for specific institutional frameworks, the analysis includes unobserved heterogeneity, as described in Section (3.2.3). In addition, there may be effects emanating from different development levels that

Table 3.4 Baseline regressions, determinants of redistribution in a broad sample. Dependent variables are absolute redistribution, REDIST and REDIST(S), in Panels A–B and relative redistribution, REDIST^{rel} and REDIST(S)^{rel}, in Panel C.

	REDIST (All available country-years)			REDIST(S) (All available country-years)		
	(2)	(4)	(5)	(2)	(4)	(5)
	Panel A: Absolute redistribution, REDIST and REDIST(S)					
GINI(M)	0.232***	0.208***	0.221***	0.334***	0.314**	0.355***
	(0.0720)	(0.0576)	(0.0636)	(0.107)	(0.135)	(0.128)
Log(GDP$_{pc}$)	0.423	0.388	0.629**	2.005***	1.756**	2.484***
	(0.258)	(0.256)	(0.281)	(0.631)	(0.772)	(0.932)
REDIST $(t-1)$	0.792***	0.813***	0.770***	0.336***	0.372**	0.274**
	(0.0793)	(0.0712)	(0.0831)	(0.121)	(0.152)	(0.120)
UNEMP	-0.00741	-0.00188	-0.0129	0.108	0.0993	0.0882
	(0.0256)	(0.0240)	(0.0256)	(0.105)	(0.0968)	(0.0943)
POLRIGHT	0.152*	0.157*	0.153*	0.582*	0.579*	0.535*
	(0.0861)	(0.0872)	(0.0885)	(0.346)	(0.336)	(0.319)
Log(FERT)	-0.381	-0.353	-1.240	-0.453	-0.536	-2.247
	(0.393)	(0.355)	(0.851)	(1.506)	(1.507)	(2.353)
MIDDLECLASS	0.182**	0.150**	0.159**	0.408***	0.386***	0.371**
	(0.0785)	(0.0667)	(0.0746)	(0.132)	(0.143)	(0.165)
TOP-1	-0.146**	-0.111**	-0.166***	-0.207	-0.210	-0.271*
	(0.0640)	(0.0550)	(0.0646)	(0.166)	(0.156)	(0.143)
BOTTOM-10		0.170			-0.0308	
		(0.204)			(0.948)	
AGE			0.0292			0.0797
			(0.0231)			(0.0606)
	Panel B: Absolute redistribution with multiple imputations, REDIST$_{MI}$ and REDIST(S)$_{MI}$					
GINI(M)$_{MI}$	0.396***	0.253**	0.206*	0.425***	0.253**	0.206*
	(0.0719)	(0.0987)	(0.114)	(0.143)	(0.0987)	(0.114)
	Panel C: Relative redistribution, REDIST^{rel} and REDIST(S)^{rel}					
GINI(M)	0.00305***	0.00316***	0.00287***	0.00418***	0.00414**	0.00411**
	(0.000885)	(0.000862)	(0.000933)	(0.00153)	(0.00161)	(0.00170)
Observations	443	443	443	253	253	253
Countries	126	126	126	66	66	66
Hansen p-val	0.937	0.970	0.985	0.137	0.152	0.133
Diff-Hansen	0.998	1.000	1.000	0.249	0.215	0.257
AR(1) p-val	0.105	0.103	0.106	0.270	0.265	0.315
AR(2) p-val	0.440	0.438	0.393	0.973	0.866	0.840
Instruments	148	161	161	39	42	42
Collapsed	No	No	No	Yes	Yes	Yes

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. Labeling of columns refers to the model specification of the baseline results reported in Table (3.1). All regressions include period fixed effects. Test statistics refer to Panel A. Hansen p-val gives the J-test for overidentifying restrictions. Diff-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the Arellano and Bover (1995) conditions. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

are common to countries in the same income group, but differ from those found in richer or poorer nations. Such effects stem mainly from underdeveloped institutions, corruption, or fraud. As in the previous estimations, we consider these effects by the inclusion of real per capita GDP.

Table (3.4) enlarges the baseline regressions of Table (3.1) by applying two different variants of the redistribution measure. The first group of regressions uses all available observations for which gross and net Ginis are available in the SWIID 5.0 (REDIST), yielding a significant increase in the number of countries included in the estimation. However, it bears emphasizing that for some of the 126 countries included in the regressions, data on either net or gross Ginis relies on estimates (see Section 3.2.1). The second concept used in Table (3.4) is based entirely on country-years for which micro data of market and net inequality is available (REDIST(S)). In both cases, Table (3.4) reports Columns (2), (4), and (5) of the baseline regressions to capture the effect of all covariates included in the baseline estimations.[20] Panel A reports the results based on absolute redistribution, whereas Panels B and C examine the effect of market inequality when the multiply-imputed and the relative measure of redistribution are used as dependent variable.

The results of Table (3.4) highlight that the change in the sample composition does not yield a considerable deviation in the main drivers of governmental redistribution. As in the baseline regressions, the effect of market inequality on redistribution is positive and strongly significant. However, when analyzing the effect in a broad sample that includes a number of less-developed countries, the marginal effect of market inequality is smaller than in the sample of OECD countries. This shrinking impact implies that the Meltzer-Richard effect is less pronounced in the additional countries included in the broader samples. Meanwhile, the results suggest that redistribution is higher in countries with more sophisticated political rights and higher income levels, as log(GDP_{pc}) and POLRIGHT now become significant in most of the cases. As argued previously, both

[20] The Table neglects the second concept of the middle class (QUINT_3), as the effects of this variable are strongly comparable to those of the broader concept MIDDLECLASS. For this reason, Column (3) of Table (3.1) is excluded in Table (3.4).

effects are undetectable in the baseline regressions, as the sample of OECD countries is composed entirely of highly advanced countries with established democratic institutions. Taken together, these findings provide a more robust indication that it is the political channel through which market inequality is transmitted to redistribution. In developing economies, market inequality may raise demand for redistribution in the same way that it does in OECD countries. However, less developed democratic structures may impede the transmission of redistributive preferences in the political process. In addition, Table (3.4) also implies that there are further differences in the Meltzer-Richard effect between rich and poor countries that go beyond the quality of institutions.

As in the baseline estimations, redistribution is negatively related to the top income share, which again underscores the political power of the rich. In contrast, a broad middle class is positively associated with redistributional activity of the government. The findings also imply that social benefits are weakly targeted to the poor, as neither the unemployment rate, nor the income level of the bottom 10 percent assume a significant impact on redistribution. Finally, the age dependency ratio of the population older than 64 is positively related to redistribution, but this effect is not significant.

The test statistics given in the lower part of Table (3.4) again attest the validity of our results. To prevent instrument proliferation, the regressions based on REDIST(S) again use a collapsed version of the instrument matrix. However, this procedure is not possible with regard to REDIST, as Hansen's J test in this case implies that the choice of instruments is invalid.

3.3.4 Sensitivity analysis

To investigate the robustness of our results, this section provides a sensitivity analysis of the baseline findings. This analysis is concerned with two questions. First, we want to examine whether different econometric specifications yield different outcomes. Second, in light of the problems that arise when using cross-country data collections on inequality (see Section 3.2.1), we aim to analyze changes in the results when using other data sources than the SWIID.

Table 3.5 Sensitivity analysis of the baseline results, different estimation techniques. Dependent variables are absolute redistribution, REDIST and REDIST(S), in Panels A and B, and relative redistribution, $\text{REDIST}^{\text{rel}}$ and $\text{REDIST(S)}^{\text{rel}}$, in Panel C.

	OLS		Within Group		First-Difference GMM	
	(OECD)	(all)	(OECD)	(all)	(OECD)	(all)
	Panel A: Absolute redistribution, REDIST and REDIST(S)					
GINI(M)	0.543***	0.180***	0.730***	0.290***	0.505*	0.225***
	(0.0686)	(0.0454)	(0.124)	(0.0517)	(0.280)	(0.0860)
REDIST($t-1$)	0.375***	0.824***			0.331*	-0.0433
	(0.0446)	(0.0481)			(0.184)	(0.192)
Log(GDP_{pc})	1.322***	0.312**	-0.0955	0.0643	1.113	0.597
	(0.360)	(0.145)	(1.838)	(0.739)	(2.773)	(0.803)
UNEMP	-0.00199	-0.00530	0.0818	0.0836**	0.0919	0.00180
	(0.0315)	(0.0125)	(0.0524)	(0.0398)	(0.0898)	(0.0788)
POLRIGHT	0.311	0.119**	-0.778**	-0.0179	0.132	-0.107
	(0.223)	(0.0529)	(0.295)	(0.0873)	(1.161)	(0.217)
Log(FERT)	-0.245	-0.151	-1.541	1.580**	3.091	2.818*
	(0.562)	(0.248)	(2.748)	(0.736)	(5.403)	(1.620)
TOP-1	-0.141***	-0.0531	-0.147	-0.128*	-0.268	-0.436**
	(0.0484)	(0.0357)	(0.144)	(0.0672)	(0.283)	(0.222)
MIDDLECLASS	0.514***	0.159***	0.747***	0.135**	0.300*	0.175*
	(0.0754)	(0.0437)	(0.152)	(0.0558)	(0.180)	(0.0947)
BOTTOM-10	1.663***	0.400***	0.824**	0.344	1.061	-0.619
	(0.214)	(0.148)	(0.399)	(0.223)	(0.808)	(0.731)
	Panel B: Absolute redistribution with multiple imputations, $\text{REDIST}_{\text{MI}}$ and $\text{REDIST(S)}_{\text{MI}}$					
GINI(M)	0.546***	0.323***	0.750***	0.454***	0.768***	0.379*
	(0.0723)	(0.0598)	(0.0902)	(0.0660)	(0.264)	(0.214)
	Panel C: Relative redistribution, $\text{REDIST}^{\text{rel}}$ and $\text{REDIST(S)}^{\text{rel}}$					
GINI(M)	0.00548***	0.00324**	0.00726***	0.00475***	0.00645**	0.00685*
	(0.00106)	(0.00122)	(0.00239)	(0.00139)	(0.00268)	(0.00375)
Observations	111	443	111	474	79	294
Countries	29	134	29	134	27	110
R squared	0.972	0.958	0.769	0.319		
F Stat						
Hansen p-val					0.977	0.389
Instruments					49	49

Notes: Table reports Within-Group (WG) and OLS estimations with cluster-robust standard errors, and first-difference system GMM (Arellano-Bond) estimations. The model specification refers to Column (4) of the baseline regressions in Table (3.1). All regressions include period fixed effects. The test statistics refer to Panel A. F p-val gives the p-value of the F test, Hansen p-val reports the J-test for overidentifying restrictions. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table (3.5) reports the results of the baseline model specifications when OLS, Within-Group (WG), and First-Difference GMM estimators are used as empirical technique. The utilized model is specified identically to Column (4) of the baseline table. We report two variants of this model. While the first version is based on our standard OECD sample used in Table (3.1), the second version employs all available data in the SWIID.[21] Due to the high probability of a dynamic panel bias, the WG estimates exclude the lagged dependent variable (see Nickell, 1981). Again, the table reports results of three different Panels to illustrate the effects of market inequality and our covariates based on absolute redistribution (Panel A), multiply-imputed market inequality (Panel B), and relative redistribution (Panel C).

The results of Table (3.5) strongly support the findings of our baseline outcomes, suggesting that a higher level of market inequality significantly enhances the scope of redistribution. This effect is visible regardless of the redistribution measure used as dependent variable. Similar to the baseline results, the effect of market inequality is larger in the sample of highly developed OECD countries with sophisticated political rights. In addition, the models in Table (3.5) again highlight that the shape of the income distribution matters. While the effects of top incomes and the middle class remain stable compared to the previous estimates, some of the regressions in Table (3.5) suggest that individuals at the bottom of the income distribution have a similar influence on the redistribution process.

While the results obtained by alternative estimators emphasize the stability of our previous findings, it must be underscored that these techniques possess substantial weaknesses in identifying the determinants of redistribution. Both the OLS and the WG estimator are insufficient to satisfyingly capture the persistency inherent in social security systems. More severely, the results are very likely to be biased as the estimators neglect potential problems of endogeneity and reversed causation. In addition, the WG estimator neglects the information in the equation in levels. The latter also holds true for First-Difference GMM, which would be particularly advantageous if the restrictions on the

[21] The results obtained via the other specifications of Table (3.1) provide highly comparable outputs.

initial conditions necessary for validity of the additional orthogonality conditions of system GMM were violated. Yet the Difference-in-Hansen statistics reported in Tables (3.1) and (3.4) show quite clearly that the extra moment conditions are valid, which implies substantial efficiency losses when using First-Difference GMM. Moreover, the application of Arellano-Bond results in a decline in the number of observations, as the estimator requires having at least three consecutive observations for each of the regressors, thereby magnifying gaps in our sample. As a result, the baseline sample of OECD countries is reduced to only 79 observations.

We mentioned previously the need to account for the uncertainty in the SWIID, which is why each of the previous tables reports both the point estimates and the multiply-imputed variants of inequality and redistribution. Table (3.10) in the appendix is concerned with a more detailed documentation of the results obtained by MI estimations. As the main concern of data quality is raised with regard to the broad sample, we use multiple imputations of REDIST as dependent variable (REDIST$_{\mathrm{MI}}$).[22] The results of the MI estimations are encouraging, as they underscore a high degree of robustness of the baseline findings. While market inequality exerts a significant effect on redistribution in each of the estimations, the parameters reflecting the shape of the income distribution remain their direction of influence and—with the exception of the narrow definition of the middle class—their significance.

The second branch of sensitivity analyses engages in examining the robustness of our results when using data sources other than the SWIID. Although we try to base most of our analysis on observations for which micro data on the pre and post level of incomes is available, some of the regressions include country-years that rest upon estimations conducted by Solt (2016). Table (3.6) illustrates the exact replication of the baseline table when using the WIID 3.0 A instead of the SWIID 5.0. As the robustness across different data sources is a highly important issue, the table reports all model specifications analyzed in Table (3.1). As is the case with each cross-country dataset on inequality, both the SWIID and the WIID are characterized by missing country-years, which is

[22]Note, however, that there are little changes if the system instead utilizes REDIST(S) in the OECD countries.

Table 3.6 Sensitivity analysis of the baseline regressions. Dependent variables are absolute redistribution, $\text{REDIST}_{\text{WIID}}$, in Panel A and relative redistribution, $\text{REDIST}^{\text{rel}}_{\text{WIID}}$, in Panel B. Redistribution data is from WIID 3.0 A.

	OECD	All available observations				
	(1a)	(1b)	(2)	(3)	(4)	(5)
	Panel A: Absolute redistribution $\text{REDIST}_{\text{WIID}}$					
$\text{GINI(M)}_{\text{WIID}}$	0.867***	0.957***	0.718***	0.712***	0.737***	0.798***
	(0.121)	(0.155)	(0.0940)	(0.0862)	(0.0669)	(0.122)
$\text{Log}(\text{GDP}_{pc})$	9.992	-1.075	2.367	2.164	3.379*	2.515**
	(6.728)	(2.974)	(1.739)	(1.615)	(1.763)	(1.200)
$\text{REDIST}_{\text{WIID}}(t-1)$	0.0562	0.188	0.147**	0.163**	0.169***	0.133
	(0.086)	(0.117)	(0.0712)	(0.0672)	(0.0623)	(0.103)
UNEMP			-0.393	-0.355	-0.147	-0.371
			(0.283)	(0.306)	(0.188)	(0.359)
POLRIGHT			-0.0393	0.00721	-0.495	-0.0621
			(0.888)	(0.935)	(0.625)	(0.797)
Log(FERT)			-5.115	-4.863	-4.078	0.954
			(4.030)	(4.557)	(3.161)	(4.113)
MIDDLECLASS			0.592**		0.694***	0.613*
			(0.264)		(0.227)	(0.324)
TOP-1			-0.575*	-0.525*	-0.291	-0.703
			(0.330)	(0.303)	(0.223)	(0.550)
QUINT_3				1.707***		
				(0.573)		
BOTTOM-10					1.467	
					(0.903)	
AGE						-0.243
						(0.149)
	Panel B: Relative redistribution $\text{REDIST}^{\text{rel}}_{\text{WIID}}$					
$\text{GINI(M)}_{\text{WIID}}$	0.0140**	0.0233***	0.0164***	0.0165***	0.0142***	0.0168***
	(0.0054)	(0.00353)	(0.00223)	(0.00224)	(0.00194)	(0.00263)
Observations	149	181	116	116	116	116
Countries	33	48	41	41	41	41
Hansen p-val	0.324	0.523	0.378	0.465	0.595	0.343
Diff-Hansen	0.457	0.206	0.575	0.727	0.911	0.315
AR(1) p-val	0.702	0.798	0.0320	0.0280	0.0736	0.110
AR(2) p-val	0.790	0.678	0.919	0.847	0.458	0.783
Instruments	23	23	37	37	46	45
Collapsed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses based on inequality data in the WIID 3.0 A. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the Arellano and Bover (1995) conditions. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2 and collapsed to prevent instrument proliferation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

inevitable due to missing underlying micro data on the country level. However, this drawback is particularly severe when calculating redistribution measures based on WIID data. Whereas the WIID provides an extensive collection of a variety of inequality data based on different income concepts, the distinction between gross and net incomes is less explicit, which hinders comparability of the computed levels of redistribution (see Section (3.2.1) for a detailed description). When utilizing data of the WIID, the number of observations reduces to a total of 264 country-years and declines further when a lagged value (181 country-years) or the sub-sample of OECD members (149 country-years) is to be considered. Thus, Table (3.6) reports the results based on all available observations in the WIID, denoted by $\text{REDIST}_{\text{WIID}}$.[23]

The results reveal a remarkable degree of robustness of our baseline findings. The redistribution-enhancing effect of market inequality is strongly pronounced in each of the regressions. Moreover, the marginal effect of GINI(M) on redistribution based on the WIID data is slightly stronger than implied by the SWIID. The results again highlight that the level of redistribution is persistent over time, and that richer economies tend to redistribute more. In addition, a broader middle class is positively associated with redistribution, whereas top incomes tend to impede redistributive policies. Supporting the findings of the baseline estimates, we find that redistributive measures are not significantly affected by the income share held by the poor or by the unemployment rate.

Finally, Table (3.11) in the appendix provides a detailed robustness check with respect to the influence of top income earners, as there has been some concern regarding the data quality of the top income shares in the SWIID 4.0 (Jenkins, 2015). The table reports the effect of the Top-1%, Top-0.5%, Top-0.1%, and the Top-0.01% on redistribution based on the WID, the source data upon which the top income series of the SWIID 4.0 relies. Whereas the WID perhaps provides the most reliable data series of top incomes, it does so with reduced scope compared to the SWIID 4.0. The obvious drawback is a strong decline in data availability, which is why the table focuses on the reduced effect of top incomes on REDIST(S), holding constant only market inequality, redistribution in $(t-1)$,

[23] In addition, we are unable to directly replicate the sample composition of Table (3.1), as the differences in data availability between the WIID and SWIID would yield a loss of another 56 country-years.

and the development level. Using the highest possible number of comparable country-years (89 observations), it turns out that the marginal effect of the Top-1% based on the WID (-0.971***) is strongly comparable to the effect identified by the SWIID (-1.110***). When narrowing the scope of the analysis to more explicitly capture the effect of the (super) rich—i.e. examining the effect of the Top-0.5% to Top-0.01%—the marginal effect increases considerably. This result highlights that it is primarily the extraordinary wealthy that exercise political power.

3.3.5 Different levels of economic and political development

The previous estimations revealed differences in the determination of redistribution between the sample of highly advanced OECD members and the broader sample of countries. As argued in Section (3.3.3), the shrinking influence of market inequality on redistribution is a strong indication that the Meltzer-Richard effect is less prevalent in developing countries. The positive effect of political rights in the enlarged sample of countries further documents that the political mechanism crucially affects the degree to which policy measures are redistributive. This section is concerned with a more in-depth analysis of the development process in the explanation of redistribution.

Table (3.7) uses identical model specifications as the baseline estimates of Table (3.1), but includes an interaction term GINI$\times$GDP$_{pc}$, which is the product of the market GINI and the logarithmic value of real per capita GDP. The advantage of this interaction is that it allows for examination of the effect of different levels of development without using fixed income levels to distinguish between different stages of development. As there are virtually no changes in the effect of the covariates, the table concentrates on the variables of interest, for reasons of lucidity. Column (1a) replicates the reduced model of the baseline table, using exactly the same country-years, while Column (1b) carries out this analysis based on all available data. In both cases, the effect of market inequality is essentially negative when considering less developed economies. At the same time, the interaction term has a positive sign, suggesting that the influence of gross inequality becomes positive with an increasing development level. This result emphasizes that the Meltzer-Richard

Table 3.7 The determinants of redistribution for different development levels. Dependent variable is absolute redistribution, REDIST.

	(1a)	(1b)	(2)	(3)	(4)	(5)
	Panel A: Absolute redistribution REDIST					
GINI(M)	-1.058*	-0.152*	0.0560	0.0381	0.0431	0.0892
	(0.5660)	(0.0850)	(0.126)	(0.112)	(0.0996)	(0.118)
Log(GDP$_{pc}$)	-0.416*	-0.407	-0.425	-0.300	-0.519	-0.385
	(0.219)	(0.412)	(0.559)	(0.583)	(0.490)	(0.545)
GINI(M) × Log(GDP$_{pc}$)	0.1207*	0.0255**	0.0213*	0.0174	0.0259**	0.0170
	(0.0679)	(0.0101)	(0.0121)	(0.0111)	(0.0111)	(0.0110)
REDIST $(t-1)$	0.867***	0.896***	0.760***	0.806***	0.725***	0.735***
	(0.1299)	(0.0343)	(0.0719)	(0.0695)	(0.0841)	(0.0672)
	Panel B: Absolute redistribution with multiple imputations, REDIST$_{\mathrm{MI}}$					
GINI(M)$_{\mathrm{MI}}$	-0.669***	-0.262***	0.145	0.0468	-0.412***	-0.423***
	(0.2025)	(0.0657)	(0.340)	(0.703)	(0.117)	(0.123)
GINI(M)$_{\mathrm{MI}}$ × Log(GDP$_{pc}$)	0.1025***	0.0509***	0.0290	0.0372	0.0930***	0.0912***
	(0.0241)	(0.0112)	(0.0402)	(0.0819)	(0.0172)	(0.0170)
Observations	111	849	430	433	430	430
Countries	29	145	126	126	126	126
Hansen p-val	0.999	0.643	0.984	0.963	0.999	0.996
Diff-Hansen	0.951	0.886	1.000	1.000	1.000	1.000
AR(1) p-val	0.004	0.0000148	0.0303	0.0262	0.0335	0.0280
AR(2) p-val	0.142	0.149	0.913	0.714	0.996	0.714
Instruments	19	147	161	161	174	174

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the Arellano and Bover (1995) conditions. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. The specifications of the equations equal the specifications in the baseline table. Covariates are excluded for reasons of lucidity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

effect cannot be observed in poorer economies, but becomes prevalent in richer economies. Apparently, market inequality plays a less pronounced role for redistribution in developing economies, where democratic structures are often less firmly established. Yet with an increase in wealth—which is typically accompanied by the implementation of free elections and active participation in the political process, as well as enhanced human rights and the rule of law—the Meltzer-Richard effect gains in importance. This basic result remains stable across the different specifications of the baseline regressions, where the effect of market inequality at low development levels is either negative or strongly insignificant, and the effect of the interaction term is positive in each of the regressions. Both effects are even more pronounced in Panel B, which again documents the results of the equivalent MI regressions.

Figure (3.5) illustrates the effect graphically, using the reduced model of Table (3.7). At early stages of development, the marginal effect of GINI(M) is zero, but it increases as the economy develops. The effect becomes significant if economies exceed a critical income level of roughly 2,500 USD. In the post-2010 period, 38 countries were still below that critical level. At the median level (gray vertical line), the effect of market inequality on redistribution is positive and strongly significant.

Figure (3.6) graphs the marginal effect of market inequality for different levels of political rights. The change in the marginal effect of inequality strongly resembles the results found with respect to the economic development level. Even more distinct than in the previous sections, these results imply that market inequality exerts its influence on redistribution via the political process, which is why the Meltzer-Richard effect is considerably less pronounced in countries with less sophisticated democratic structures. With regard to the democracy indicator of Freedom House (2014) used in our empirical specification (POLRIGHT, which runs on a scale from 1 to 7), the average level of democratization in the group of advanced economies is 6.20, whereas political institutions and electoral rights are substantially less established in non-OECD economies (3.59). In some of these countries, the elite control political power including the electoral process, preventing a higher demand for redistribution from translating into real policy action.

3.3.6 Perceived inequality

The results so far imply that greater income disparities enhance redistribution. However, evidence stems from actual market inequality, whereas individual perceptions may be of greater importance in the creation of demand for redistribution, as discussed in recent studies (Niehues, 2014; Engelhardt and Wagener, 2014; Gimpelson and Treisman, 2015). These examinations emphasize that perceptions of inequality are often biased, since individuals hold erroneous beliefs about income inequality, where the true extent of inequality is often underestimated. Forming judgments about subjective inequality is essentially a statistical inference problem which agents build on limited information that may be difficult and costly to access. In a seminal paper, Cruces et al. (2013) show that

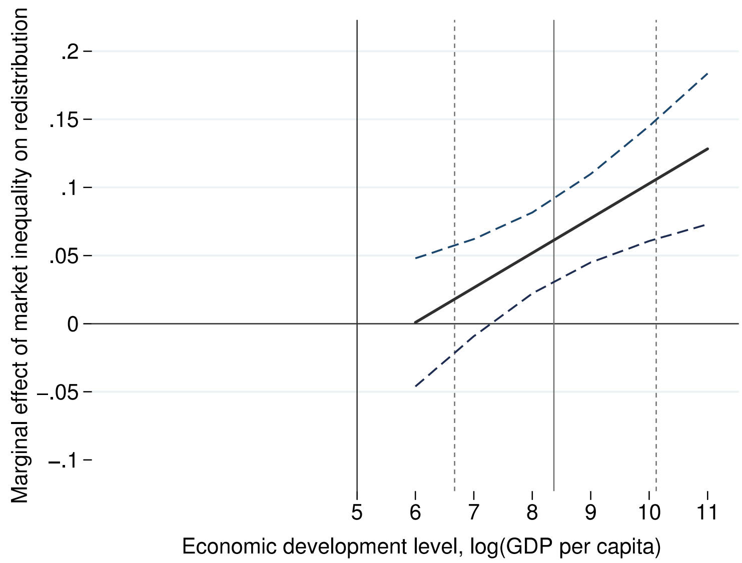

Figure 3.5 The effect of market inequality on redistribution at different levels of economic development. Values are calculated using Column (1b) of Table (3.7). The upwards sloping line plots the marginal effect of market inequality, surrounding dashed lines represent the 90% confidence interval. Vertical lines indicate the distribution of the development level in the sample: dashed gray lines mark the 10th and 90th percentiles, the solid gray line marks the median value.

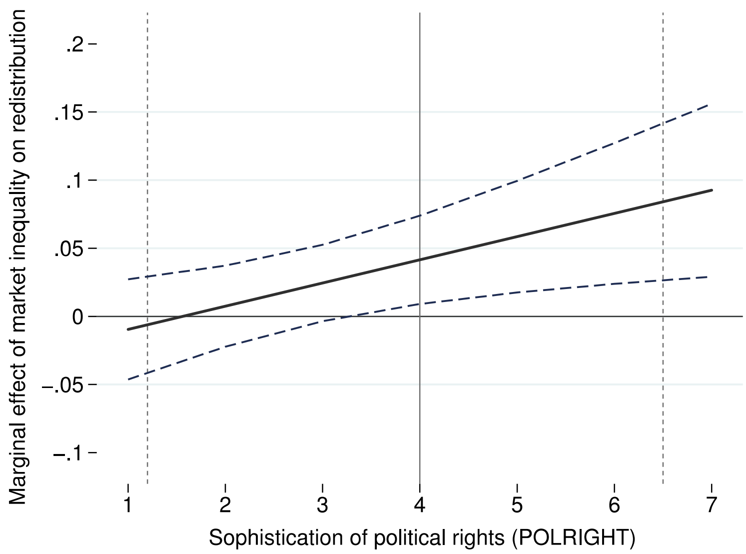

Figure 3.6 The effect of market inequality on redistribution at different levels of political development. Values are calculated similarly to the specification of Column (1b) of Table (3.7) via inclusion of the interaction term GINI×POLRIGHT. The upwards sloping line plots the marginal effect of market inequality, surrounding dashed lines represent the 90% confidence interval. Vertical lines indicate the distribution of the political development level in the sample: dashed gray lines mark the 10th and 90th percentiles, the solid gray line marks the median value.

preferences for redistribution increase when respondents who overestimate their individual position are informed of their true ranking. Therefore, it is to be expected that demand for redistribution is higher if the degree of misperception is low. When comparing official inequality statistics with subjective perceptions across countries, it can be observed that misperceptions vary across countries, with the result that inequality rankings of countries change. In this section, we investigate whether the baseline results are altered if we consider perceptions rather than officially reported statistics.

To achieve suitable measures of perceived inequality, we follow the approach of Cruces et al. (2013) and Engelhardt and Wagener (2014) based on data from the International Social Survey Programme (ISSP). The ISSP is a continuing annual program of cross-national collaboration on surveys covering topics relevant to social science research. Founded in 1984 by research institutions from Australia, the United States, the United Kingdom, and Germany, it currently includes comparable data for 48 countries. Our measure refers to the question (V44 in the 2009 ISSP wave):[24]

> *"In our society there are groups which tend to be towards the top and groups which tend to be towards the bottom. Below is a scale that runs from top to bottom (10 top — 1 bottom). Where would you put yourself now on this scale?"*

Data on this question is available for 44 countries—26 of which are OECD members—for the years 1987, 1992, 1999, and 2006-2009. As a result, the data allows for calculation of perceived inequality measures for the five-year periods 1985-1989, 1990-1994, 1995-1999, and 2005-2009 of our empirical specification. We assume that self-assessments are mainly made in terms of income, so that the answers can be interpreted as the perceived position of the individual in the income distribution. Figure (3.7) illustrates the distribution of the self-assessment in the United States, Denmark, France, and the United Kingdom as documented in the ISSP 2009. Whereas income distributions are typically right-skewed, the figure highlights that the respondents tend to classify their subjective

[24] Note that the exact wording of the question deviates slightly between different countries. The exact formulation for each country can be reviewed in the official ISSP documentation.

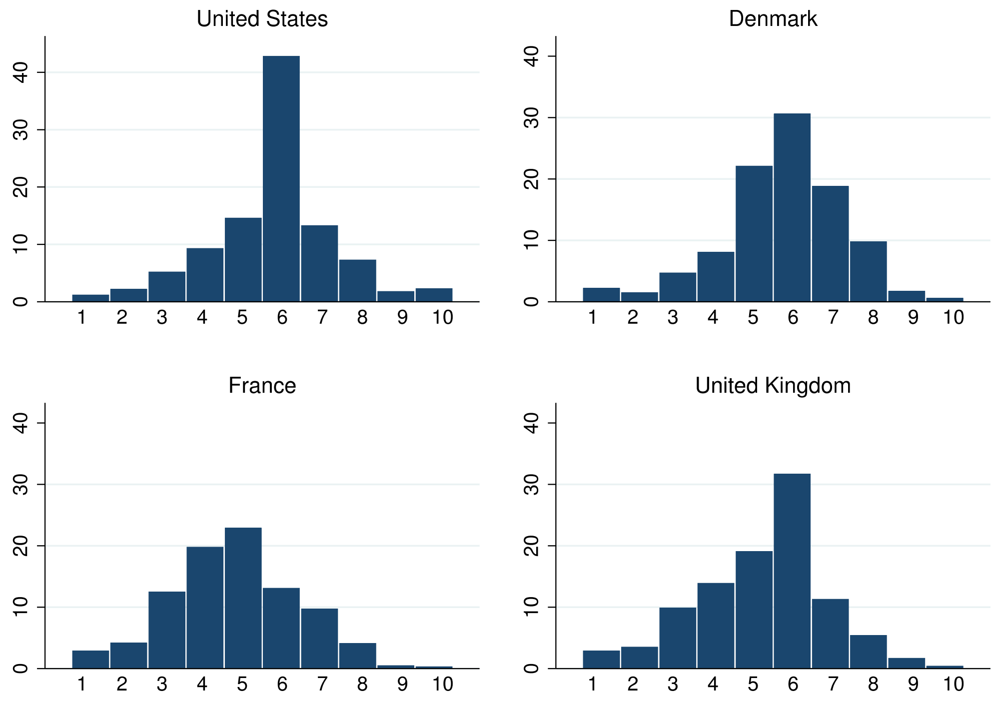

Figure 3.7 The subjective distribution of incomes in the United States, Denmark, France, and the United Kingdom. Data on perceived inequality is from ISSP 2009 (GESIS Study No. 5400 v3.0.0).

income level following a normal distribution. In the United States and the United Kingdom, an extraordinarily large fraction of the population classifies themselves as earning above-average incomes equivalent to the 6th category on the scale.

Using the empirical discrete probability density function $\Phi(y_i)$ implied by the ISSP, we compute a Gini index G_{per} on income perception y_i as

$$G_{\text{per}} = 1 - \frac{\sum_{i=1}^{10} \Phi(y_i)(B_{i-1} + B_i)}{B_{10}}, \tag{3.9}$$

where $B_i = \sum_{k=0}^{i} \Phi(y_k) y_k$, $B_0 = 0$, and $i = 1, \ldots, 10$ are the empirical realizations of the particular groups. To form their views, individuals need to make inferences about the income distribution based on limited information (for a detailed discussion of this process, see Cruces et al., 2013). These individual point estimates can then be used to recover subjective probability distributions of continuous variables (Manski, 2004), where the Gini coefficient described in Equation (3.9) provides a summary statistic of these distributions.

While this procedure provides an advantageous opportunity to compute perceived inequality measures under the given constraint of unavailability of more detailed data with respect to cross-country inequality assessments of individuals, the obtained Gini indices must be treated with caution. This is for three reasons. First, subjects are asked to classify their income on a scale ranging from 1 to 10, where the implicit assumption is that incomes in each class are identical. Particularly with respect to the 10th class, this is a rather bold assumption, as measures of income distribution are often driven by top income earners. As a result, G_{per} neglects the high degree of inequality usually detected in the top income groups. Second, the ability of the applied strategy to recover the subjective probability density heavily relies on the composition of households in the underlying study and the number of respondents. This is because individuals form subjective distributions based on the relevant social reference groups the individuals interact with (see Cruces et al., 2013). Finally, the number of country-years for which subjective income rankings are available in the ISSP is scarce.

To mitigate these methodological drawbacks, we enlarge the analysis by two additional variables. The first is an alternative measure of perceived inequality based on question V32 of the ISSP:

> *"To what extent do you agree or disagree to the following statement: Differences in income in your country are too large?"*

Respondents are asked to classify their assessment on a scale running from 1 (strongly agree) to 5 (strongly disagree). Our variable INC-DIFF is built using the average of all assessments, which is then recoded so that higher values of INC-DIFF represent higher levels of subjective inequality.

Second, we use data on subjective assessments from the World Value Survey (WVS) to compute an alternative Gini index of perceived inequality. As the quality of the perceived Gini index depends upon the representativeness of the included households in the underlying study, building Gini indices based on WVS rules out the possibility that the measured subjective inequality is driven by the household composition of the ISSP survey. The WVS employs a question quite similar to the subjective assessment of the ISSP:

"On this card is an income scale on which 1 indicates the lowest income group and 10 the highest income group in your country. We would like to know in what group your household is. Please, specify the appropriate number, counting all wages, salaries, pensions and other incomes that come in."

Data on this question is available for 84 countries in six waves, which allows us to calculate inequality measures for the 5-year periods 1980-1984, 1990-1994, 1995-1999, 2000-2004, 2005-2009, and 2010-2014. Yet, as in the case of ISSP data, the composition of countries changes between the waves. We denote the Gini coefficients built on the ISSP and the WVS as $\mathrm{GINI}_{\mathrm{ISSP}}$ and $\mathrm{GINI}_{\mathrm{WVS}}$, respectively. In computing the perceived measures, we follow Engelhardt and Wagener (2014) in weighting the Ginis by the actual inequality. The reason for this is that perceptions of inequality are larger the more unequal a country actually is. Indeed, actual inequality can be expected to exert feedback effects on perceived inequality: if reported official statistics discussed in the media or in political debates indicate a large level of inequality, individuals are likely to adjust their subjective assessment.

Part A of Figure (3.8) illustrates the relationship between perceived and both actual market and actual net inequality. With regard to the ISSP measures, the correlation between actual and perceived inequality is weak and insignificant. Whereas the bivariate correlation between the variables remains relatively weak when considering perceived measures obtained by the WVS, the relationship is significant at the 5% level. This implies that there is a slight tendency for unequal societies to classify their level of inequality higher than societies with a more equal distribution of incomes. Part B graphs the linkage between INC-DIFF and the Gini measures of perceived and actual inequality. The data implies a positive relationship between the subjective Gini coefficient and perceived income differences (34 percent). However, such a relationship is not visible with respect to actual market inequality (-12.9 percent).

Figure (3.9) lists the countries with the highest and the lowest misjudgment of national inequality in the group of OECD countries. Employing data from the ISSP 2009, it can be seen that inequality is perceived to be much lower than actual inequality in

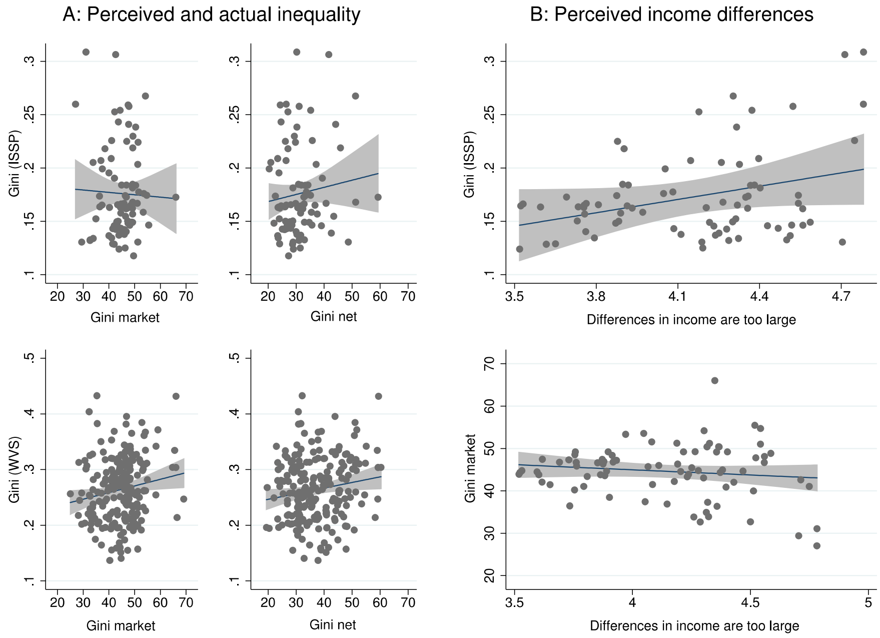

Figure 3.8 The relationship between actual and perceived inequality, measured with data based on the ISSP and the WVS. The gray-shaded area around the regression line marks the 95% confidence interval.

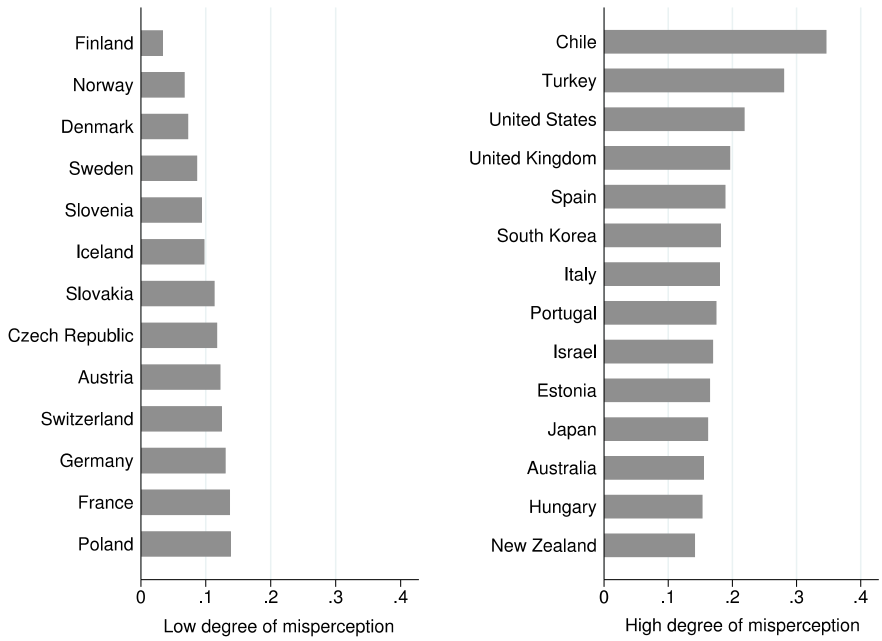

Figure 3.9 The difference between actual and perceived inequality in the period 2005-2009. Data on perceived inequality is from ISSP 2009 (GESIS Study No. 5400 v3.0.0).

each OECD member state. Whereas citizens in some of the non-OECD countries tend to overrate income disparities, they are systematically underestimated in the group of advanced economies. Actual net inequality in the OECD countries averages 30.73 Gini points, while the mean of perceived Ginis is 17.2 ($\text{GINI}_{\text{ISSP}}$) and 27.0 ($\text{GINI}_{\text{WVS}}$), respectively. Differences between the ISSP and the WVS have their origin in deviating survey designs and sample sizes. There are, however, only minor differences in the ranking of inequality misjudgments between the ISSP and the WVS. Particularly in the Scandinavian countries, perceived inequality is close to officially reported Gini coefficients. This also holds for some of the eastern European countries, such as the Slovak Republic, Slovenia, and the Czech Republic. The highest misperceptions of inequality can be found in Chile and Turkey, followed by the Anglo-Saxon nations the United States and the United Kingdom, and the Mediterranean economies of Spain, Italy, and Portugal.

Figure (3.14) in the appendix provides a direct comparison between the perceived and the actual income distribution based on a scale running from 1 to 10. To compile actual distributions of income, we use data of Round 7 of the European Social Survey (2014) (ESS), which is available for 14 European countries. Illustrated are subjective assessments and actual distributions for Finland, Austria, France, and Switzerland. The figure underscores that citizen's self-positioning in each of the graphed countries is strongly biased to the center of the distribution, resulting in a considerable misjudgment of the individual rank. While very few of the probands classify themselves as having incomes coinciding with the borders of the $(1, 10)$ interval, the actual distribution of incomes implies that a much higher fraction of individuals tends to rank in the classes 1-3 and 8-10 than implied by subjective assessments. This bias is less pronounced in Finland, which is in accordance with the (relatively) low degree of misperception depicted in Figure (3.9). Note, however, that the limited number of included countries in the ESS impedes the illustration of countries with a high degree of misperception, as data concerning countries located on the right side of Figure (3.9) is unavailable.

While the extent of misjudgement differs substantially among OECD countries, there is a distinct relationship between errors in perception and the level of redistribution. Figure

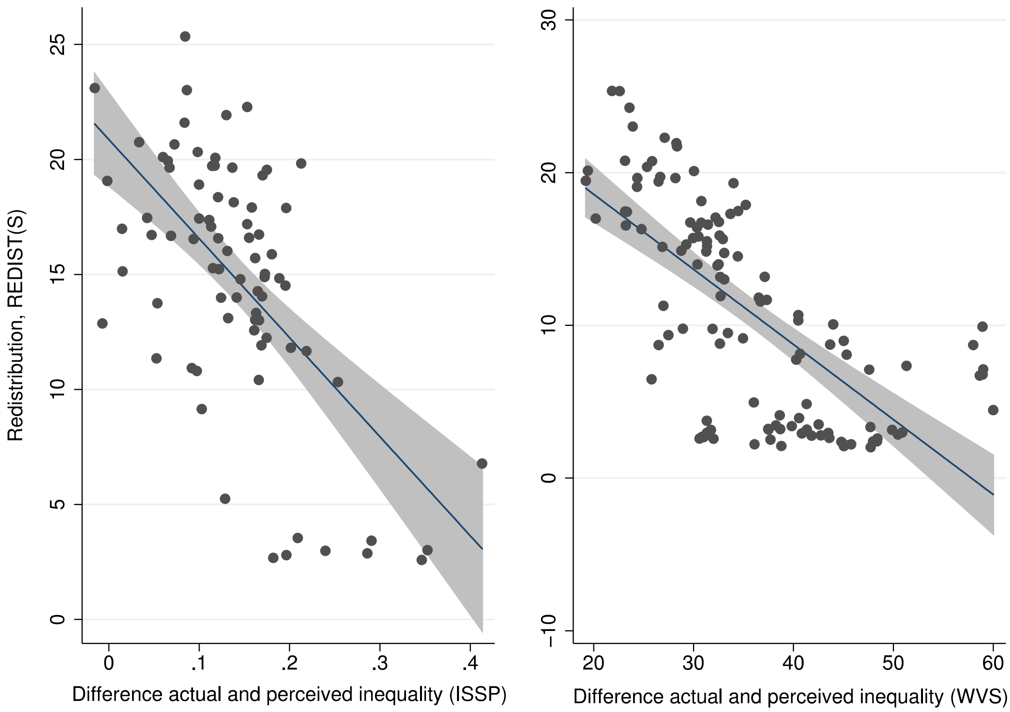

Figure 3.10 The relationship between the extent of misjudgment and governmental redistribution in the period 2005-2009. Redistribution variable is REDIST(S). The gray-shaded area around the regression line marks the 95% confidence interval.

(3.10) depicts the relationship between redistribution and the degree of misperception, highlighting a strong negative correlation of -61.39 (ISSP) and -67.38 (WVS), respectively, that emerges regardless of the data source used to compile perceived inequality measures. This emphasizes that the preference for redistribution is lower if individuals underestimate the "true" degree of inequality. However, the figure implies that if the individuals are more aware of national income disparities, demand for redistribution is higher, resulting in greater redistributional activity in the political process.

While Figure (3.10) provides a first intuitive sign for a redistribution-enhancing effect of subjective inequality, Figures (3.15) and (3.16) in the appendix illustrate this relationship more directly. In both cases, the positive relationship between inequality and redistribution is much more distinct compared with the analysis of Figure (3.4) that is based on actual inequality.

Table (3.8) is concerned with a more in-depth examination of this link. The table analyzes the effect of perceived inequality measures in the reduced model specification

Table 3.8 The effect of perceived inequality on redistribution. Dependent variables are absolute redistribution, REDIST and REDIST(S), in Panels A and C, and relative redistribution, $\text{REDIST}^{\text{rel}}$ and $\text{REDIST(S)}^{\text{rel}}$, in Panel B.

	Perceived inequality (ISSP)		Perceived inequality (WVS)		Income Differences	
	OECD	All data	OECD	All data	OECD	All data
	Panel A: Absolute redistribution, REDIST and REDIST(S), system GMM					
$\text{GINI}_{\text{ISSP}}$	0.105**	0.0710***				
	(0.0456)	(0.0188)				
GINI_{WVS}			0.106*	0.0939**		
			(0.0635)	(0.0453)		
INC-DIFF					5.795***	4.276*
					(2.204)	(2.504)
$\text{Log}(\text{GDP}_{pc})$	2.217	6.152	3.894*	8.005**	-2.569	5.605
	(4.984)	(5.625)	(2.164)	(3.263)	(4.257)	(7.351)
$\text{REDIST}(t-1)$	-0.165	0.210	0.684**	-0.0204	0.700*	0.155
	(0.532)	(0.506)	(0.331)	(0.346)	(0.414)	(0.835)
	Panel B: Relative redistribution, $\text{REDIST}^{\text{rel}}$ and $\text{REDIST(S)}^{\text{rel}}$, system GMM					
$\text{GINI}_{\text{ISSP}}$	0.00149**	0.00120***				
	(0.000751)	(0.000444)				
GINI_{WVS}			0.00329*	0.00109		
			(0.00186)	(0.00178)		
INC-DIFF					0.344**	0.0739
					(0.146)	(0.115)
	Panel C: Absolute redistribution, REDIST and REDIST(S), OLS					
$\text{GINI}_{\text{ISSP}}$	0.104***	0.0938***				
	(0.0322)	(0.0302)				
GINI_{WVS}			0.116***	0.101***		
			(0.0320)	(0.0260)		
INC-DIFF					2.236	6.640**
					(2.267)	(2.918)
Observations	61	77	72	207	61	73
Countries	28	38	25	84	28	35
Hansen p-val	0.474	0.154	0.296	0.588	0.340	0.172
AR(1) p-val	0.850	0.580	0.307	0.931	0.179	0.474
Instruments	13	18	15	15	13	15
Collapsed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses and OLS estimations with cluster-robust standard errors. Regressions are based on perceived inequality measures based on the ISSP and the WVS. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. AR(1) p-val reports the p-values of the AR(1) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2 and collapsed to prevent instrument proliferation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

used in Column (1) of Table (3.1), as the limited availability of subjective Ginis yields a severe reduction in the included country-years when incorporating a wide range of covariates. To ensure comparability of the results with the previous findings, we report the outcomes of two different sample compositions with respect to each of the perceived measures. The first sample takes into account data from OECD countries, while the second specification is built on all country-years for which data is available. The table investigates the effect on both absolute (Panel A) and relative (Panel B) redistribution. To ensure comparability to our baseline outcomes, both panels are again estimated via system GMM. In addition, Panel C reports the results when OLS is used as estimation technique. The latter may be advantageous owing to the limited number of country-years available for our subjective measures.

The results suggest that redistributional efforts of the government are considerably influenced by subjective assessments. With respect to the ISSP data, we find a positive and strongly significant effect of perceived inequality on both absolute and relative redistribution. As in the previous estimations based on market inequality, this effect is particularly strong in OECD countries with established democratic structures. When using information from the whole sample for which data is available, the marginal effect shrinks slightly. This reduction is weaker than in the case of market inequality; however, data on self-assessment in the ISSP is available only for relatively advanced economies. This results in both a less pronounced reduction in the marginal effect across the different sample compositions and insignificance of the development level. The subjective inequality measure based on WVS data confirms the positive relationship between perceptions of inequality and redistribution. This effect is more prevalent in absolute rather than in relative terms. Note, however, that drawing on all available data on subjective measures yields a substantial increase in the number of observations, particularly with respect to GINI_{WVS}.

Our sensitivity variable INC-DIFF supports the positive effect of subjective inequality on redistribution. If individuals perceive income differences as being too large, the demand for redistribution rises, which eventually channels into actual policy measures. This result

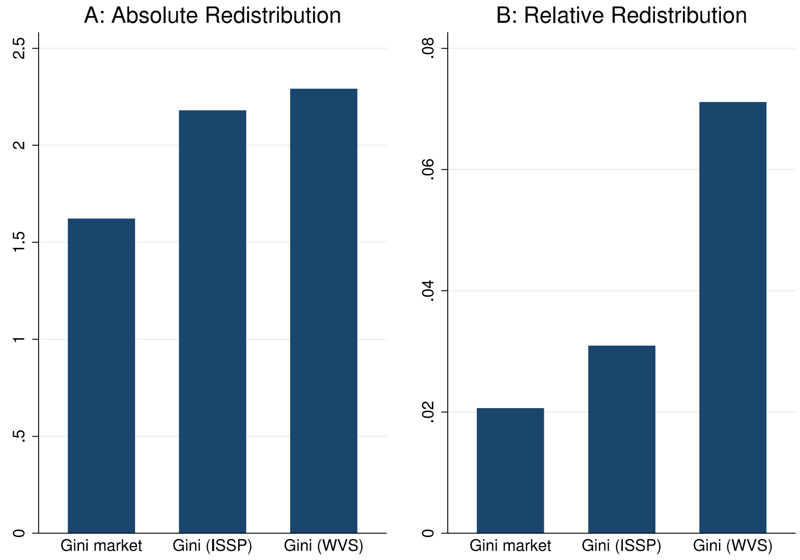

Figure 3.11 The marginal effect of actual and perceived inequality on redistribution at a one standard-deviation-change of the underlying variable in the sample of OECD countries. The graph illustrates the marginal effects estimated in Tables (3.1) and (3.8). Each effect is computed based on the reduced model specification.

also implies that the methodological drawbacks that are inherent to the computation of subjective Gini indices based on self-assessment do not yield a substantial bias in the estimation. Finally, the positive effect of subjective inequality on redistribution is stable when OLS is used as estimation technique (see Panel C).

The findings thus far imply that both officially reported market inequality and perceived Ginis exert strong influences on redistribution. However, the estimated parameters cannot be compared directly, as the mean and standard deviation of the measures are different. Meanwhile, comparisons of the marginal effects between actual and perceived inequality measures should be treated with caution, as the underlying concepts are different. Bearing these concerns in mind, Figure (3.11) depicts the marginal effect of a one standard-deviation-change in the inequality measures on redistribution in the sample of OECD countries. The figure suggests a substantially stronger impact of subjective inequality compared to officially reported Gini indices. While a change in GINI(M) of one standard deviation results in an increase in redistribution of 1.62 Gini points, perceived inequality measures imply a considerably higher marginal effect of 2.18 ($\text{GINI}_{\text{ISSP}}$) and 2.29 ($\text{GINI}_{\text{WVS}}$), respectively. The same holds true if we assess the effect on relative redistribution in the second panel of Figure (3.11).

Overall, the marginal effect on redistribution seems to be higher when considering perceived measures rather than officially reported market inequality. This result emphasizes that a higher level of income inequality translates to greater redistributional efforts by the government if citizens are aware of national income disparities. In the presence of misperceptions, however, demand for redistribution may be low, even if market incomes may be distributed highly unequally.

3.4 Concluding remarks

This article investigates the empirical relationship between income inequality and redistribution on a broad basis. Retesting the Meltzer-Richard hypothesis, we present affirmative evidence which is robust to various sample compositions, several model specifications, and different social security systems. Our study incorporates a variety of actual and perceived inequality measures from multiple recently collected cross-national inequality datasets, allowing to assess the entanglement between income disparities and redistributive policies in a panel context.

Additionally, we account for the shape of the income distribution and determine the impact of different income groups on redistribution. The results imply that the middle class exerts a significant influence on the extent of redistribution in all specifications. However, top incomes also appear to play a crucial role in redistributional issues, supporting notions of cronyism which might arise to reduce the financial burden from redistribution. Meanwhile, our findings indicate that governments do not incorporate the objectives of the poorest in determining the amount of redistribution.

Accounting for different development levels and varying sophistication of political rights, our analysis provides evidence for the importance of the political channel which translates market inequality into more redistribution. We observe that the Meltzer-Richard effect is less pronounced when democratic structures are less developed, impeding the transmission of redistributive preferences of the population in the political process.

Finally, we demonstrate that individual perceptions of inequality are often biased.

Based on different data sources, we show that perceived inequality is often lower than actual disparity of incomes, albeit to varying degrees. In countries where citizens are aware of the "true" extent of inequality, demand for redistribution is higher. The regression estimates imply that the Meltzer-Richard effect is even stronger when using perceived inequality measures, indicating that governmental redistribution is influenced by subjective perceptions rather than actual inequality.

This chapter offers a cross-nationally comparable analysis of the Meltzer-Richard hypothesis, including countries for which data has long been rather scarce. It should, however, be underlined that the political economy literature has arrived at the consensus that individuals are motivated by more than self-interest, which is why preferences for redistribution may also be influenced by factors beyond the median voter model. While future research on this topic may be promising, prospective studies may focus on the improvement of perceived inequality measures. Yet such improvements necessitate the extension of data availability for a longer time span, achievement of which is unrealistic in the near future, since we cannot expect reliable micro data of earlier periods to become available. Future projects may also evaluate the redistributive effect of specific fiscal policy instruments, as they may have varying redistributional consequences. This may shed light on how governments best perform the balancing act of effective redistribution while avoiding disturbing side effects.

Appendix

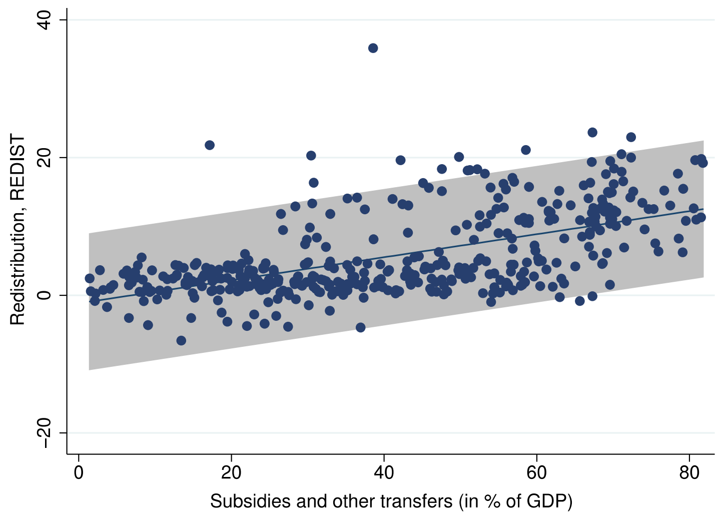

Figure 3.12 The relationship between REDIST and social transfer payments. The gray-shaded area around the regression line marks the 95% confidence interval. Data source is World Bank (2016).

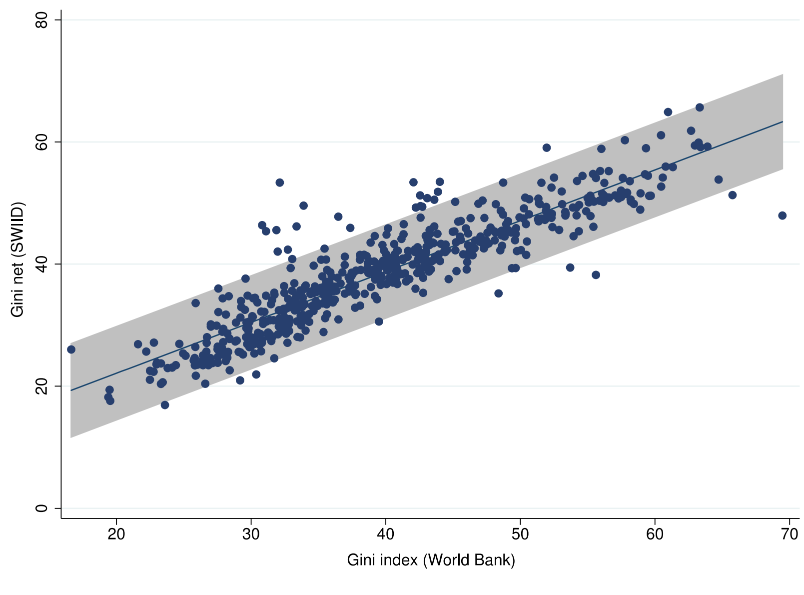

Figure 3.13 The relationship between inequality levels implied by the data of the World Bank and the SWIID. The gray-shaded area around the regression line marks the 95% confidence interval. The regression of Gini net (SWIID) on net inequality reported by the World Bank yields a marginal effect of 0.9996*** (0.021) and R-squared of 0.80, suggesting consistency across both data sources.

Table 3.9 Descriptive statistics of the variables used in the regressions.

	Obs.	Mean	Std. Dev.	Min	Max
	Whole sample				
GINI(M)	1128	44.00543	8.58483	18.75223	71.29995
GINI(N)	1128	37.4484	9.956986	16.91599	67.55808
REDIST	1128	6.556924	6.443803	-14.73038	26.06834
REDIST(S)	453	9.646837	7.347301	-2.461385	26.06834
Log(GDP$_{pc}$)	1626	8.387529	1.30292	5.317263	11.80222
UNEMP	855	8.955421	6.1094	.5333334	36.95
POLRIGHT	1616	4.06414	2.182818	1	7
Log(FERT)	2029	1.2833	.5502135	-.1369659	2.21336
MIDDLECLASS	613	47.08253	6.258872	20.27	57.42
TOP-1	1139	9.453331	4.38978	2.467996	29.64182
BOTTOM-10	624	2.571311	1.081332	.02	5.43
QUINT$_3$	628	15.02097	2.330285	5.46	18.92
AGE	2007	73.33025	20.10824	16.89672	120.6592
ARP	606	.0361298	.0310677	-2.86e-10	.1262349
TAP	606	.054579	.0685522	-1.76e-07	.3524257
SOT	517	37.15542	21.03387	.5685228	81.75859
INC	185	4.801959	2.469696	.1126	11.3222
PRO-POOR	363	.4848485	.5004602	0	1
INC-DIFF	82	4.137436	.3351408	3.518802	4.782004
GINI$_{\mathrm{WVS}}$	230	.2612377	.0577208	.1368072	.4326859
GINI$_{\mathrm{ISSP}}$	88	.1761149	.0423805	.1176887	.3087203
GINI$_{\mathrm{WVS}}$ (norm)	212	35.72963	19.83772	0	100
GINI$_{\mathrm{ISSP}}$ (norm)	88	39.81584	22.27918	0	100
	OECD countries				
GINI(M)	337	43.69385	5.853104	28.17671	55.89581
GINI(N)	337	29.899	7.057057	16.91599	54.75827
REDIST	337	13.79485	5.921812	-.2931641	26.06834
REDIST(S)	235	14.94206	5.498173	.3727439	26.06834
Log(GDP$_{pc}$)	346	9.787823	.5831261	7.416579	11.00429
UNEMP	170	7.630284	3.718025	2.325	22.4
POLRIGHT	306	6.202015	1.622269	1	7
Log(FERT)	374	.7108145	.3346427	.1587117	1.912944
MIDDLECLASS	155	51.398	4.464039	35.10667	57.42
TOP-1	333	8.189326	3.348493	3.242794	22.00286
BOTTOM-10	161	2.942903	.9535844	.75	5.43
QUINT$_3$	155	16.59013	1.674238	10.62	18.92
AGE	374	54.81633	9.968972	37.21658	101.8449
ARP	159	.0689553	.0251178	.0069986	.1262349
TAP	159	.1221109	.0750928	-1.76e-07	.3524257
SOT	124	60.75277	13.90548	17.15351	81.75859
INC	185	4.801959	2.469696	.1126	11.3222
PRO-POOR	363	.4848485	.5004602	0	1
INC-DIFF	66	4.073168	.3060476	3.518802	4.749338
GINI$_{\mathrm{WVS}}$	81	.2700892	.0589075	.1404138	.4326859
GINI$_{\mathrm{ISSP}}$	68	.1719835	.0349464	.1176887	.267476
GINI$_{\mathrm{WVS}}$ (norm)	81	46.22332	21.60697	5.058921	100
GINI$_{\mathrm{ISSP}}$ (norm)	68	41.54862	20.75491	0	100

Notes: The computation of the perceived inequality measures is explained in detail in Section (3.3.6). The perceived Gini coefficients denoted with the supplement (norm) reflect normalized values.

Table 3.10 Baseline regressions, determinants of redistribution in a broad sample, multiple imputations estimations. Dependent variable is redistribution, $\text{REDIST}_{\text{MI}}$.

	OECD	All available observations				
	(1a)	(1b)	(2)	(3)	(4)	(5)
$\text{GINI(M)}_{\text{MI}}$	0.221**	0.294***	0.537***	0.506***	0.518***	0.482***
	(0.1060)	(0.0805)	(0.118)	(0.119)	(0.141)	(0.118)
$\text{Log(GDP}_{pc})$	2.912***	2.307***	2.665**	2.831**	2.377**	3.328***
	(0.9712)	(0.634)	(1.106)	(1.174)	(1.143)	(1.282)
$\text{REDIST}_{\text{MI}}(t-1)$	0.640***	0.465***	0.183	0.212	0.203	0.143
	(0.067)	(0.125)	(0.155)	(0.166)	(0.159)	(0.157)
UNEMP			0.0373	0.0358	0.0386	-0.00866
			(0.117)	(0.131)	(0.116)	(0.120)
POLRIGHT			0.604*	0.615*	0.627*	0.567*
			(0.336)	(0.360)	(0.345)	(0.318)
Log(FERT)			0.688	0.430	0.620	-2.971
			(1.543)	(1.576)	(1.674)	(2.789)
MIDDLECLASS			0.418*		0.470*	0.327
			(0.232)		(0.280)	(0.253)
TOP-1			-0.431**	-0.499**	-0.432*	-0.477**
			(0.217)	(0.220)	(0.239)	(0.209)
QUINT_3				0.801		
				(0.597)		
BOTTOM-10					-0.369	
					(1.575)	
AGE						0.117
						(0.0751)
Observations	111	873	443	443	443	443
Countries	29	146	126	126	126	126
MI F Stat	37.45	12.32	27.09	23.41	21.95	22.26
MI F p-val	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Average RVI	1.2589	0.460	0.458	0.415	0.429	0.376
Largest FMI	0.577	0.428	0.373	0.364	0.356	0.357
Imputations	100	100	100	100	100	100
Instruments	19	69	39	39	42	42

Notes: Table reports multiple imputations two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. $\text{REDIST}_{\text{MI}}$ and $\text{GINI(M)}_{\text{MI}}$ denote the multiply-imputed variants of REDIST and GINI(M) as they originally appear in the SWIID 5.0. MI F Stat gives the F statistic of the multiple imputation estimations, MI F p-val reports the referring p-values. Average RVI documents the average relative variance increase due to nonresponse, largest FMI reports the largest fraction of missing information. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.11 The effect of top income shares on redistribution. Dependent variable is redistribution, REDIST(S).

	SWIID	World Wealth and Income Database (WID)			
	(1)	(2)	(3)	(4)	(5)
GINI(M)	0.832***	0.752***	0.520***	0.781***	0.759***
	(0.215)	(0.203)	(0.138)	(0.149)	(0.194)
Log(GDP$_{pc}$)	1.907	4.172	7.685***	4.114	3.135
	(1.470)	(2.898)	(1.081)	(2.668)	(3.880)
REDIST($t-1$)	0.298***	0.136	0.0194	0.191*	0.194
	(0.102)	(0.0843)	(0.0925)	(0.108)	(0.138)
Top-1%	-1.110***	-0.971***			
	(0.415)	(0.208)			
Top-0.5%			-0.926***		
			(0.326)		
Top-0.1%				-1.823***	
				(0.384)	
Top-0.01%					-2.994**
					(1.495)
Observations	89	89	89	89	89
Countries	18	18	18	18	18
Hansen p-val	0.526	0.527	0.831	0.674	0.668
Diff-Hansen	0.454	0.747	0.922	0.441	0.574
AR(1) p-val	0.672	0.672	0.275	0.430	0.516
AR(2) p-val	0.128	0.182	0.193	0.177	0.178
Instruments	19	19	19	19	19
Collapsed	Yes	Yes	Yes	Yes	Yes

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. The Table uses top income shares of the World Wealth and Income Database (WID) of Alvaredo et al. (2015). Hansen p-val gives the J-test for overidentifying restrictions. Diff-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the Arellano and Bover (1995) conditions. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

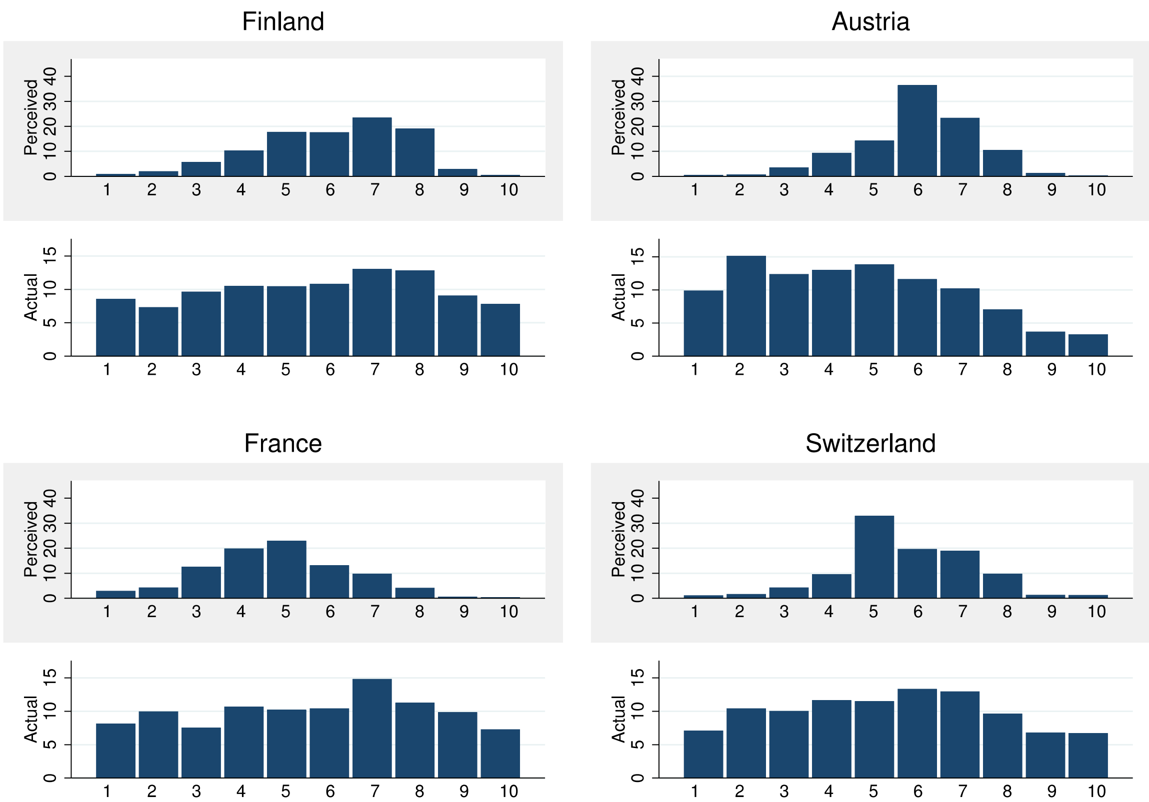

Figure 3.14 Perceived and actual distribution of incomes among classes on a scale from 1 to 10. Data on actual distribution of incomes is from European Social Survey (2014), perceived measurements are calculated as described in Section (3.3.6). Gray-shaded areas mark the distribution of perceptions.

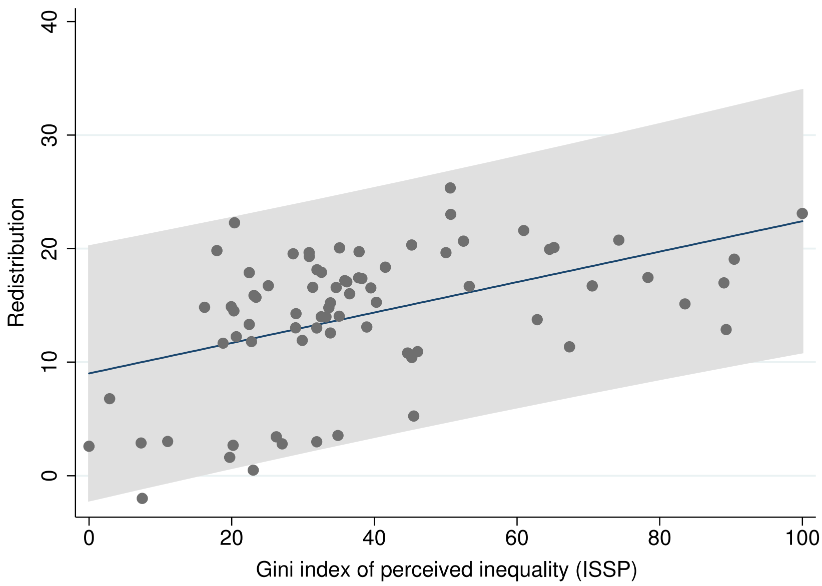

Figure 3.15 The relationship between redistribution and perceived inequality computed with the ISSP data. The solid line marks the regression line between the two variables. Perceived Gini indices are normalized to cover the interval from 0 to 100.

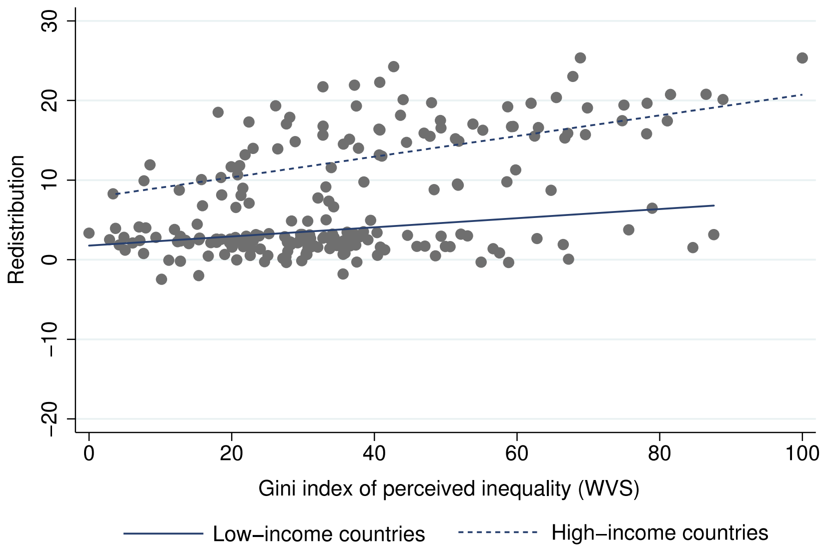

Figure 3.16 The relationship between redistribution and perceived inequality computed with the WVS data. "High-income countries" (dashed line) and "Low-income countries" (solid line) illustrate the regression lines between perceived inequality and redistribution in the subsamples of advanced and developing economies, respectively. Country classification refers to the World Bank. Perceived Gini indices are normalized to cover the interval from 0 to 100.

Chapter 4

Consequences of culture and diversity for governmental redistribution

Preliminary remarks:[25] The previous chapter highlighted the crucial determinants of governmental redistribution. While the Meltzer-Richard effect turns out to be highly robust across different model specifications and various sample compositions, the analysis points to further channels which appear to be relevant for redistributional activities of the government. The findings point to a decisive role of the middle class, though also approving a negative impact of top incomes. The relationship between inequality and redistribution is less pronounced in developing economies with a lower sophistication of political rights, illustrating that it is the political channel through which higher inequality translates into more redistribution. Apart from the political channel, the empirical literature emphasizes culture to be a further influential factor in determining the size of the social security system (Luttmer and Singhal, 2011; Luttmer, 2001).

The following chapter investigates the effects of culture and diversity on governmental redistribution for a broad sample of countries, indicating a significant impact of cultural values on the size of the welfare state. The sharp rise in migration in recent years raises questions on whether different cultural backgrounds between migrants and natives con-

[25] This chapter is based on joint work with Klaus Gründler.

tribute to a change in redistributive policies in the host country. The results suggest that an increase in cultural or ethnic diversity is negatively related to redistributional activities of the government, though via a non-linear relationship. The findings imply that migrants' preferences for redistribution are strongly affected by preferences in their home countries and emphasizes the relevance of racial group loyalty.

4.1 Introduction

The past years saw the highest level of human displacement on record. Roughly 65 million people around the world were forcibly displaced, 21 million among them having escaped war or political pressure and seeking refuge in foreign countries (UNHCR, 2016). There is a large literature focusing on the benefits and costs of immigration within *preexisting* social security systems (Rowthorn, 2008; Stichnoth and Van der Straeten, 2013). But even more important, the recent development intensifies the significance of a related question economists have only recently begun to address: Does immigration yield *changes* in the existing social security systems?

While such a change may have its roots in a number of channels, a prominent line of reasoning argues that differences in cultural values between the native population and the immigrants affect the welfare state (Alesina and Glaeser, 2004). The recent literature has shown that culturally-induced changes in the social security system may have their origin in two main channels: (1) preferences for redistribution of immigrants are strongly determined by their country of birth and may deviate from the preferences of the native population (Luttmer, 2001) and (2) cultural protectionism of the native population is dependent on the degree of cultural, religious and ethnic fractionalization (Oesch, 2008).

In this paper, we empirically study both effects in a broad panel of countries. Leaving the exclusive focus on immigration, our contribution is twofold: First, we examine to what extent different cultural traits explain cross-country differences in social security systems. Second, we analyze the effect of ethnic and religious diversity on the extent of redistribution, thereby investigating (racial) group loyalty based on a large international sample.

With regard to both research questions, there is a surprising scarcity in the economic and political science literature. This scarcity has its origins in two challenges that accompany cross-country studies concerning redistribution and cultural values. The first difficulty lies in the acquisition of comparable international data on inequality and redistribution, while the second hurdle is to disentangle cultural traits from institutions. Fortunately, in recent years the empirical literature has made some major progress towards meeting both challenges. The latest update of the *Standardized World Income Inequality Database* (SWIID 5.1) from July 2016 includes 174 countries from 1960 to the present and enables access to roughly 4,600 country-year observations on inequality before and after taxes and transfers that are comparable to those obtained by the LIS Cross-National Data Center. The distinction between inequality before and after government intervention allows us to measure redistribution via the "pre-post-approach". Second, our analysis is based on four types of external instruments for culture emphasized by the recent empirical literature. These instruments include jack-knifed regional averages of cultural traits (as used in Chapter (2.4.3) and in the literature on democracy, see Acemoglu et al., 2014; Madsen et al., 2015, for trade see Autor et al., 2013; Dauth et al., 2014), language differences and pronoun drop (Kashima and Kashima, 1998), and two biological variables associated with different types of culture: genes, measured in terms of frequencies of blood types (Gorodnichenko and Roland, 2016), and prevalence of the pathogen *Toxoplasma gondii* (Maseland, 2013).

We find that culture plays an important role in the formation of redistributive policies. Specifically, countries in which strong family ties are prevalent and those with a high preference for a tightly-knit connection with other members of the society feature lower degrees of redistribution. In contrast, societies that are shaped more by individualistic values tend to have more expansive welfare systems, shifting insurance from the family level to the state level. In addition, we find that support for the indigent is weaker in countries that accept an unequal distribution of power and that consider obedience a desirable attitude. The results also suggest that redistribution is lower if people are convinced that hard work rather than connections or luck is key to success. Conversely, we provide strong evidence that societies whose members exhibit a high level of trust and tolerance towards individuals outside their social group tend to be more supportive of equalizing policies.

We further find that cultural values do not only *directly* influence social policies, but also trigger *indirect* effects by influencing the transmission of inequality to redistribution. While we find a strongly significant average effect of market inequality on redistribution that is in line with Meltzer and Richard (1981), this effect only sets in in societies with low acceptance of unequally distributed power, a high level of trust, a lower preference for hard work, and in those that are predominantly shaped by feminine values. In contrast, countries with strong family ties that promote collectivist values tend to be much more reluctant to respond to periods of increasing inequality with redistributive policies. In these countries, the family provides the social safety net, which is why members of collectivist societies do not consider the provision of social security an important task of the state.

Finally, our results demonstrate that an increase in diversity yields a significantly negative effect on the generosity of the welfare state that is most pronounced with regard to cultural and ethnic fractionalization and much weaker for religious multiplicity. Digging deeper into this relationship, we find that diversity and redistribution are linked via a non-linear function. The negative effect of diversity is most strongly pronounced in countries with an ethnic, religious or cultural majority, and much less prevalent once a certain tipping point of variety is exceeded.

The paper is organized as follows. Section (4.2) discusses the various facets of culture and its potential consequences for redistributive policies, while Section (4.3) describes the data used for our analysis and illustrates the differences in cultural traits across countries. Section (4.4) details the employed estimation and instrumentation strategy, which is applied in Sections (4.5) and (4.6), the latter sections reporting the empirical effects of culture and diversity on redistribution. Finally, Section (4.7) concludes.

4.2 Economic consequences of culture and the recent literature

4.2.1 Cultural values, economic outcomes, and redistribution

While economists have long been reluctant to consider culture a possible source of economic outcomes, there is now a widespread belief that cultural values and economic performance are closely entangled (Guiso et al., 2006). A large body of literature has examined the consequences of culture, stressing its impact on institutions and economic performance (Tabellini, 2010; Alesina et al., 2015), corruption (Licht et al., 2005; Jing and Graham, 2008), and collective decision making (Fine, 2001; Knack, 2002).

The study of decision making further allows to approach the nature of culture from a scientific perspective, as the frequent and various usage of the term in common parlance makes it a rather undefined and vague concept. In general, decision making depends on three different levels of uniqueness in human mental programming (Hofstede, 2001): The *universal* level is shared by all mankind and includes the biological system of the human body, expressive behavior, and associative and aggressive behaviors. The *collective* level, in contrast, is shared only with people who belong to a certain social group, distinguishing this group from other societies. This comprises the entire area of human culture, which is passed from one generation to the next. Finally, the most unique part is *personality*, which uniquely distinguishes individuals from one another even if they belong to the same social group. Whereas economic research traditionally placed great emphasis on this level of mental programming, the more recent literature has shown that the collective level contributes substantially to the way people interact and, consequently, to economic outcomes (see, e.g., Gorodnichenko and Roland, 2011; Alesina and Giuliano, 2015).

Another branch of the literature traces the formation of social security systems back to cultural factors and diversity. Alesina and Giuliano (2011b) show that individual preferences for redistribution are determined by cultural traits and attitudes towards other members of the society. In addition, Luttmer and Singhal (2011) find that immigrants from countries with a high average preference for redistribution tend to be more likely to vote for redistributive policies.

4.2.2 Different dimensions of culture

The literature at hand stresses that culture as such does not yield a uniform influence on economic outcomes, but emphasizes that its various dimensions trigger different—and often contradictory—effects (Alesina and Giuliano, 2015). During the past decades, several concepts have been developed to classify and measure culture, all of which emphasize different aspects of collective behavior. In this section, we briefly discuss the most commonly used of these concepts and provide a short summary of the empirical literature on how these cultural traits have affected economic outcomes. Additionally, in light of the scarcity of studies linking cultural differences to differences in national social security systems, we present hypotheses of how collective values might contribute to more or less redistribution.

Individualism

The individualism-collectivism dimension considers whether a society is shaped more by the individual or the collective, measuring the extent to which individuals are supposed to take care of themselves as opposed to being strongly integrated and loyal to a cohesive group. Several studies emphasize that this cultural trait is the main dimension of cultural variation (Gorodnichenko and Roland, 2016; Heine and Ruby, 2010), exerting a positive and robust effect on innovation and long-term growth (Gorodnichenko and Roland, 2011, 2016), as well as the adoption of democracy (Gorodnichenko and Roland, 2015). More individualistic societies may foster governmental redistribution since loose ties between individuals reduce the importance of alternative ways of social protection (e.g. via the family network).

Power Distance

Power distance refers to the extent to which less powerful individuals are willing to accept an unequal distribution of power. Previous research suggests a negative relationship between this cultural dimension and R&D investments (Varsakelis, 2001) and a positive link between power distance and corruption (Husted, 1999; Jing and Graham, 2008). Higher power distance is believed to negatively affect demand for redistribution since large differences in status or income are more likely to be tolerated.

Masculinity

Hofstede's dimension of masculinity determines whether a society is characterized more by masculine or by feminine values. Advancement, assertiveness or competitiveness are considered masculine values, while cooperation, tolerance, and humility are thought of as more feminine ones. In most studies, masculinity does not exert a significant influence on economic outcomes (Gorodnichenko and Roland, 2011; Licht et al., 2005). Meanwhile, this cultural trait has been subject to some conceptual criticism, which is why masculinity is often not incorporated into empirical regressions (Williams and McGuire, 2010; Maseland, 2013). A stronger prevalence of masculine values is expected to lower redistribution, as cooperation and providing aid for the indigent is reduced.

Uncertainty Avoidance

Uncertainty avoidance expresses the degree of aversion to unpredictable situations. Recent research indicates that uncertainty avoidance is negatively related to investor legal rights (Licht et al., 2005), financial development (Dutta and Mukherjee, 2012), institutional quality, and per capita income (Maseland, 2013), as well as economic creativity and innovation implementation (Williams and McGuire, 2010). Higher degrees of uncertainty avoidance may hamper redistributional activities, as individuals might feel uncomfortable in unknown situations, preferring private insurance to social protection by the state.

Long-term Orientation

Long-term orientation describes a society's time horizon and illustrates whether people attach more importance to the future or the present. It is associated with values of thrift and perseverance. While most studies do not incorporate this cultural dimension, the findings of Tang and Koveos (2008) suggest that individualism, power distance, and long-term orientation are more prone to economic dynamics than are uncertainty avoidance and masculinity. Long-term orientation is expected to be negatively related to governmental redistribution since protection against social risks can be ensured individually given a long-term planning horizon.

Family Ties

Strong family ties signify the importance of small family/kin networks, while weak ties enable the individual to identify oneself with a society of unrelated people outside the family network and with abstract institutions. Previous research indicates a negative relationship between family ties and labor market participation of women and young adults, generalized trust, civic engagement (Alesina and Giuliano, 2011a, 2014), and preferences for labor-market flexibility (Alesina et al., 2015). Strong family networks provide insurance to their members, which is particularly relevant in countries where no public social safety net exists (La Ferrara, 2010). Varying family structures also help to explain different types of pension systems (Galasso and Profeta, 2011), as well as the development over the past centuries of corporations as an alternative to social protection provided by family or kinship groups (Greif, 2006). Thus, stronger family ties should reduce the amount of governmental redistribution.

Generalized Trust

Generalized trust comprises mutual confidence between the respondent and people whom they do not know. Recent empirical literature points to lower levels of trust across ethnically diverse groups (Alesina and La Ferrara, 2002) and between individuals of different nationalities (Guiso et al., 2009). As virtually every commercial transaction entails an element of trust (Arrow, 1972), this trait affects economic performance (Knack and Keefer, 1997), FDIs and trade (Guiso et al., 2009), and firm productivity (Bloom et al., 2012). Another article by Uslaner (2008) implies that trust is a moral virtue which is stable over time and does not depend on day-to-day experiences. Trust is the basis for economic activities outside a small network of known individuals and includes trust in governmental institutions, thus it exerts a positive influence on redistribution.

Generalized Morality

The concept of generalized morality, originating from Platteau (2000), refers to cooperative behavior toward everyone in a society beyond immediate family members. Thus, rules of good conduct and honest behavior apply to many social situations, and not just to a small network of friends and relatives. Tabellini (2008, 2010) uses two to four questions from the WVS to quantify this cultural value. In a recent paper, Alesina and Giuliano (2015) argue that morality can be decomposed into the societies' attitudes towards obedience, respect/tolerance, and trust.

Work-Luck

The work-luck dimension of culture relates to the attitude toward work, typically asking whether hard work or luck is more relevant in determining success in life. Several articles reveal that different beliefs about how personal income is to be generated (Bénabou and Ok, 2001; Alesina et al., 2001; Alesina and Angeletos, 2005) and varying individual perceptions of social mobility (Alesina and La Ferrara, 2005) are crucial in establishing rules of economic organization and redistribution. Furthermore, initial cultural differences relating to whether or not the initial level of inequality is considered to be fair (Alesina et al., 2012), as well as the experience of macroeconomic shocks (Giuliano and Spilimbergo, 2014), result in long-lasting differences in beliefs about the role of luck versus effort in determining economic success, and therefore about the need for extensive government intervention and redistribution.

Table (4.1) summarizes the different cultural traits and illustrates their impact on redistribution as implied by theory. While this table shows the *direct* effect of cultural values on redistribution, we also expect culture to have an *indirect* effect by influencing the Meltzer-Richard channel. The extent to which a greater degree of inequality translates to redistribution may well be affected by the cultural values of a society, particularly with

Table 4.1 Summary of the cultural traits and their relationship with redistribution as implied by theory.

Cultural trait	Effect	Expected channel from theory
Individualism	positive	Loose ties between individuals reduce the importance of alternative ways of protection against social risks (e.g. family network) and increase the demand for governmental redistribution
Power distance	negative	Higher degrees of power distance reflects societies in which class mentality is pronounced. In these societies, greater differences in status or income increase demand for redistribution to a lesser extent than in societies in which an unequal distribution of power is less tolerated
Masculinity	neutral / negative	Stronger focus on masculine values reduces cooperation and therefore reduces the tendency to provide aid for the indigent
Uncertainty avoidance	negative	Higher uncertainty avoidance decreases demand for redistribution, as individuals may feel uncomfortable in unknown situations, preferring private insurance to public social protection
Long-term orientation	negative	Protection against social risks can be ensured individually (i.e. without governmental intervention) with a long-term planning horizon
Family ties	negative	Family network provides an alternative means of protection against social risks without governmental intervention
Generalized Trust	positive	Trust as a basis for all economic activities outside a small network of known individuals, including trust in governmental institutions and therefore redistributional activities
Generalized Morality	positive	Cooperative behavior toward everyone in a society translates into an affirmative attitude toward societal and governmental institutions
Hard work vs. luck	negative	Societies in which success is considered to be the result of hard work provide less support for correcting mechanisms such as governmental redistribution

respect to individualism, family ties, trust, and power distance.

4.3 Cultural values around the globe

4.3.1 Data on culture and redistribution

To acquire measures for the cultural traits summarized in Table (4.1), we collect data from different sources. The levels of individualism (IND), power distance (PDI), masculinity (MAS), uncertainty avoidance (UAI) and long-term orientation (LTO) are taken from Hofstede (2001). Data on these dimensions stems from national surveys where each dimension is calculated on the basis of a multitude of different questions. Altogether, the questionnaire of the Hofstede (2001) study consists of 60 core questions and 66 recommended questions, which are consolidated to reflect what is broadly known as the five "Hofstede-dimensions".[26] In some cases, the Hofstede data provides cultural classifications for regions rather than countries, particularly for African nations. For instance, Cameroon, the Central African Republic, Chad, Djibouti, Eritrea, Ethiopia, Kenya, Somalia, South Sudan, and Sudan are all included in the single measure of East Africa. While it is reasonable to define culture based on social groups rather than countries, this classification entails the problem that all control variables are available only at the country level. Assigning each country the same regional value would thus substantially reduce the variation in our data and yield a bias in the estimation. We therefore refrain from including regional observations in our analysis.

In addition, we use data from the World Value Survey (WVS) to construct our measures of family ties, trust, morality, and the work-luck nexus in accordance with a recent literature survey conducted by Alesina and Giuliano (2015). More specifically, we employ three survey questions from the WVS to measure the strength of kinship ties. These questions involve the importance of the family in one's life (V4 in the most recent wave of the WVS), as well as the degree to which people agree with the statements *"Regardless of what the qualities and faults of one's parents are, one must always love and respect them"* (V13) and *"It is the parents duty to do their best for their children even at the expense of their own well-being"* (V14). With respect to V13 and V14, we combine the data with that obtained from identical questions included in the European Value Survey (Q49 and Q50 in the EVS) to fill the gaps for European countries for whom this information is missing. The variables are denoted by FAMILY_1 - FAMILY_3, where larger numbers reflect an individual's greater devotion to the family. Alesina and Giuliano (2015) evaluate generalized morality by using the principal component of three questions involving obedience, tolerance, and trust, respectively. In order to avoid arbitrariness in the aggregation strategy and to exploit all information in the data, we use each of these variables separately. The

[26] Note that Hofstede et al. (2010) added a sixth dimension named "Indulgence versus Restraint". This dimension, however, is computed based on data from the World Value Survey, which we include separately in our analysis.

degree to which a society is shaped by trust (denoted with TRUST) refers to question V24 of the WVS, which evaluates the degree to which respondents agree with the statement that *"most people can be trusted"*. Meanwhile, the variables TOLERANCE and OBEDIENCE follow from two questions that ask whether respect/tolerance (V16) and obedience (V21) are qualities that children should be encouraged to learn at home. To increase data availability for African, Asian, and Latin American countries, we merge the WVS data with those of the Afrobarometer, the East Asia Barometer, and the Latinobarometer, all of which ask identical questions with respect to trust.[27] The Latinobarometer further includes data for the tolerance and the obedience variable. Finally, we use question V100 of the WVS, which assesses the degree to which people agree with the statement *"In the long run, hard work usually brings a better life"* on a scale running from 1 to 10.

To measure redistribution, the analysis again relies on the "pre-post-approach", as introduced in Chapter (3.2.1). Governmental intervention in the income distribution is computed as the difference of inequality before and after taxes and transfers (see Lupu and Pontusson, 2011 and Van den Bosch and Cantillon, 2008):

$$\text{REDIST}_{it} = \text{GINI(M)}_{it} - \text{GINI(N)}_{it} \tag{4.1}$$

where GINI(M) and GINI(N) denote market and net Ginis, and REDIST is the amount of redistribution in country $i = 1, \dots, N$ at time $t = 1, \dots, T$. We employ data from the SWIID compiled by Solt (2009, 2016) as it best fits the underlying research topic (Solt, 2015; Atkinson and Brandolini, 2009). To address issues concerning the quality of the included country-year observations, we make use of a subsample of redistribution data which only consists of country-years for which micro data on net and gross inequality is available, denoted as REDIST(S).[28]

[27]For TRUST, the included questions refer to Q020 of the East Asia Barometer, Question 87 of the Afrobarometer, and Q55ST of the Latinobarometer.

[28]For a detailed discussion of the use of data on inequality and redistribution see Chapter (3.2.1).

4.3.2 Cultural differences in the world

How large are the differences in cultural values across the globe? Figures (4.1)–(4.6) map the distribution of six cultural dimensions in the world. The figures point to substantial variation in collective mental programming. For instance, only 5.6 percent of the Philippines believe that most people can be trusted, which stands in sharp contrast to the Norwegian attitude, where trust is deeply anchored in the thinking of the population (67 percent). In addition, there is no distinct pattern in terms of a general correlation between the cultural dimensions. With respect to some of the depicted dimensions, we see a clear correlation between the distribution of values across countries. This is particularly noticeable when considering the distribution of individualism in Figure (4.1) and the distribution of family ties depicted in Figure (4.2), which appear to be mirror images of each other. This is because kinship ties are much more prevalent in collectivist societies. In contrast, there are other dimensions where no such pattern is visible at all. For instance, the correlation between the prevalence of tolerance and that of obedience is < 1 percent, pointing to no noteworthy relationship at all.

Figures (4.1) and (4.2) show that individualism is predominantly prevalent in Western cultures of Europe, Northern America, Australia, and New Zealand. In contrast, members of societies in all parts of Asia and Latin America seem to be much more influenced by collectivist attitudes and exhibit a strong sense of obligation to their family. We also observe a strong correlation between the income level and the degree to which nations are shaped by individualistic values (60 percent) or family ties (-66 percent). Figure (4.3) displays the distribution of trust, which presents a very heterogeneous picture. While people in Australia, Northern America, China, and the Scandinavian countries show a strong tendency to trust other people, the opposite is true in large parts of Latin America and Africa.

There are similar regional patterns with respect to the other cultural dimensions pictured in Figures (4.4)–(4.6). People living in Latin America and Asia generally share an acceptance of an unequal distribution of power; however, both regions also tend to agree that hard work brings success. In contrast, people of European cultures believe

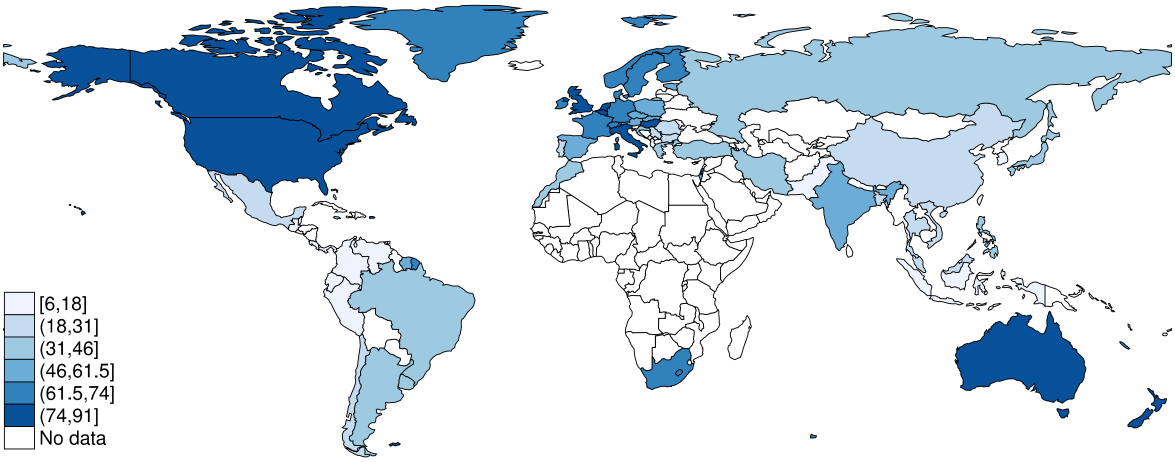

Figure 4.1 The distribution of individualism (IND) in the world.

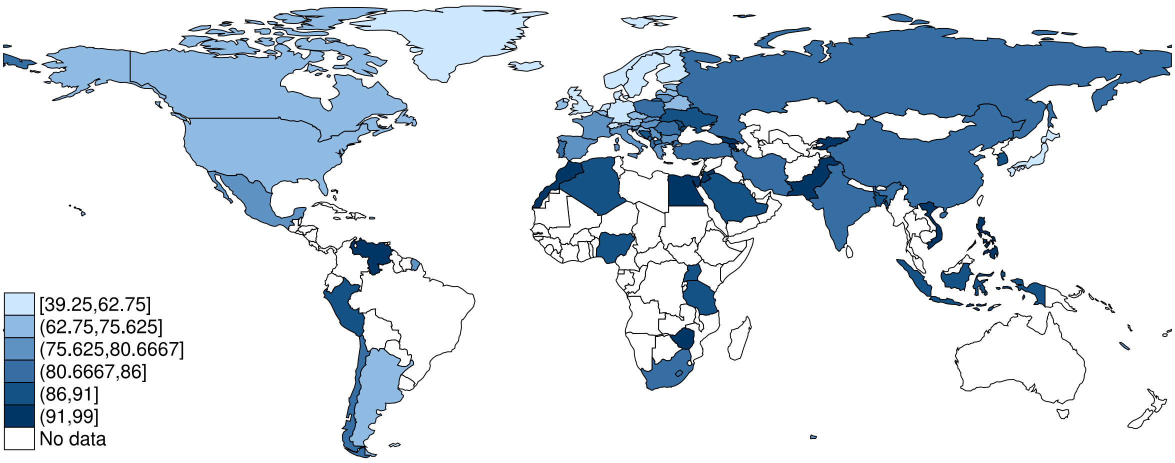

Figure 4.2 The distribution of family ties (FAMILY_1) in the world.

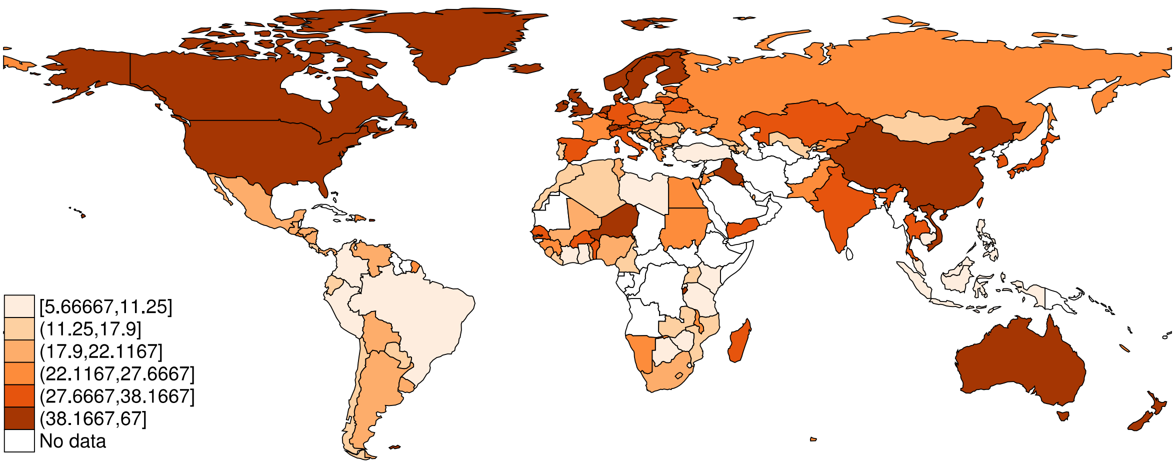

Figure 4.3 The distribution of trust (TRUST) in the world.

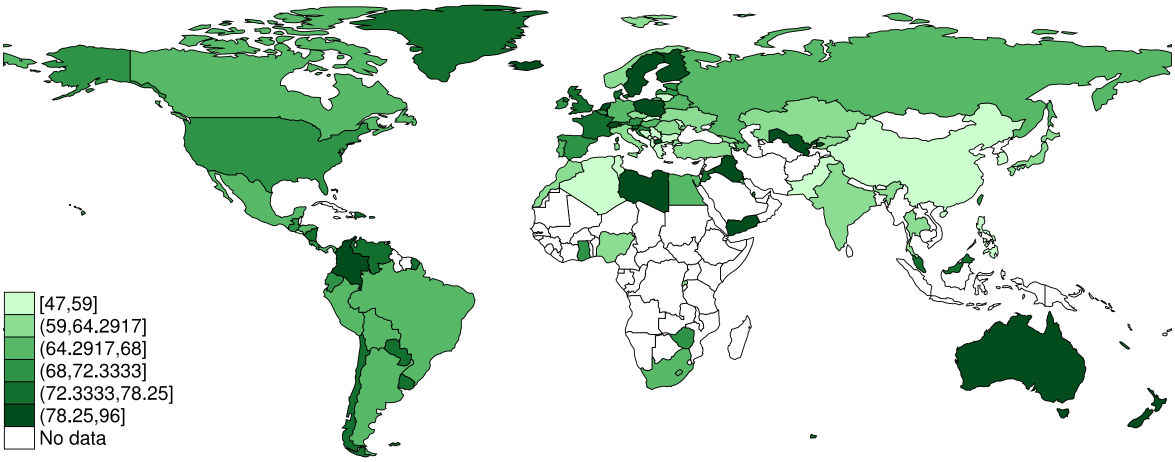

Figure 4.4 The distribution of the degree to which individuals agree that tolerance is a quality children should be encouraged to learn at home (TOLERANCE).

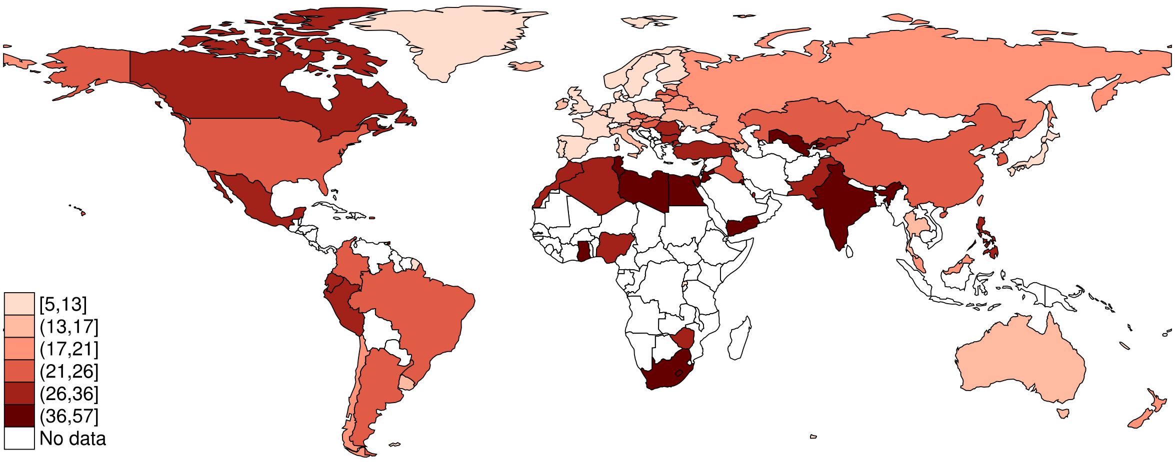

Figure 4.5 The distribution of individuals that believe that hard work brings success (WORK).

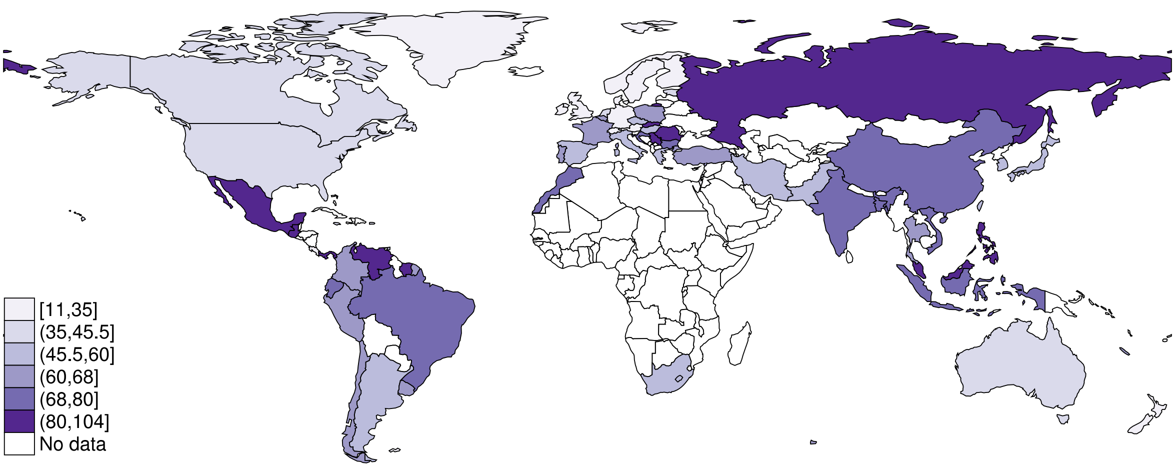

Figure 4.6 The distribution of power distance (PDI) in the world.

Table 4.2 Correlations among cultural dimensions.

	IND	PDI	MAS	UAI	LTO	FAM.$_1$	TRUST	TOLER.	OBED.
PDI	-0.59								
MAS	0.04	0.25							
UAI	-0.26	0.27	0.07						
LTO	0.10	-0.10	0.18	-0.37					
FAMILY$_1$	-0.60	0.68	0.37	0.33	-0.29				
TRUST	0.35	-0.66	-0.43	-0.43	0.25	-0.82			
TOLER.	0.58	-0.55	-0.41	-0.08	-.30	-0.62	0.48		
OBED.	-0.15	0.31	0.08	0.03	-0.39	0.51	-0.51	0.01	
WORK	-0.37	0.46	0.27	0.12	-0.34	0.67	-0.55	-0.63	0.43

Notes: Variables are described in detail in Section (4.3.1). Due to the strong relationship between our three measures of family ties (FAMILY$_1$–FAMILY$_3$), the table focuses on the first variable FAMILY$_1$.

that success is rather a matter of luck and connections. In addition, most societies in Europe consider tolerance an important characteristic and tend to accept power distance to a much lesser extent. The latter also holds for the United States, Canada, Australia, and New Zealand. The countries located in Northern America, however, strongly deviate from European societies in that they believe hard work is the key to success.

Table (4.2) reports the correlations between the cultural variables used in our analysis. These results suggest a strong negative relationship between trust and family ties (-82 percent), implying that societies with strong kinship ties tend to distrust people outside their social group. Trust is also less pronounced in societies with strong acceptance of power distances (-66 percent). The data further reveals a strong link between family ties and both power distance (68 percent) and the belief in hard work (67 percent).

4.4 Empirical strategy

4.4.1 Empirical model and estimation technique

Our basic specification to study the effect of culture on redistribution is given by the following econometric model

$$\text{REDIST}_{it} = \lambda C_{it} + \gamma \mathbf{D}_{it} + \theta \mathbf{I}_{it} + \xi_t + v_{it}, \tag{4.2}$$

where the extent of redistribution in country i at time t depends on the applied measurement of culture C_{it}, a set of covariates that includes the shape of the income distribution $\mathbf{D}_{it}$, and institutional controls $\mathbf{I}_{it}$. To estimate long-run effects, and to rule out short-term fluctuations, we construct a panel where t and $t-1$ are five years apart. Equation (4.2) also captures time effects ξ_t in order to account for exogenous period-specific shocks, such as economic crises. The term $v_{it} \equiv u_{it} - \xi_t$ denotes the idiosyncratic error of the model. The model does not include unobserved heterogeneity, as the inherent nature of collective programming requires that cultural time-series are strongly persistent, making them—fully or partly—time-invariant when exploring panel data in the "small T" context, i.e. $C_{it} \approx C_i$. This very nature rules out application of traditional Within-Group or differencing approaches.

Our list of control variables, which have proven to be very robust to changes in the empirical strategy, is based on that from Chapter (3). These determinants comprise a set of variables that describe the level of inequality and the shape of the income distribution, along with a number of institutional controls. In the standard economic model, voting behavior for redistributive policies is exclusively motivated by the expected benefit or loss which would result from such policies (Meltzer and Richard, 1981). To test this assumption, we include the level of market inequality GINI(M) in the set of distributional controls, as a higher level of inequality before taxes and transfers suggests a higher share of the population that gains from redistribution. Recent research further shows that the shape of the income distribution is decisive for the extent of redistribution, as levels of political power vary between income groups. For this reason, we account for the income share held by the richest 1 percent (TOP-1) as well as that of the middle class (MIDDLECLASS). The latter is modeled by adding the income shares of the lower middle, middle, and upper middle quintiles of the income distribution. The institutional controls include the level of political rights (POLRIGHT) to account for the differences in redistribution between democracies and non-democracies. While inequality reduction is only 2.8 Gini points in autocratic regimes, the extent of redistribution is substantially higher if democratization has reached a sophisticated level (8.4 Gini points). Further, we incorporate the logarithmic value of the fertility rate, denoted with Log(FERT), as higher fertility rates imply a more binding budget constraint for the household, which may affect redistributional policies of the government. The labor market enters into the regression by inclusion of the unemployment rate (UNEMP).

Data regarding fertility, unemployment, and the quintiles and deciles of the income distribution are taken from World Bank (2016). The level of political rights is extracted from Freedom House (2014). The income share held by the top-1% is taken from SWIID 4.0, which is the latest version covering data on the income share of top income earners.[29] Finally, market inequality and redistribution are taken from the SWIID 5.1. Table (4.8) in the appendix provides descriptive statistics of the variables used in the empirical analysis, including their means, standard deviations, and the number of observations, as well as their minima and maxima.

To estimate Equation (4.2), we apply three different empirical strategies. The first strategy is pooled OLS, which has been used in a number of recent studies dealing with the consequences of culture for economic outcomes (Gorodnichenko and Roland, 2011; Alesina et al., 2015). Application of pooled OLS, albeit afflicted with some obvious drawbacks, follows from the time-invariance of many of our cultural variables, which prohibits exploitation of the panel structure with respect to C. The second strategy is 2SLS, where we employ three different instruments that are described in the following section. The 2SLS version of Equation (4.2) is given by

[29]Note that there have been some concerns about the data quality of version 4.0 of the SWIID. For this reason, we assessed robustness of our results by employing data on top incomes from the World Wealth and Income Database (WID), compiled by Alvaredo et al. (2015). As there were no noteworthy changes in the results, we decided to work with the SWIID 4.0 data, which enables inclusion of a considerably larger number of country-year observations. In addition, as data regarding the shape of the income distribution is partly from World Bank and partly stems from the SWIID, we tested for consistency across the two groups of data. Our tests imply a high degree of comparability between the data.

$$\text{REDIST}_{it} = \alpha_R + \lambda_R C_{it} + \gamma_R \mathbf{D}_{it} + \theta_R \mathbf{I}_{it} + u_{R,it} \tag{4.3}$$

$$C_{it} = \alpha_C + \lambda_C \Omega_{it} + \gamma_C \mathbf{D}_{it} + \theta_C \mathbf{I}_{it} + u_{C,it} \tag{4.4}$$

where Ω is the instrumental variable for culture. Finally, we use system GMM whenever there is enough variation in the data to utilize internal instruments in the absence of reliable exogenous instruments. In this case, the dynamic panel model is

$$\begin{aligned} \text{REDIST}_{it} = {} & \alpha \text{REDIST}_{it-1} + \psi \text{GINI(M)}_{it} + \phi \text{GINI(M)}_{it} \times C_{it} + \lambda C_{it} \\ & + \gamma \mathbf{D}_{it} + \theta \mathbf{I}_{it} + \eta_i + \xi_t + \tilde{v}_{it}, \end{aligned} \tag{4.5}$$

specifying that redistribution in t also depends on its level in $t-1$, which includes path dependencies in the model. This incorporation reflects the idea that institutions, once established, are difficult to change in the short to medium term (Acemoglu et al., 2015). In contrast to the baseline model in Equation (4.2), Equation (4.5) also captures country-specific effects η_i and period effects ξ_t, thereby taking into account the various historical and environmental aspects of the countries. In this case, the idiosyncratic error is given by the term $\tilde{v}_{it} \equiv u_{it} - \xi_t - \eta_i$. Additionally, we are interested in the extent to which culture influences the traditional Meltzer and Richard (1981) relationship. To investigate potential conditionalities in these effects, we include the interaction term $\text{GINI(M)}_{it} \times C_{it}$ in a later section of the paper.

Blundell and Bond (1998) and Bond et al. (2001) show that the standard difference GMM estimator can be poorly behaved if time-series are persistent or if the relative variance of the fixed effects η_i is high. The reason is that in these cases, lagged levels provide only weak instruments for subsequent first-differences, resulting in a large finite sample bias. This is particularly relevant in our case, as the within-variation of our cultural measures is significantly lower than the between-variation and sometimes even equals zero. Asymptotically, the inclusion of time-invariant regressors in system GMM does not affect coefficient estimates for other regressors, as all instruments for Equation (4.5) are assumed to be orthogonal to fixed effects and other time-invariant regressors (Roodman, 2009a). As opposed to difference GMM, the system GMM framework exploits the cross-sectional information in the data if researchers are willing to assume a mild stationary restriction on the initial conditions of the underlying data generating process.[30] In this case, additional orthogonality conditions for the level equation in (4.5) can be exploited. Satisfying the Arellano and Bover (1995) conditions, system GMM has been shown to have better finite sample properties (see Blundell et al., 2000). To assess the validity of the Arellano and Bover (1995) conditions, we routinely report Difference-in-Hansen tests for each of the system GMM regressions.[31]

In constructing our estimator, we use a collapsed version of our instrument matrix. Roodman (2009b) emphasizes the advantage of this procedure, as otherwise the problem of "instrument proliferation" may lead to severe biases.[32]

4.4.2 Instruments used for the 2SLS regressions

When studying culture, a substantial challenge is to disentangle its effects from those of institutions. While it is argued that culture and institutions exhibit a symbiotic relationship (Hofstede, 2001; Tabellini, 2008) and complement each other (Alesina and Giuliano, 2015), there is still a potential causal link running from culture to institutions and vice versa. To tackle this issue, the most commonly applied strategy is the epidemiological approach, linking behavior and attitudes of immigrants to measures of culture available for their countries of origin (Luttmer and Singhal, 2011; Fernández, 2011). However, this approach does not entirely solve the problem of endogeneity, as different groups of immigrants may well encounter different informal institutional frameworks (Maseland, 2013;

[30] The assumption on the initial condition is $\mathrm{E}(\eta_i \Delta \mathrm{REDIST}_{i2}) = 0$, which holds when the process is mean stationary, i.e. $\mathrm{REDIST}_{i1} = \eta_i/(1-\alpha) + v_i$ with $\mathrm{E}(v_i) = \mathrm{E}(v_i \eta_i) = 0$.

[31] A more detailed description of the estimator in the context of the empirical application can be found in Bond et al. (2001) and Roodman (2009b).

[32] In principle, our specification can be estimated using one-step or two-step GMM. Whereas one-step GMM estimators use weight matrices independent of estimated parameters, the two-step variant weights the moment conditions by a consistent estimate of their covariance matrix. Bond et al. (2001) show that the two-step estimation is asymptotically more efficient. Yet it is well known that standard errors of two-step GMM are severely downward biased in small samples. We therefore rely on the Windmeijer (2005) finite sample corrected estimate of the variance, which yields a more accurate inference.

Rauch and Trindade, 2002).

In our analysis, we follow a relatively new branch of the literature that attempts to find truly exogenous instruments. We compute two groups of instruments, the first group relying on regional cultural values, the second making use of the observation that cultural differences are strongly correlated with biological and linguistic characteristics (Gorodnichenko and Roland, 2016).

Regional instruments

Utilization of jack-knifed regional levels as instruments for national measures is on the rise in many areas of economic research (for democracy see Madsen et al., 2015; Acemoglu et al., 2014, for trade see Autor et al., 2013; Dauth et al., 2014). We argue that a similar instrument can be constructed for culture. A considerable difficulty in measuring culture at the national level is that collective values are shared by social groups which often do not correspond directly to the national population (Hofstede, 2001). The relevant social group may well extend beyond a country's frontiers, particularly since cultural values are often much older than national borders. This argument is most obvious with respect to the partitioning of African countries during the Congo Conference of 1884-85. However, a distinct empirical pattern found in Section (4.3.2) is that in most cases, culture has a strong regional character. We can make use of this feature to construct an external instrument for national culture by making the following assumption:

(Exclusion restriction of national culture): Let $\tilde{C}^r_{it}$ be the regional cultural value that is used as an instrument for country-year $\{i, t\}$ and that is defined for some disjoint sets of regions $r = 1, \ldots, R$. Then it must hold that

$$\begin{aligned} &\mathrm{E}(v_{it}|\mathrm{REDIST}_{it-1}, \ldots, \mathrm{REDIST}_{it_0}, \tilde{C}^r_{it-1}, \ldots, \tilde{C}^r_{it_0}, \eta_i, \xi_t) = 0 \\ &\forall\ \mathrm{REDIST}_{it-1}, \ldots, \mathrm{REDIST}_{it_0}, \tilde{C}^r_{it-1}, \ldots, \tilde{C}^r_{it_0}, \eta_i, \xi_t \text{ and } \forall i, t \geq t_0. \end{aligned} \tag{4.6}$$

This assumption essentially means that, conditional on covariates, cultural values in neighboring countries should be uncorrelated with a country's national level of redistribution. In order to satisfy the exclusion restriction, we leave out the value for i in the calculation of $\tilde{C}_{it}^{r}$. In constructing $\tilde{C}_{it}^{r}$, we split each continent into four disjoint regions as illustrated in Table (4.9) in the appendix. Let $\mathcal{R} = \{1, ..., R\}$ denote our set of regions, where each country i belongs to exactly one region r. In addition, let N_{rt} be the number of countries in region r at period t and C_{it} denote the cultural dimension in country-year $\{i, t\}$. Then the instrumental variable $\tilde{C}_{it}^{r}$ is calculated via

$$\tilde{C}_{it}^{r} = \frac{1}{N_{rt} - 1} \sum_{\{j \neq i | r' = r, r' \in \mathcal{R}\}} C_{jt}. \tag{4.7}$$

Figure (4.11) in the appendix illustrates the relationship between cultural values and their regional instruments. The figure highlights strong correlations ranging from 27 percent (tolerance) and 49 percent (family ties) to 66 percent (uncertainty avoidance) and 73 percent (obedience).

Biological instruments

In order to rule out the possibility that the results are triggered by the chosen instrumentation strategy, the second set of instrumental variables uses biological conditions to isolate the effect of culture. This strand of the literature is relatively new and involves the linkage of pathogen prevalence to culture and an individual's personality (Fincher et al., 2008; Murray and Schaller, 2010). These studies argue that societies in which infectious diseases are prevalent tend to be more reluctant to interact with individuals outside their group, viewing them as potential fomites. Consequently, these societies are shaped by collectivist values and a lower degree of trust (Fincher et al., 2008). While pathogens offer an interesting tool for studies linking their prevalence to political outcomes (such as democracy, see Thornhill et al., 2009), a distinct disadvantage for our study is that the dissemination of (life-threatening) diseases has been shown to affect institutional quality (Easterly and Levine, 2003) and most likely results in a higher demand for redistribution. For this reason, we rely on the prevalence of *Toxoplasma gondii*, a protozoan parasite commonly found in felines. This instrument was first introduced by Maseland (2013). While Toxoplasma gondii has been shown to alter the behavior of its intermediate hosts

(Skallova et al., 2006), it very rarely leads to manifest disease (Havelaar et al., 2007). More specifically, biological studies have found that the parasite causes impaired motor performance (Hutchinson et al., 1980) and reduced avoidance of both predators and open spaces (Berdoy et al., 2000), increasing the chance of the host being eaten by felines.

About one third of the human population has been exposed to Toxoplasma gondii, with prevalence rates differing considerably across countries (Hill and Dubey, 2002). While causing only mild physical health effects, infection with the parasite leads to a stronger focus on competition and personal achievement and yields a decrease in the host's morality, trust, and concern for others (Flegr et al., 1996; Webster, 2001; Lindova et al., 2006). These changes in behavior translate into observable differences at the societal level and explain a substantial part of the cross-country variation in cultural values (Laferty, 2005, 2006). As there are no immediately perceptible effects of a Toxoplasma gondii infection, a higher prevalence rate may—unlike with pathogens infections—not yield an increase in redistribution policies via better public health provision. Therefore, we assume that the usual exclusion restriction holds:

(Exclusion restriction of national culture): Let G^r_{it} be the prevalence rate of Toxoplasma gondii in country i at time t. Then it must hold that

$$\begin{aligned} &\mathrm{E}(v_{it}|\mathrm{REDIST}_{it-1},\ldots,\mathrm{REDIST}_{it_0},G_{it-1},\ldots,G_{it_0},\eta_i,\xi_t)=0 \qquad (4.8)\\ &\forall\ \mathrm{REDIST}_{it-1},\ldots,\mathrm{REDIST}_{it_0},G_{it-1},\ldots,G_{it_0},\eta_i,\xi_t \text{ and } \forall i,t\geq t_0. \end{aligned}$$

Data on the prevalence of Toxoplasma gondii is extracted from Pappas et al. (2009), who provide a survey of the global status of seroprevalence of the parasite based on a large number of country-based studies.[33]

As a second strategy, we use genetic data to form an alternative biological instrument. The rationale for using genes is that parents transmit DNA to their offspring in addition to their transfer of cultural values. Consequently, we do not argue that there is

[33]Prevalence of Toxoplasma gondii is measured routinely, as prenatal infection may cause ocular conditions and mental retardation later in life. In addition, the parasite may cause complications for organ transplant patients and individuals infected with AIDS.

any causal link running from genes to culture, but rather exploit the correlation between genetic markers and culture. Application of genes can be reasonably expected to satisfy the exclusion restriction in Equation (4.8), as redistribution is very unlikely to affect the genetic pool of nations, at least in the relatively short time period which we are able to reconstruct with empirical data. We follow Gorodnichenko and Roland (2016) in using the frequency of blood types as specific genetic markers for two reasons. First, blood types are neutral in that they do not directly influence personal behavior. Second, the frequency of alleles distinguishing blood types is by far the most widely accessible genetic information when working with cross-national data. In constructing our instrument, we use the Euclidean distance for frequencies of blood types A and B in a way similar to that of Gorodnichenko and Roland (2011). Data on blood types is gathered from the Red Cross, Mourant et al. (1976), and Tills et al. (1983). Figures (4.12) and (4.13) in the appendix display the relationship between our biological instruments and culture, the latter measured as the principle component of family ties, trust, obedience, and uncertainty avoidance. In each case, the correlation is roughly 40 percent.[34]

As a final robustness check, we use the entanglement between culture and language, as with Tabellini (2008) and Licht et al. (2007). Utilization of language as an instrument for culture may be traced back to what is now referred to as the "Sapir-Whorf" or the "Linguistic Relativity" hypothesis (Whorf, 1956; Sapir, 1970). As argued by Kashima and Kashima (1998), culture can be linked to linguistic phenomena, particularly to pronoun drop in the case of person-indexing pronouns. For instance, while the English phrase *"I run"* refers to the German expression *"Ich renne"*, neglect of the pronoun is quite common in other languages such as Spanish and Italian (where it most often would be simply *"corro"*, and the pronouns "*Yo*" and "*Io*" are dropped and the context can be recovered from the verb). The hypothesis of Kashima and Kashima (1998) is that the requirement of pronoun usage is a result of the psychological differentiation between speakers and their social context, where utilization of pronouns is particularly prevalent in individualistic

[34]We use principal component analyses (PCA) to illustrate the relationship in order to reduce the number of scatter graphs. Selection of the cultural variables is based on (1) capturing the most important cultural dimensions and (2) maximizing data availability. Naturally, the PCA only draws on the intersecting set of the available country-years provided by the included components.

societies. As with blood type distance, it is unlikely that language affects redistributive policies of the government, thus satisfying the required exclusion restriction.

4.5 The influence of culture on redistribution

4.5.1 Baseline results

We now turn to the empirical investigation of the effect of cultural values on government redistribution. Table (4.3) reports the results of the POLS estimations and the IV regressions based on regional culture as instruments. For each of our cultural variables, we show the outcomes of three different specifications of the empirical system. The first column (labeled "isolated effect") gives the reduced effect of the respective cultural variable on redistribution. The second ("distribution controls") and third ("institution controls") columns gradually introduce a number of covariates, including the Gini coefficient of market incomes, the income share held by the middle class, and the income share held by the Top-1% (Column 2), as well as the unemployment rate, the degree of democratization, and the fertility rate (Column 3).

The dependent variable in Table (4.3) is REDIST(S), the sub-sample of high-quality observations provided by the SWIID which relies entirely on national micro data. As the cultural variables vary in their availability, we use all obtainable country-year observations to compute the regressions illustrated in the table in order to exploit as much of the information as possible. Given the inevitable trade-off between comparability and a sample-selection bias, we carefully chose this strategy due to the fact that the intersecting set of all culture variables is much smaller than the total set of data available for each of the variables.[35] The most drastic reduction in country-years, however, comes from the time-dimension. As culture is *per se* time-invariant in the medium-term, the issue here is not the familiar one of missing data, but rather the more deep-rooted problem that it is simply *not possible* to observe changes in collective programming over a few decades. While some of the recent studies (e.g. Gorodnichenko and Roland, 2016; Tabellini, 2010)

[35] For instance, using the identical sample would reduce the number of countries included in WORK to 39, whereas the results in Table (4.3) are based on data from 54 nations.

Table 4.3 The effect of culture on redistribution. Baseline results using all available redistribution data. Dependent variable is REDIST(S).

	POLS estimates			IV estimates		
	isolated effect	distribution controls	institution controls	isolated effect	distribution controls	institution controls
	Panel A: Hofstede Dimensions					
IND	0.218***	0.0827***	0.0618***	0.291***	0.140***	0.119***
	(23.44)	(5.70)	(4.52)	(17.73)	(4.82)	(4.25)
N (R^2)	352 (0.56)	225 (0.82)	186 (0.85)	352 (0.49)	225 (0.81)	186 (0.84)
PDI	-0.175***	-0.0449***	-0.0283**	-0.408***	-0.205***	-0.267**
	(-11.85)	(-3.80)	(-2.18)	(-9.06)	(-2.92)	(-2.09)
N (R^2)	352 (0.30)	225 (0.81)	186 (0.84)	352 (0.30)	225 (0.64)	186 (0.54)
MAS	-0.0224	-0.0211**	-0.00898	0.323***	0.0570*	0.0187
	(-1.12)	(-2.30)	(-0.92)	(4.39)	(1.77)	(0.85)
N (R^2)	352 (0.01)	225 (0.80)	186 (0.84)	352 (0.41)	225 (0.76)	186 (0.85)
UAI	-0.0181	0.00636	-0.0134	-0.111***	-0.0389***	-0.0547***
	(-1.09)	(0.52)	(-1.29)	(-4.42)	(-2.79)	(-2.66)
N (R^2)	352 (0.01)	225 (0.79)	186 (0.84)	352 (0.68)	225 (0.79)	186 (0.84)
LTO	-0.0112	-0.00758	0.0185	-0.447***	0.0153	0.0954
	(-0.79)	(-0.53)	(1.46)	(-4.08)	(0.22)	(0.55)
N (R^2)	352 (0.01)	225 (0.79)	186 (0.83)	338 (0.09)	220 (0.78)	180 (0.79)
	Panel B: Alesina and Giuliano Dimensions					
FAMILY_1	-0.306***	-0.137***	-0.101***	-0.383***	-0.208***	-0.200***
	(-21.28)	(-10.83)	(-6.05)	(-15.32)	(-7.85)	(-5.39)
N (R^2)	318 (0.40)	220 (0.83)	192 (0.86)	318 (0.38)	220 (0.80)	192 (0.83)
FAMILY_2	-0.146***	-0.0568**	-0.0559***	-0.201***	-0.0488	-0.215***
	(-4.37)	(-2.33)	(-2.71)	(-2.87)	(-0.71)	(-2.76)
N (R^2)	318 (0.05)	220 (0.78)	192 (0.84)	318 (0.04)	220 (0.77)	192 (0.79)
FAMILY_3	-0.117**	0.0204	-0.0275	-0.0142	-0.156	-0.274**
	(-2.09)	(0.52)	(-0.76)	(-0.10)	(-1.47)	(-2.07)
N (R^2)	355 (0.01)	237 (0.78)	204 (0.83)	355 (0.03)	237 (0.76)	204 (0.80)
TRUST	0.205***	0.0431***	0.0456***	0.348***	0.118***	0.116***
	(10.49)	(2.76)	(3.16)	(12.13)	(5.20)	(4.54)
N (R^2)	431 (0.17)	298 (0.81)	258 (0.85)	431 (0.08)	298 (0.79)	214 (0.84)
OBEDIENCE	-0.141***	-0.0291*	-0.0254*	-0.189***	-0.0149	-0.0907*
	(-12.35)	(-1.82)	(-1.78)	(-11.64)	(-0.44)	(-1.94)
N (R^2)	422 (0.15)	291 (0.81)	251 (0.85)	422 (0.13)	291 (0.81)	251 (0.84)
TOLERANCE	0.286***	0.144***	0.120***	0.662***	0.484***	0.469***
	(9.03)	(6.72)	(5.01)	(7.33)	(6.13)	(4.11)
N (R^2)	422 (0.14)	291 (0.83)	251 (0.86)	422(0.61)	291 (0.70)	251 (0.74)
WORK	-0.449***	-0.203***	-0.136***	-0.942***	-0.397***	-0.332***
	(-15.50)	(-5.69)	(-3.43)	(-11.07)	(-7.47)	(-4.80)
N (R^2)	345 (0.28)	235 (0.82)	203 (0.85)	345 (0.66)	235 (0.78)	203 (0.81)

Notes: Table reports OLS and IV regression results with Huber-White-robust standard errors. t (OLS) and z (IV) statistics in parentheses. IV regressions use jack-knifed regional cultural values. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

use cross-sectional analyses to assess the effect of culture on economic and political outcomes, such a strategy always involves the arbitrary selection of the time-period during which culture's influence should be measured. Since cultural values do not change over time, arbitrary selection of the dependent variable may influence the obtained results. For this reason, we use data from a panel consisting of 134 countries that are evaluated at eight 5-year periods, these being 1975-1979; 1980-1984; 1985-1989; 1990-1994; 1995-1999; 2000-2004; 2005-2009; and 2010-2014.[36]

The results show that culture substantially influences redistributive policies of the government. Panel A reports the consequences of culture implied by the Hofstede dimensions. The positive effect of individualism on redistribution (along with the negative influence found with respect to all of our measures of family ties in Panel B) provides evidence that collectivist societies have less expansive social security systems. Historically, people living in patrilineal or matrilineal extended families or in tribal units based on kinship ties typically developed a broad sense of responsibility for the members of their group (Hofstede, 2001). While people living in collectivist groups may only see a limited need for public redistribution, societies shaped by a high degree of individualism lack family-based safety nets, thus insurance is shifted from the family level to the government level.

The findings also point to a negative effect of power distance on redistribution. If collective values emphasize (innate) differences across social classes, people are much more willing to accept their individual fate and are less ready to support the indigent. In contrast, members of societies with a lower degree of power distance tend to favor equalizing government policies. We also find that redistribution is negatively related to uncertainty avoidance. The reason may be that citizens that feel threatened by uncertain or unknown situations tend to be reluctant to support redistribution. Rather than providing aid for the indigent, these individuals prefer their income to be used for private insurance against potential future risks. With respect to masculinity (MAS), the findings do not reveal any stable link to redistribution.

[36]Note that the variation in the remaining variables is sufficiently high enough to allow for this strategy. Note also that we intentionally do not account for unobserved heterogeneity in the empirical model, see Section (4.4).

The Alesina and Giuliano dimensions illustrated in Panel B provide further evidence for the influence of culture on redistribution. We find that trust and tolerance are strong predictors of redistributive policies, reflecting that cooperative behavior towards other members of a society increases positive attitudes regarding societal and government institutions. In contrast, a greater devotion to obedience reduces public equalization of incomes, which is in line with the negative effect found with respect to power distance. Finally, societies whose members are convinced that success is the result of hard work tend to support public redistribution much less compared with those who consider success to be a matter of luck and connections. Citizens from countries with high levels of WORK are typically confident that each individual has the potential to succeed in the labor market. In these societies, being indigent is mainly thought of as resulting from a lack of effort and devotion, a situation which is not considered to be worthy of support via public policies.

The instrumental variable regressions using regional cultural values support the POLS estimates. While the IV regressions point to some (mostly minor) changes in the strength of the marginal effects of culture, the only substantial difference compared with the POLS estimates is the effect of uncertainty avoidance, which in case of the IV estimates turns significantly negative. Likewise, while long-term orientation is insignificant in the POLS outcomes, it is negatively associated with redistributive policies when instrumented with regional culture, at least in the reduced model. In fact, this result is highly plausible with respect to theory (see Section 4.2.2), implying that individuals with a long-term planning horizon tend to privately insure against potential future risks.

Naturally, the IV results hinge critically on the ability to instrument culture with jackknifed regional averages. To investigate the strength of our instruments, Table (4.10) in the appendix reports the results of two tests proposed by Sanderson and Windmeijer (2016), including diagnostics of weak instruments (Sanderson-Windmeijer (SW) F-test) and underidentification (SW χ^2 test). With respect to each of the variables instrumented in Table (4.3), both tests point to a satisfactory instrument strength, resulting in consistent estimates and correct standard errors. In addition, the null of underidentification is significantly rejected for each of the models. Table (4.11) in the appendix further shows the first-stage results of the 2SLS regressions. In each case, the regional instruments are significant at the 0.01 level. The marginal effects range from 0.44 (LTO) to 0.90 (FAMILY_1), providing strong indication that regional values satisfyingly instrument national culture.

4.5.2 Sensitivity analysis I: Cross-sectional analyses and multiply-imputed redistribution

While Table (4.3) identifies strong effects running from culture to national social security systems, there is still the possibility that these implications have their roots in the chosen estimation strategy. This strategy relies on three crucial assumptions: First, we argue that application of panel data is more appropriate to reveal culture's consequences on redistribution than use of cross-sectional analyses at a given (more or less arbitrary) point in time. Second, we rely on point estimates of Gini coefficients before and after taxes and transfers, and third, we assume that the exclusion restriction in Equation (4.6) is valid.

In this section, we alter the first two of these assumptions. Table (4.12) in the appendix deviates from Table (4.3) by estimating the effect of the cultural variables based on a cross-section of countries that uses data from the 2005–2009 period. The selection of the period aims at the maximization of available country-years: The most recent period for which redistribution measures can be constructed (2010-2014) allows for inclusion of 105 countries, whereas the 2005-2009 period covers 153 nations. To maximize the sample of country-years, this analysis utilizes REDIST as the dependent variable. In this case, the results strongly support the baseline outcomes by confirming that redistribution is lower in (1) collectivist societies with strong family ties, (2) nations in which power distance and obedience are pronounced, and (3) countries in which citizens believe that hard work is key to success. Meanwhile, the results again highlight that redistribution is higher in countries whose collective values promote trust and tolerance. The cross-sectional analysis, however, yields a reduction in the underlying country-years. As expected, the

Table 4.4 The effect of culture on redistribution. Regressions based on multiply-imputed redistribution data (Imputations = 100). Dependent variable is $\text{REDIST(S)}_{\text{MI}}$.

	POLS estimates			IV estimates		
	isolated effect	distribution controls	institution controls	isolated effect	distribution controls	institution controls
	Panel A: Hofstede Dimensions					
IND	0.218***	0.0827***	0.0620***	0.291***	0.141***	0.120***
	(22.13)	(5.36)	(4.09)	(17.12)	(4.62)	(4.05)
N	352	225	186	352	225	186
PDI	-0.174***	-0.0447***	-0.0284**	-0.408***	-0.205***	-0.267**
	(-11.44)	(-3.61)	(-2.06)	(-8.90)	(-2.85)	(-2.06)
N	352	225	186	352	225	186
MAS	-0.0229	-0.0212**	-0.00926	0.318***	0.0561*	0.0185
	(-1.13)	(-2.21)	(-0.89)	(4.30)	(1.66)	(0.80)
N	352	225	186	352	225	186
UAI	-0.0169	0.00689	-0.0132	-0.110***	-0.0386**	-0.0548**
	(-1.00)	(0.53)	(-1.20)	(-4.28)	(-2.50)	(-2.52)
N	352	225	186	352	225	186
LTO	-0.0124	-0.00808	0.0184	-0.442***	0.0148	0.0951
	(-0.84)	(-0.52)	(1.35)	(-4.08)	(0.21)	(0.54)
N	352	225	186	352	225	186
	Panel B: Alesina and Giuliano Dimensions					
FAMILY_1	-0.305***	-0.137***	-0.102***	-0.382***	-0.208***	-0.201***
	(-17.52)	(-8.51)	(-5.33)	(-13.75)	(-7.21)	(-5.20)
N	318	220	192	318	220	192
FAMILY_2	-0.144***	-0.0562**	-0.0552**	-0.196***	-0.0458	-0.213**
	(-4.15)	(-2.11)	(-2.28)	(-2.70)	(-0.61)	(-2.43)
N	318	220	192	312	214	187
FAMILY_3	-0.114*	0.0220	-0.0259	-0.0151	-0.156	-0.273*
	(-1.93)	(0.52)	(-0.63)	(-0.10)	(-1.28)	(-1.73)
N	355	237	204	355	237	204
TRUST	0.204***	0.0426**	0.0451***	0.348***	0.118***	0.116***
	(9.77)	(2.27)	(2.70)	(11.01)	(4.49)	(4.28)
N	431	298	258	431	298	258
OBEDIENCE	-0.141***	-0.0291*	-0.0251	-0.189***	-0.0147	-0.0909*
	(-11.16)	(-1.71)	(-1.60)	(-10.81)	(-0.39)	(-1.76)
N	422	291	251	422	291	251
TOLERANCE	0.285***	0.144***	0.119***	0.661***	0.484***	0.470***
	(8.42)	(5.65)	(4.35)	(6.87)	(5.39)	(3.77)
N	422	291	251	422	291	251
WORK	-0.449***	-0.203***	-0.136***	-0.942***	-0.397***	-0.332***
	(-13.55)	(-5.10)	(-3.21)	(-9.95)	(-6.31)	(-4.42)
N	345	235	203	345	235	203

Notes: Table reports the results of multiple regressions based on 100 multiply-imputed redistribution values available in the SWIID 5.0. Results are obtained via OLS and IV regressions with Huber-White-robust standard errors. t (OLS) and z (IV) statistics in parentheses. IV regressions use jack-knifed regional cultural values. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

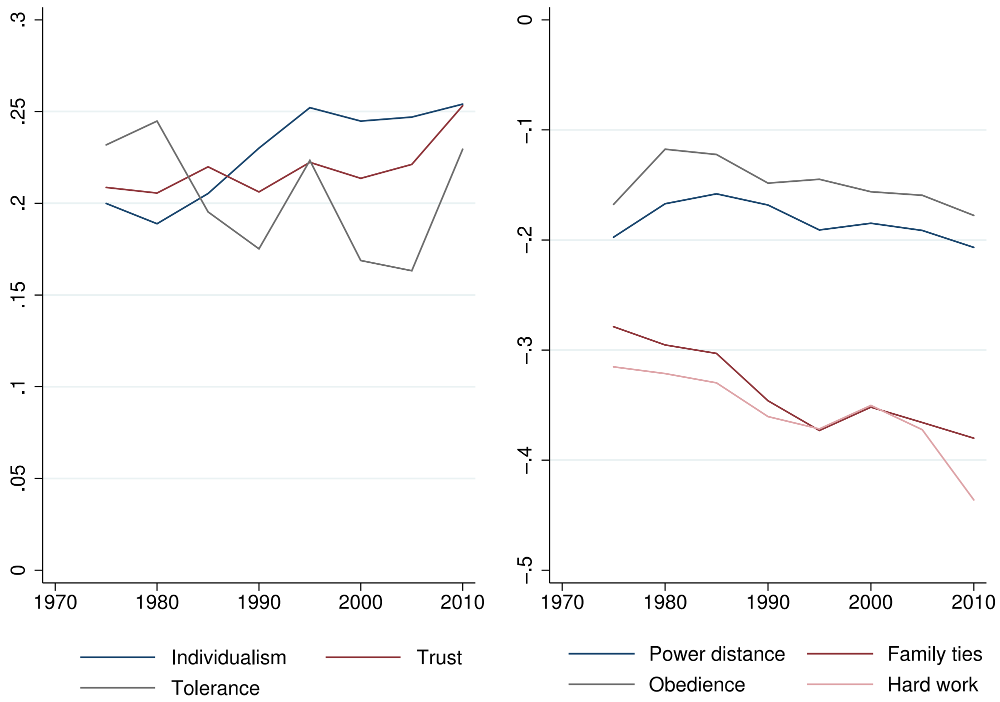

Figure 4.7 Development of the influence of cultural dimensions over time. The figure illustrates the computed marginal effect of the cross-sectional regressions in the respective 5-year time period, variables with a positive (left panel) and a negative (right panel) effect.

results are slightly less pronounced with respect to some of the cultural values, particularly in the case of the Hofstede dimensions MAS, UAI and LTO. Apart from these deviations, the findings are strongly comparable to those obtained via panel data methods.

In a further step, we ask how the influence of the cultural values has evolved over time. When comparing the parameter estimates of Tables (4.3) and (4.12), a striking feature is that the marginal effects deviate slightly. These deviations may have their origins in differences in the strength of the influence of cultural traits over time. Figure (4.7) plots the estimated marginal effects at each of the 5-year periods beginning with 1975-1979 and ending with 2010-2014. There seems to be only a weak change over time in the effect of tolerance, power distance, and obedience. In contrast, the figure shows that individualism currently tends to play a greater role than during past decades. This is indicated by both an increase in the estimated parameter of IND and an effect of family ties that becomes increasingly negative. Likewise, the support for redistribution within societies that believe in hard work has fallen during the observed time period. The deviations in the effect of culture on redistribution over time underscore the advantage of employing panel data, as this technique allows us to capture the bigger picture rather than merely focusing on one of its brushstrokes.

Thus far, we relied on point estimates of inequality obtained via averaging of the 100 multiple imputations for each country-year provided by the SWIID. As a second sensitivity analysis, we use these imputations to directly compute multiple imputation (MI) estimates, which allows us to account for the uncertainty in the inequality data upon which our redistribution measure is built. Specifically, we compute 100 regressions for each country-year in the sample and combine the results with the help of the rules of Rubin (1987). Table (4.4) displays the result of this approach. Due to the imputation variability, the standard errors in the reported estimations are (slightly) larger, which is reflected in smaller t and z values. The increase in the standard errors, however, has little effect on the significance levels. In addition, the computed marginal effects are virtually identical. In summary, the outcomes highlight a high degree of robustness of the baseline findings in Table (4.3).

4.5.3 Sensitivity analysis II: Different dependent variables

In Sensitivity analysis I, we asked how changes in the utilization of our standard redistribution measure affect the implied influence of culture on redistributive policies. In the next step, we pose a different yet related question: Are there deviations in the impact of culture if we employ other proxies for redistribution? To assess the stability of our baseline results, we use four alternative strategies to measure redistribution. The first variant (REDIST (WIID)) replicates the traditional pre-post approach based on data obtained from the WIID, allowing us to rule out the possibility that the results are driven by the selected underlying data source. The second variant (REDIST (rel)) is based on relative redistribution, which relates the degree of inequality reduction to the initial level of market inequality, i.e.

$$\text{REDIST (rel)}_{it} = \frac{\text{GINI(M)}_{it} - \text{GINI(N)}_{it}}{\text{GINI(M)}_{it}}. \tag{4.9}$$

The third and fourth measures of redistribution concentrate on specific dimensions of the social security system, including social transfer payments and the progressivity of the tax system. To gauge the generosity of transfer payments (SOT), we employ the share of social transfers relative to total expense using data from the World Bank (2016). In addition, we follow Arnold (2008) and Attinasi et al. (2011) by utilizing an index of tax progressivity that is computed via

$$\text{Tax} = 1 - \frac{100 - \text{marginal tax rate}}{100 - \text{average tax rate}}, \tag{4.10}$$

where average and marginal tax rates are evaluated at the average production worker wage, with higher values of Tax implying higher progressivity.

To facilitate comparison and presentation of the results, Figure (4.8) illustrates the standardized coefficients of the reduced POLS model of Table (4.3). Standardization is necessary due to the large differences in the means and standard deviations between the four redistribution measures. The colors of the bars show the levels of significance, where dark blue ($p < 0.01$), medium blue ($p < 0.05$), and light blue ($p < 0.1$) suggest a significant impact, and gray ($p > 0.1$) indicates an insignificant effect. Due to the lower number of available country-year observations compared with our standard measure of redistribution, the figure focuses on the reduced specifications estimated via POLS, as inclusion of covariates and instruments or concentration on the cross-sectional information would be statistically unjustifiable. For a detailed overview of the descriptive statistics, see Table (4.8) in the appendix.

Overall, the parameter estimates strongly coincide with the baseline results, suggesting a strong positive effect of individualism, trust and tolerance on redistribution that goes along with a negative influence of power distance, family ties, obedience, and the belief in hard work. In addition, as previously indicated in Table (4.3), the effects of masculinity, uncertainty avoidance, and long-term orientation are less distinct and much smaller in magnitude. In most cases, the size of the computed parameter is largest with regard to relative redistribution, and smaller if the WIID data is used to compute the pre-post measure. When naively comparing the standardized versions of the estimates

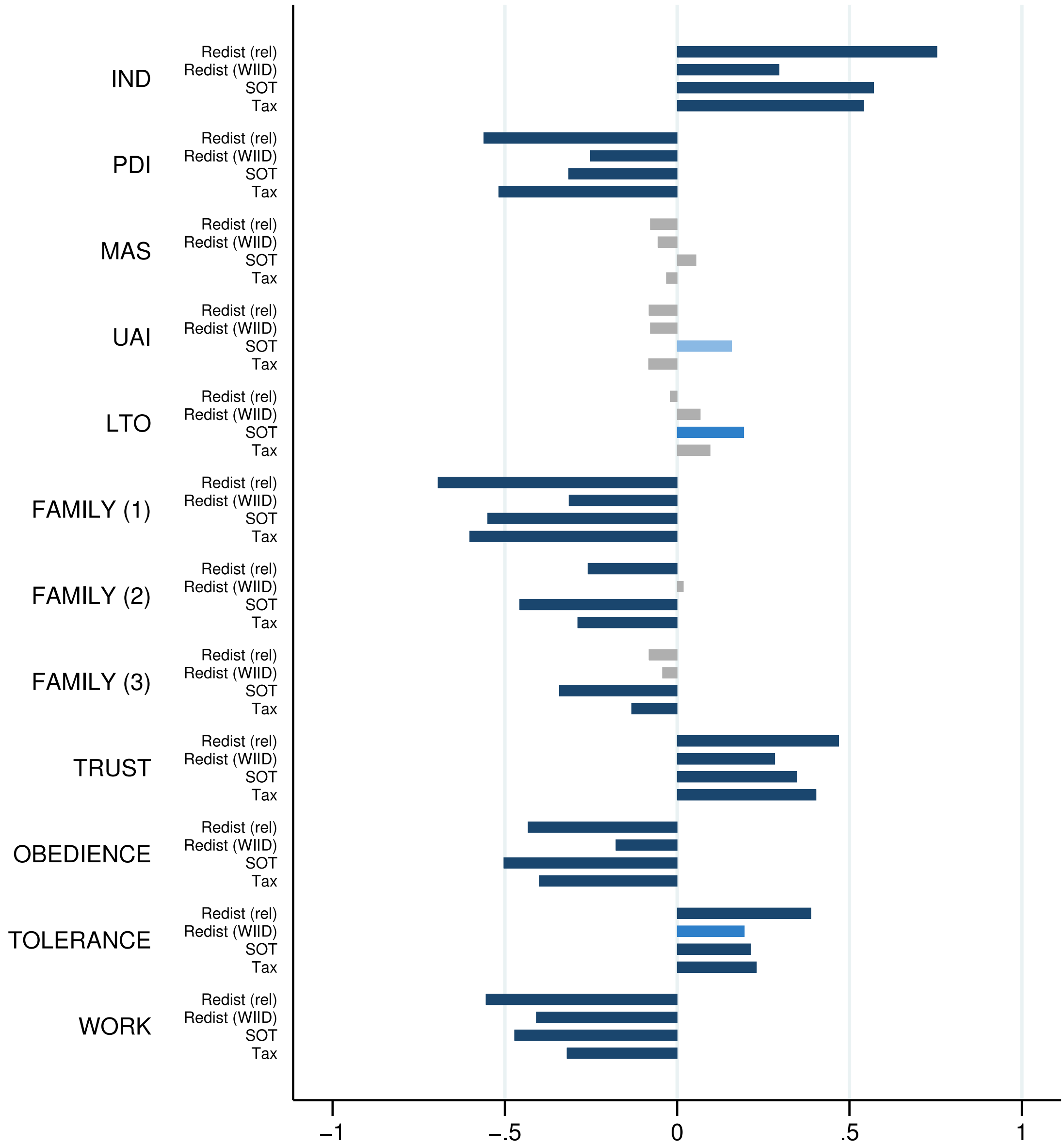

Figure 4.8 The effect of culture on redistribution based on four different proxies for redistribution. Redist (WIID) replicates our baseline variable using data from the WIID, Redist (rel) measures inequality reduction relative to the initial level of market inequality, SOT is the share of social transfers relative to total expense, and Tax denotes an index of tax progressivity that is computed according to Arnold (2008) and Attinasi et al. (2011). The colors indicate the levels of significance: dark blue ($p < 0.01$), medium blue ($p < 0.05$), light blue ($p < 0.1$), and gray ($p > 0.1$).

based on the SWIID with those obtained via application of the WIID data, we once again observe lower coefficients for the REDIST (WIID) data. However, these differences originate in a sample selection bias which arises as a result of the reduced number of country-year observations for which pre-post redistribution can be calculated using the WIID data.[37] If the models are based on the identical—yet strongly reduced—sample of data, the estimated parameters of REDIST (WIID) approximate those obtained via our standard redistribution measure.

4.5.4 Blood type distance and prevalence of Toxoplasma gondii

One crucial assumption remains to be tested: the exclusion restriction formulated in Equation (4.6). While both the weak IV and underidentification tests, as well as the first-stage results, suggest that the IV strategy is valid, this section further employs a second set of external instruments drawing on biological characteristics prevalent in the countries (see Section 4.4.2). Table (4.5) illustrates the effect of the cultural dimensions when the Euclidean distance between blood types A and B, as well as the seroprevalence of Toxoplasma gondii, are used as instruments.

The results obtained via application of the biological instruments strongly resemble the previous findings, with three exceptions. First, the effect of tolerance is less pronounced. While contributing significantly to redistribution when using a reduced specification based on blood type distance, TOLERANCE becomes insignificant in each of the remaining estimations. Second, whereas the effect of long-term orientation was rather indistinct in Tables (4.3) and (4.4), the results now strongly indicate a positive influence of LTO on redistribution. Finally, much more strongly than in the previous regressions, the outcomes suggest that citizens with masculine values are less supportive of redistribution. Apart from these deviations, the table again confirms each of the previously drawn conclusions.

The results of the IV technique depend crucially upon the ability of biological characteristics to instrument culture. Tables (4.10) and (4.11) provide a rich set of weak IV and

[37]While the number of included observations in the baseline model varies between 318 ($FAMILY_1$) and 431 (TRUST) country-years, it is reduced to, respectively, 221 ($FAMILY_1$) and 254 (TRUST) when using REDIST (WIID).

Table 4.5 The effect of culture on redistribution. IV regressions using Toxoplasma gondii prevalence and blood type distance as instruments. Dependent variable is REDIST.

	Blood Type Distance			Prevalence of Toxoplasma gondii		
	isolated effect	distribution controls	institution controls	isolated effect	distribution controls	institution controls
	Panel A: Hofstede Dimensions					
IND	0.273***	0.201***	0.150***	0.198***	0.162***	0.112**
	(22.53)	(8.92)	(4.55)	(6.14)	(3.53)	(2.32)
N (R^2)	464 (0.52)	216 (0.78)	164 (0.83)	387 (0.62)	187 (0.74)	141 (0.81)
PDI	-0.430***	-0.412***	-0.347**	-0.354***	-0.352***	-0.317
	(-12.89)	(-4.14)	(-2.33)	(-4.61)	(-2.75)	(-1.60)
N (R^2)	464 (0.59)	216 (0.24)	164 (0.52)	387 (0.05)	187 (0.25)	141 (0.47)
MAS	-1.099***	-0.572***	-0.339*	0.659	-0.0997	-0.0790
	(-5.11)	(-2.89)	(-1.86)	(0.69)	(-1.54)	(-1.53)
N (R^2)	464 (0.46)	216 (0.39)	164 (0.35)	387 (0.26)	187 (0.69)	141 (0.81)
UAI	1.018***	1.338	0.764	-0.197***	-0.150**	-0.0836**
	(3.92)	(1.51)	(1.00)	(-3.62)	(-2.57)	(-2.00)
N (R^2)	464 (0.00)	216 (0.01)	164 (0.01)	387 (0.55)	187 (0.50)	141 (0.76)
LTO	0.775***	0.388***	0.216***	0.163***	0.0562	-0.0912
	(5.01)	(2.59)	(2.66)	(3.88)	(1.16)	(-1.25)
N (R^2)	464 (0.01)	216 (0.32)	164 (0.82)	387 (0.25)	187 (0.84)	141 (0.78)
	Panel B: Alesina and Giuliano Dimensions					
FAMILY_1	-0.491***	-0.312***	-0.186***	-0.161	-0.422***	-0.688**
	(-18.02)	(-7.28)	(-3.80)	(-0.88)	(-3.77)	(-2.09)
N (R^2)	394 (0.39)	193 (0.76)	151 (0.85)	311 (0.53)	159 (0.57)	124 (0.23)
FAMILY_2	-2.846***	-1.473**	3.434	-0.121	-0.641***	-0.892*
	(-3.00)	(-2.08)	(0.41)	(-0.77)	(-2.62)	(-1.71)
N (R^2)	394 (0.01)	193 (0.07)	151 (0.00)	311 (0.40)	159 (0.46)	124 (0.23)
FAMILY_3	-4.309**	-14.74	1.514	-1.653***	-1.903	-2.108
	(-2.38)	(-0.44)	(0.92)	(-2.71)	(-1.14)	(-0.24)
N (R^2)	437 (0.01)	198(0.01)	152 (0.62)	377 (0.38)	190 (0.38)	146 (0.52)
TRUST	0.641***	0.369***	0.253***	0.0468	0.127***	0.121**
	(10.26)	(5.84)	(4.03)	(1.13)	(2.88)	(2.56)
N (R^2)	504 (0.40)	236 (0.56)	187 (0.76)	391 (0.08)	198 (0.66)	152 (0.79)
OBEDIENCE	-1.679***	-0.382***	-0.340***	-0.249***	-0.257	-0.257*
	(-3.42)	(-4.87)	(-2.63)	(-3.94)	(-0.32)	(-1.90)
N (R^2)	466 (0.01)	214 (0.52)	167 (0.66)	377 (0.42)	183 (0.48)	138 (0.76)
TOLERANCE	1.328***	4.774	-1.855	-0.191	0.174	0.696
	(6.88)	(1.38)	(-1.20)	(-0.81)	(0.38)	(1.30)
N (R^2)	466 (0.20)	214(0.01)	167 (0.06)	377 (0.52)	183 (0.55)	138 (0.55)
WORK	-0.969***	-0.867***	-12.59	-0.286***	-0.0379	-8.186
	(-14.31)	(-4.82)	(-0.16)	(-2.80)	(-0.15)	(-0.12)
N (R^2)	436 (0.62)	197(0.32)	152 (0.01)	324 (0.50)	157 (0.73)	118 (0.01)

Notes: Table reports IV regression results with Huber-White-robust standard errors. z statistics in parentheses. IV regressions use seroprevalence of the parasite Toxoplasma gondii as well as the distance between blood types A and B as external instruments. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

underidentification tests. These tests point to a satisfying degree of instrument strength, which is implied by both the SW F-test and the SW χ^2 test. However, while the SW F-test surpasses the critical Stock-Yogo value of a 15 % IV size in each case, it also suggests that regional instruments are stronger than biological characteristics. The first-stage regression results, however, imply that both blood type distance and seroprevalence of Toxoplasma gondii significantly contribute to the explanation of cultural values.

As a final robustness check, Table (4.13) in the appendix reports the effect of culture on redistribution, obtained via instrumentation with language. The estimates based on the prevalence of pronoun drop strongly support the previous findings, pointing to a higher level of redistribution in individualistic societies and in those which consider trust and tolerance to be desirable attitudes. Likewise, a higher degree of power distance, obedience, and the belief in hard work are negatively associated with redistributive policies. However, while the weak instrument tests imply that the employed biological characteristics are universal instruments in the sense that they provide strong instrumentation for all of the applied cultural dimensions, the first-stage results and the SW χ^2 F-test provide a heterogeneous picture in the case of our language variable. These tests show that pronoun drop is a very strong instrument—even stronger than biological characteristics—for individualism, power distance, most dimensions of family ties, trust, and tolerance. In contrast, this instrument fails with respect to masculinity and FAMILY_3. The data does not imply any noteworthy relationship between societies with masculine values and the tendency to drop pronouns (correlation: 1.9 percent), whereas there are considerable correlations with IND (83 percent), PDI (-72 percent), FAMILY_1 (-66 percent), TRUST (57 percent), and TOLERANCE (40 percent).[38]

4.5.5 Cultural values and the Meltzer-Richard effect

Recent empirical research supports the classical Meltzer and Richard (1981) model, suggesting that higher inequality triggers stronger demand for redistributive policies (Gründler and Köllner, 2016). Along with the strong effect of culture on redistribution identified in

[38]Note that the variable is coded as: 1 – pronoun drop, 2 – no pronoun drop.

the previous sections, it may also be possible that different collective values influence the effect of market inequality on redistribution. For instance, Tables (4.3)–(4.5) showed that governments of countries in which cultural values promote equality among individuals tend to redistribute more. On top of this, we might also expect that a higher degree of market inequality in these countries results in a stronger redistribution-enhancing effect than in countries with a higher prevalence of power distance. Motivated by this thought experiment, Table (4.6) investigates the *conditional* effect of culture dependent on the level of market inequality.

As discussed in Section (4.4), we study these effects via system GMM. This is for three reasons: First, unlike in the reduced models in (4.3)–(4.5), the more comprehensive specification obtained via inclusion of market inequality and a lagged dependent variable yields sufficient variation to apply this strategy. Second, the lack of reliable external instruments for market inequality and the interaction terms between culture and inequality forces us to rely on lagged variables as internal instruments. Third, when relying on internal instruments, there is a much greater need to disentangle the effects of culture and institutions via inclusion of unobserved heterogeneity.[39]

We do not identify any significant conditionalities of uncertainty avoidance, long-term orientation, or obedience. However, we find that the remaining cultural values distinctively influence the degree to which inequality translates into redistribution. These conditionalities are reported in Table (4.6). The most important conclusion is that the strength of kinship ties matters for the Meltzer-Richard effect. Both the results referring to individualism and those for devotion to family show that the Meltzer-Richard effect is much stronger in societies with individualistic values. In countries shaped by collectivist attitudes, a higher degree of inequality does not yield an increase in redistribution. A similar observation is that countries whose citizens accept an unequal distribution of power (PDI) and those favoring masculine values (MAS) tend to be reluctant to demand higher redistribution in the presence of rising inequality. With respect to MAS, however, this

[39]The challenge of including unobserved heterogeneity is best dealt with in a system GMM framework, as the time-invariant character of culture rules out applications that rely on time-demeaning or differencing strategies.

Table 4.6 Culture and the Meltzer-Richard effect. Conditional effect of culture on redistribution dependent upon market inequality. Dependent variable is REDIST(S).

	IND	PDI	MAS	FAMILY_1	TRUST	WORK
C	-0.0043	0.0948	0.208	0.487***	-0.398*	0.996*
	(0.0647)	(0.0898)	(0.140)	(0.163)	(0.238)	(0.550)
GINI(M)	-0.15599**	0.170	0.167	1.041***	-0.187	0.648**
	(0.0704)	(0.134)	(0.182)	(0.289)	(0.156)	(0.262)
GINI(M)$\times$ C	0.0043***	-0.00328*	-0.00431	-0.0132***	0.00931*	-0.0263*
	(0.0015)	(0.00180)	(0.00308)	(0.00374)	(0.00529)	(0.0138)
REDIST($t-1$)	0.6049***	0.799***	0.956***	0.769***	0.885***	0.645***
	(0.0499)	(0.0664)	(0.0439)	(0.0819)	(0.0613)	(0.190)
Observations	300	346	346	314	422	344
Countries	52	52	52	50	69	54
Hansen p-val	0.132	0.373	0.156	0.118	0.292	0.390
Diff-Hansen	0.234	0.811	0.705	0.370	0.335	0.151
AR(1) p-val	0.052	0.0437	0.0228	0.0675	0.0299	0.0856
AR(2) p-val	0.554	0.618	0.501	0.487	0.557	0.836
Instruments	39	41	41	44	44	44

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the Arellano and Bover (1995) conditions. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is collapsed to prevent instrument proliferation. For a detailed discussion, see Section (4.4). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

effect is not significant at the 10 percent level.

Another conditionality has its roots in the level of trust. If people do not trust others, there is virtually no effect of market inequality on redistribution at all. However, the more individuals trust others outside their group, the higher the transmission from inequality to redistributive taxes and transfers. Finally, the results also suggest that people who believe that hard work is a major condition for success are much less supportive of equalizing policies. Figure (4.9) provides a graphical illustration of the results documented in Table (4.6).

These results explain many of the observable differences in the redistributional responses of governments to market inequality. For instance, it has been shown that preferences for redistribution in Finland are much higher than would be implied by the Finnish degree of market inequality, while Italians tend to have disproportionately low prefer-

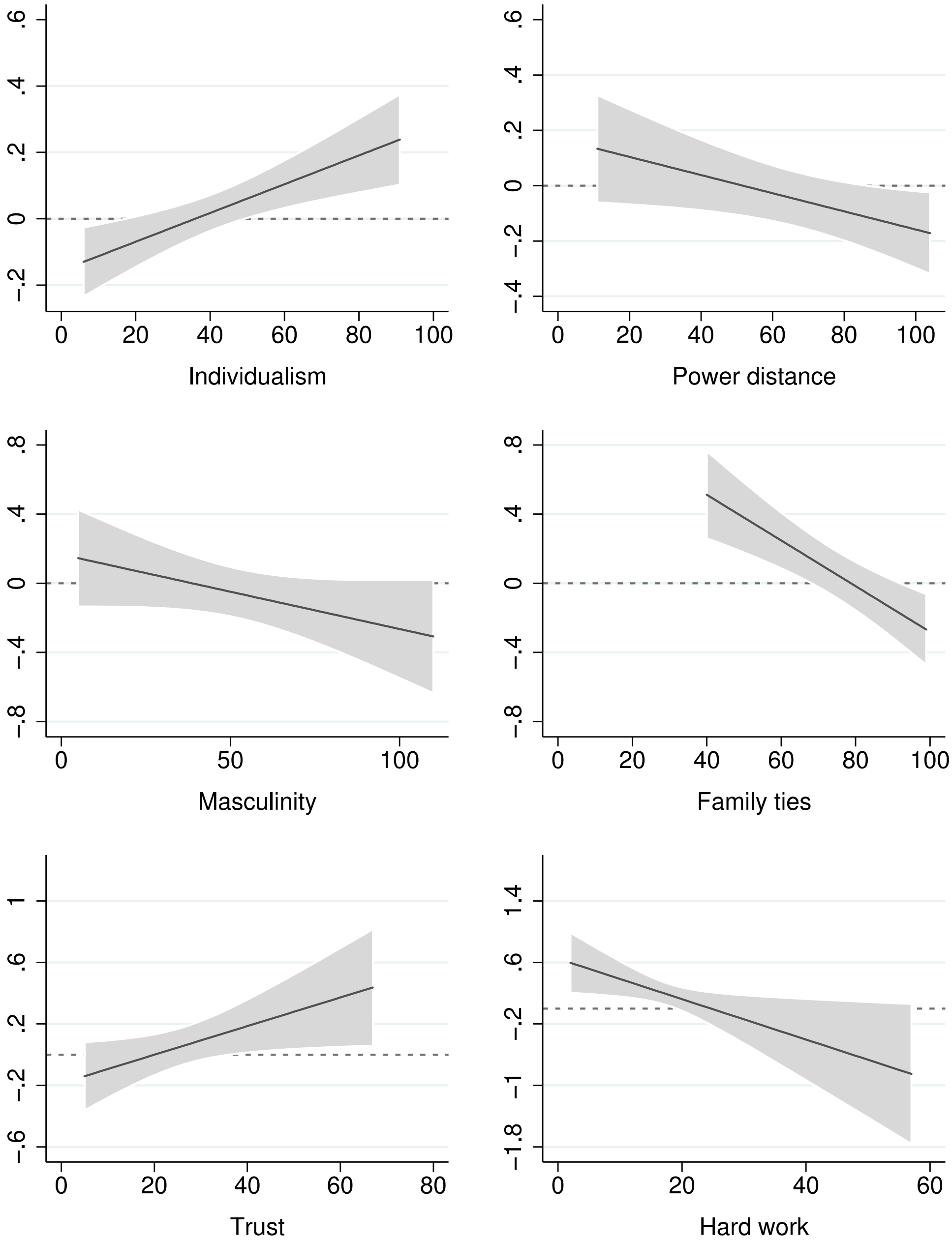

Figure 4.9 Marginal effect of market inequality on redistribution conditional upon different cultural traits. The gray-shaded area shows the 90 % confidence interval, the dashed gray line marks the point at which the effect of market inequality on redistribution is zero. The graphs are generated based on the results of Table (4.6).

ences for redistributive policies (Finseraas, 2009). A substantial part of this deviation can be traced back to culture. With a high degree of trust (63) and individualism (63), along with the belief that hard work does not necessarily bring success (9), the results illustrated in Figure (4.9) suggest that the Meltzer-Richard effect should be strongly pronounced in Finland. In contrast, Italians on average possess a much lower degree of trust (32) and live together with strong family ties (81). Both attitudes are insignificantly—or negatively—related to government redistribution.

4.6 The influence of diversity on redistribution

The findings of the previous chapters highlight that different cultural values are associated with different redistributive policies. The implicit assumption of these analyses was that each nation possesses a form of "ubiquitous culture" shared by all members of the society. However, during the past decades and centuries, migration between countries has led to a rich diversity within nations, and many national populations are increasingly composed of different cultures, religions, and ethnic groups. Apart from the direct effect of culture on redistribution, a higher degree of diversity may also influence voting behavior and thus redistributive policies. In a pioneering paper, Luttmer (2001) shows that *racial group loyalty* crucially influences interpersonal preferences for redistribution, emphasizing that individuals tend to increase their support for welfare spending as the share of local recipients of their own racial group increases. In contrast, individuals typically prefer that less transfer payments be received by indigents outside their social group. While Luttmer (2001) uses data on individual support for redistribution in the United States, this section examines the group loyalty effect based on a broad panel of countries. In line with recent research on the topic (Habyarimana et al., 2007; Fong and Luttmer, 2009; Eger, 2010), our hypothesis is that a higher degree of diversity is negatively related to redistribution. Due to past comparability issues with the redistribution variable, cross-country evidence on the effect of diversity on fiscal policy and the welfare state is surprisingly scarce. There is, however, a rich literature investigating this effect at the country level, commonly featuring experimental designs (see Stichnoth and Van der Straeten, 2013).

Table 4.7 The effect of diversity on redistribution. Linear and non-linear effects. Dependent variable is REDIST(S).

	Ethnic (HHI)	Religion (HHI)	Culture (Fearon)	Ethnic (Fearon)
	Panel A: Reduced models			
$FRAC_{POLS}$	-0.0012***	0.0001	-0.081***	-0.115***
	(-7.28)	(0.75)	(-4.44)	(-7.80)
$FRAC_{IV}$	-0.004***	0.0001	-0.253***	-0.031***
	(-6.11)	(0.16)	(-5.59)	(-6.91)
	Panel B: Distribution controls			
$FRAC_{POLS}$	-0.0002**	5.2E-05	-4.804***	-3.489**
	(-2.47)	(0.61)	(-3.31)	(-2.56)
$FRAC_{IV}$	-0.002***	-3.4E-05	-0.145***	-0.133***
	(-2.60)	(0.11)	(-3.98)	(-3.73)
	Panel C: Institution controls			
$FRAC_{POLS}$	-0.0002*	0.0001	-2.483*	-1.964
	(-1.75)	(1.40)	(-1.67)	(-1.42)
$FRAC_{IV}$	-0.0018	0.0001	-0.066*	-0.091**
	(-1.60)	(0.36)	(-1.85)	(-2.54)
	Panel D: Non-linear effects			
$FRAC_{POLS}$	-0.0025***	-0.001	0.179***	-0.2018***
	(-5.29)	(-1.26)	(3.32)	(-4.40)
FRAC $SQUARED_{POLS}$	1.8E-07***	1.3E07	-0.045***	0.00117**
	(3.48)	(1.41)	(-5.57)	(2.23)
$FRAC_{IV}$	-0.0248***	-0.0031	-3.2534	-4.8701*
	(-3.03)	(-0.34)	(-1.53)	(-1.86)
FRAC $SQUARED_{IV}$	2.8E-06***	3.9E-07	0.05033	0.05756*
	(2.93)	(0.35)	(1.49)	(1.84)
$FRAC_{ALL}$	-0.0161***	-0.0054**	-2.8927**	-1.4886***
	(-3.81)	(-2.57)	(-2.22)	(-4.47)
FRAC $SQUARED_{ALL}$	1.75E-06***	6.9E-07**	0.04114**	0.01526***
	(3.64)	(2.54)	(2.14)	(4.18)

Notes: Table reports pooled OLS and IV regression results with Huber-White-robust standard errors. t and z statistics in parentheses. IV regressions use regional levels of diversity and fractionalization as instruments. Control variables are identical to the baseline specification with regard to the effect of culture on redistribution. Columns "Ethnic (HHI)" and "Religion (HHI)" denote the Herfindahl indices based on ethnic and religious subgroups. "Culture (Fearon)" and "Ethnic (Fearon)" denote the degrees of cultural and ethnic fractionalization as computed by Fearon (2003). Regressions based on all available data on redistribution include a dummy variable for African countries. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We construct four different series to measure a country's diversity, which are based upon two different data sources. First, we use the CREG (2016) database from the Cline Center for Democracy at the University of Illinois, which compiles national data on religious and ethnic groups for 165 countries between 1945 and 2013. Based on this data, we follow Alesina et al. (2003) in computing a Herfindahl-Hirschman index (HHI) measuring the degree of ethnic and religious concentration that is re-coded so that higher values reflect a higher degree of diversity. Second, we use data on ethnic and cultural fractionalization collected by Fearon (2003). This data shows that the level of diversity differs substantially across countries. While ethnic diversity in the post-2010 period was low in Norway (0.098), South Korea (0.004) and Italy (0.04), differences are much more pronounced in the Democratic Republic of the Congo (0.930), Tanzania (0.953), and Papua New Guinea (1.000). The same also applies for cultural and religious diversity, with particularly high degrees of cultural fractionalization observable in Cameroon (0.733), Afghanistan (0.679), and India (0.667).

Table (4.7) investigates the effect of diversity on redistribution based on four different specifications. The first panel reports the isolated effect of diversity, obtained via a reduced specification in which the only determinant of redistribution is diversity. Subsequently, we introduce distribution controls (Panel B) and covariates capturing institutional differences (Panel C) in the same way as in Table (4.3). Finally, in Panel D we examine potential non-linearities in the impact of diversity on redistribution, which has been hypothesized by Selway (2011) but thus far neglected in recent empirical studies. To estimate the specifications, we again rely on both POLS and 2SLS. For the instrumentation strategy, we use jack-knifed regional degrees of diversity as instruments, obtaining a variable via a strategy similar to that applied in Equation (4.7). Utilization of regional instruments is motivated by previous empirical findings using the gravity model to explain migration patterns (see, e.g., Karemera et al., 2000; Lewer and Van den Berg, 2008). This model emphasizes that immigration is impeded by the costs of moving from one country to another. As a result, a substantial portion of the individuals migrating to a destination country were born in a geographically nearby state. Consequently, there are strong regional correlations with regard to the share of cultural and regional fractionalization, as is illustrated in Figure (4.14) in the appendix.

The results reported in Table (4.7) illustrate that diversity plays a crucial role in determining the extent of redistribution. Panel A shows that redistribution is lower in countries with a higher degree of ethnic and cultural diversity. These results are obtained via both the POLS and the IV strategies. However, we do not find any significant effect with respect to religious fractionalization. Inclusion of distribution and institution controls in Panels B and C, respectively, supports our finding of a significantly negative effect on redistribution emanating from greater cultural and ethnic diversity. As in Panel A, however, there is no such effect visible with respect to religion.

While Panels A–C investigate linear effects, Panel D emphasizes that diversity and redistribution are linked via a non-linear function. We study non-linearities based on three different reduced specifications. The first specification uses POLS as the estimation strategy, while the second specification again applies regional levels of fractionalization as instruments. While we use REDIST(S), the sample of high-quality observations, to obtain the previous results, the final specification draws on all available observations in order to investigate the link based on the broadest possible sample of countries. Taken together, the results strongly indicate a parabolic relationship between diversity and redistributive policies, which is illustrated in Figure (4.10).

In countries that are shaped by a low level of diversity, an increase in religious, cultural, and ethnic variety results in a lower tendency to support redistributive policies. In this case, ethnic minorities may be perceived as posing a political or economic threat to the cultural majority in the country. However, once a crucial tipping point of diversity has been surpassed, the negative effect on redistribution becomes increasingly relativized until the point—which is reached only in a minority of extremely fractionalized countries—at which diversity eventually triggers positive effects on redistribution. When the relationship between the variables is modeled using a non-linear function, the effect of religious diversity reaches a significance level similar to those of the impact of ethnic and cultural diversity. There are two possible explanations for why the effect of diversity changes once

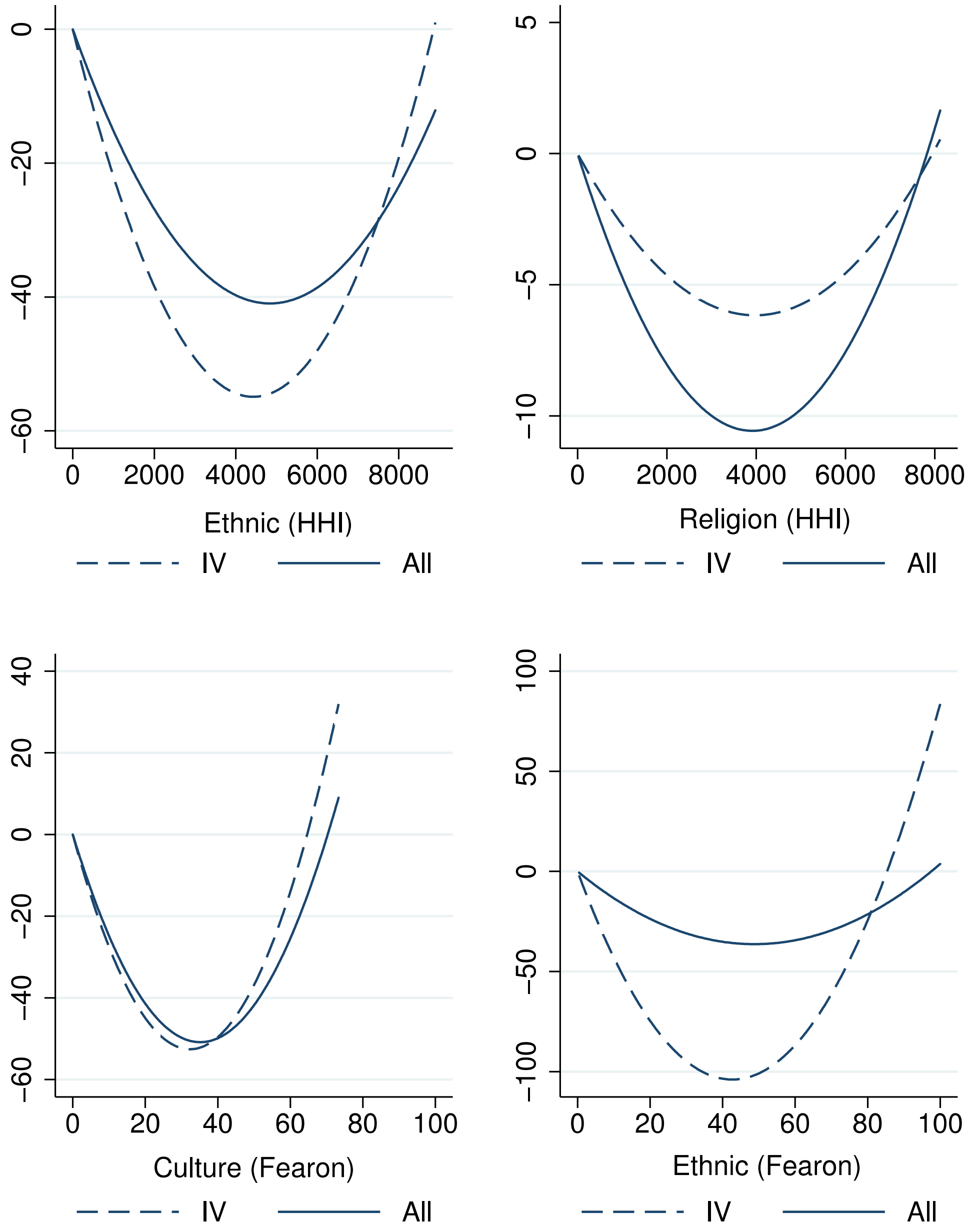

Figure 4.10 Non-linear effects of ethnic, religious and cultural fractionalization on redistribution. Function labeled "IV" refers to the outcomes of the IV estimations with REDIST(S) as dependent variable, "All" refers to the regression sample that includes all available information (dependent variable: REDIST). The graphs are generated based on the results of Table (4.7). The HHI is re-scaled so that higher values reflect a greater extent of diversity, the Fearon (2003) data is re-scaled to fit the interval $[0, 100]$.

a certain level of fractionalization is reached. First, in the absence of a leading majority, social segregation between different groups may be less prevalent, resulting is less prejudice and resentment towards members of other social groups. Second, Luttmer and Singhal (2011) demonstrate that immigrants from countries with a high average preference for redistribution are more likely to vote for more redistributive policies. The effect seems to be even stronger if individuals are less integrated into the society of the destination country. Consequently, a higher degree of diversity that is the result of immigration from high-preference countries may also result in more expansive welfare systems.

As a final remark, the effect of diversity on the welfare state may depend upon the particular composition of cultural and ethnic groups. While a certain social group A may well share some attitudes with another group B, cultural differences when compared with C might be much more pronounced. Consequently, members of A may be reluctant to assist members of group C, but may be much more supportive towards members of group B (see Rushton, 2008 for a related argument). While it is difficult to study cultural differences of subnational groups in a broad panel of countries due to the arbitrariness involved in the measurement of ethnic differences between groups that are incomparable across countries, we can approach such a study by assessing the effect of diversity separately for different regions in the world.

Table (4.14) in the appendix reports the effects of the four diversity indicators on redistribution in Europe, Asia, Africa, South America, Oceania, and North America. The parameter estimates show that diversity has by far the largest negative impact in Europe, followed by Oceania, South America, and Asia. In contrast, diversity is positively related to redistribution in Africa. These results again underscore the parabolic relationship illustrated in Figure (4.10). As Europe possesses the lowest degree of cultural and ethnic fractionalization, we expected the effect of diversity to be strongly negative. On the other hand, ethnic fractionalization in Africa is highest in the world, which is why an increase in diversity does not trigger negative effects.

4.7 Concluding remarks

Our results provide strong evidence that culture and diversity matter for the formation of equalizing government policies. Apart from their general implications, our findings also relate to a more recent question raised by economists: Does migration yield changes in the social security system? To answer this question from the perspective of our paper, it is important to consider both sides of the coin, which include the direct effect of different collective values as well as the indirect effect arising from increasing diversity. Given the substantial differences between cultural traits and their different effects on redistributive policies, the results suggest that migration may contribute to a change in national social security systems. However, the findings also stress that the magnitude and the direction of this change depend on the composition of different cultural traits that are prevalent in the country of origin and the host country, as well as the initial level of fractionalization.

Additionally, it is crucial to emphasize that these results are based on average effects obtained via cross-country regressions, whereas in a single-country context we might expect country-specific differences that have their roots in institutional frameworks and resentment towards specific cultural and ethnic groups. For instance, the ethnic tension between Arabs and Sub-Saharan Africans is one of the many well-documented racial conflicts in Africa (Welsh, 1996). A further issue concerns immigrants' voting rights, which are a prerequisite for the transmission of the cultural preferences of migrants into policy actions. Finally, a further interesting area of study lies in the examination of changes in ethnic ties and the consequences of such changes for the social security system. Economists have hardly begun to draw on knowledge offered by other disciplines about the nature and the consequences of culture and ethnicity. We are convinced that therein lies promising potential for future research.

Appendix

Table 4.8 Descriptive statistics of the variables used in the estimations.

	Obs.	Mean	Std. Dev.	Min	Max
	Panel A: Redistribution variables				
REDIST	1,128	6.556924	6.443803	-14.73038	26.06834
REDIST(S)	453	9.646837	7.347301	-2.461385	26.06834
REDIST(WIID)	264	8.592245	7.682834	-21.275	24.30342
REDIST(rel)	453	.214097	.159624	-.0483195	.5343646
SOT	517	37.15542	21.03387	.5685228	81.75859
Tax	606	.054579	.0685522	-1.76e-07	.3524257
	Panel B: Control variables				
GINI(M)	1,128	44.00543	8.58483	18.75223	71.29995
TOP-1%	1,139	9.453331	4.38978	2.467996	29.64182
MIDDLECLASS	613	47.08253	6.258872	20.27	57.42
POLRIGHT	1,624	4.06414	2.182818	1	7
Log(FERT)	2,029	1.283300	.5502135	-.1369659	2.21336
UNEMP	855	8.955421	6.1094	.5333334	36.95
	Panel C: Cultural dimensions				
IND	726	44.0303	24.11509	6	91
PDI	726	50.66667	23.98318	11	104
MAS	726	50.57576	18.93638	5	110
UAI	726	66.90909	23.987	8	112
LTO	726	45.97143	23.65	13	118
FAMILY_1	803	79.45959	14.26083	39.25	99
FAMILY_2	803	73.74726	12.28036	37.33333	96
FAMILY_3	858	87.58056	7.150792	64.66666	98
TRUST	1,397	24.7563	13.70009	5	67
OBEDIENCE	1,078	41.66258	21.42133	6	92
TOLERANCE	1,078	67.26173	10.31181	37	96
WORK	858	24.22436	12.30376	2	57
	Panel D: Instruments				
T. GONDII	539	35.47143	17.26755	2.3	75.2
BLOOD Dist.	715	0.1865569	0.1151366	0.006	0.42
LANGUAGE	803	1.287671	0.4529592	1	2

Notes: Table reports the number of observations (N), the means, standard deviations (std.), minima (min.) and maxima (max.) of our employed variables. See Section (4.4) for a description.

Table 4.9 Classification of regions in the IV regression.

I. ASIA	
Central Asia	Afghanistan, Armenia, Azerbaijan, Bhutan, Georgia, India, Iran, Kazakhstan, Kyrgyzstan, Maldives, Mongolia, Nepal, Pakistan, Sri Lanka, Tajikistan, Turkmenistan, Uzbekistan
East-Southeast Asia	Bangladesh, Cambodia, China, Japan, Laos, Myanmar, North Korea, South Korea, Taiwan, Thailand, Vietnam
Arabic Region	Bahrain, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, Turkey, United Arab Emirates, Yemen
Oceania	Australia, Brunei Darussalam, Fiji, Indonesia, Malaysia, New Zealand, Papua New Guinea, Philippines, Samoa, Singapore Solomon Islands, Tonga, Vanuatu
II. EUROPE	
Central-Northern Europe	Austria, Belgium, Denmark, Finland, Germany, Iceland, Ireland, Luxembourg, Netherlands, Norway, Sweden, Switzerland, United Kingdom
South-Southwest Europe	Cyprus, France, Greece, Italy, Malta, Portugal, Spain
East Europe	Belarus, Czech Republic, Estonia, Latvia, Lithuania, Moldova, Poland, Russia, Slovakia, Ukraine
Balkan States	Albania, Croatia, Bulgaria, Hungary, Kosovo, Macedonia, Montenegro, Romania, Serbia, Slovenia
III. AFRICA	
North Africa	Algeria, Egypt, Libya, Morocco, Tunisia
Central-East Africa	Cameroon, Central African Republic, Chad, Djibouti, Eritrea, Ethiopia, Kenya, Somalia, South Sudan, Sudan
West Africa	Benin, Burkina Faso, Cape Verde, Cote d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, Togo
Southern Africa	Angola, Burundi, Comoros, Democratic Republic of the Congo, Republic of the Congo, Equatorial Guinea, Gabon, Lesotho, Madagascar, Malawi, Mauritius, Mozambique, Namibia, Rwanda, São Tomé and Príncipe, Seychelles, South Africa, Swaziland, Tanzania, Uganda, Zambia, Zimbabwe
IV. AMERICA	
North America	Bahamas, Canada, United States
Central America	Belize, Costa Rica, El Salvador, Grenada, Guatemala, Honduras, Mexico, Nicaragua, Panama
South America	Argentina, Brazil, Chile, Colombia, Ecuador, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela
Caribbean	Antigua and Barbuda, Barbados, Cuba, Dominica, Dominican Republic, Haiti, Jamaica, St. Kitts and Nevis, St. Lucia, St. Vincent, Trinidad and Tobago

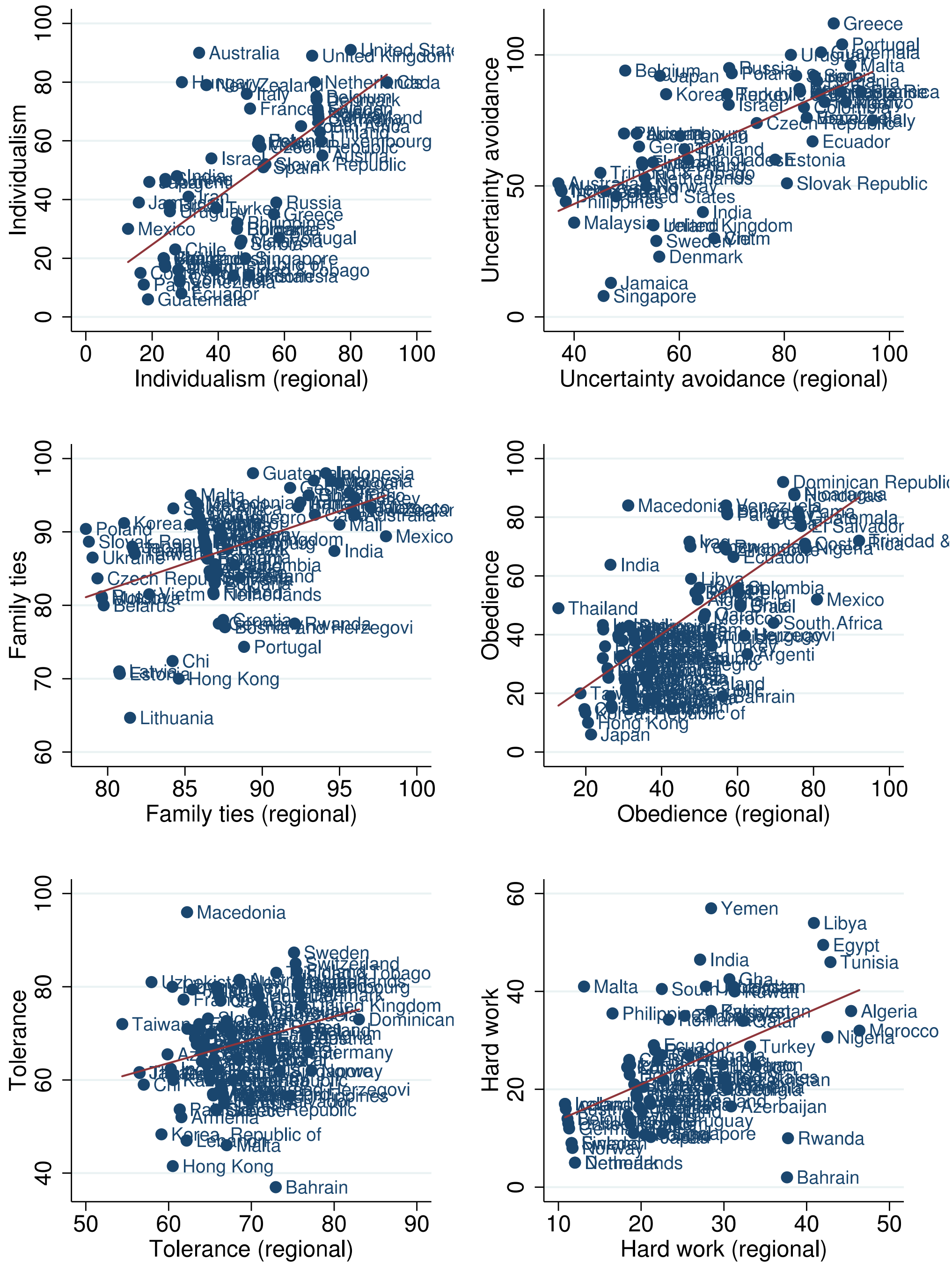

Figure 4.11 The relationship between cultural dimensions and their regional instruments. The construction of regional instruments is discussed in Section (4.4.2). Correlations: Individualism (65 percent), uncertainty avoidance (67 percent), family ties (49 percent), obedience (73 percent), tolerance (27 percent), and hard work (53 percent).

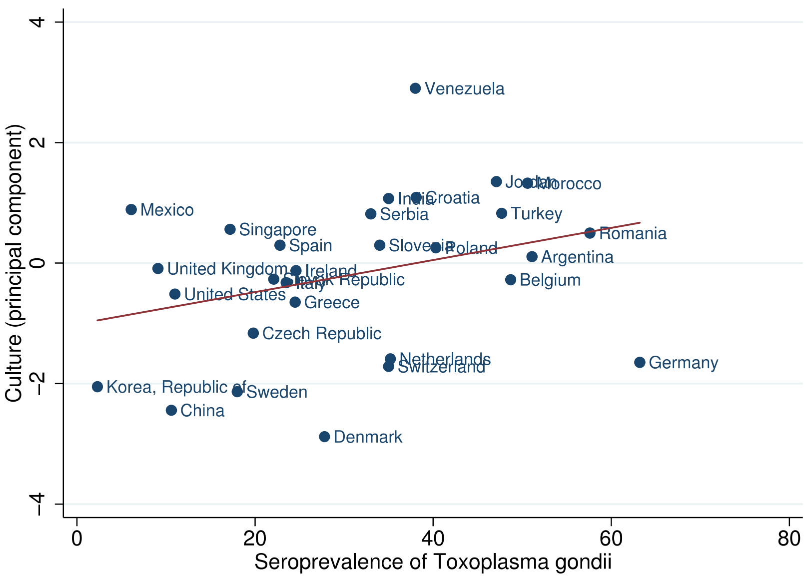

Figure 4.12 The relationship between culture and the seroprevalence of Toxoplasma gondii. "Culture" is the principal component of four variables: family ties, trust, obedience, and uncertainty avoidance.

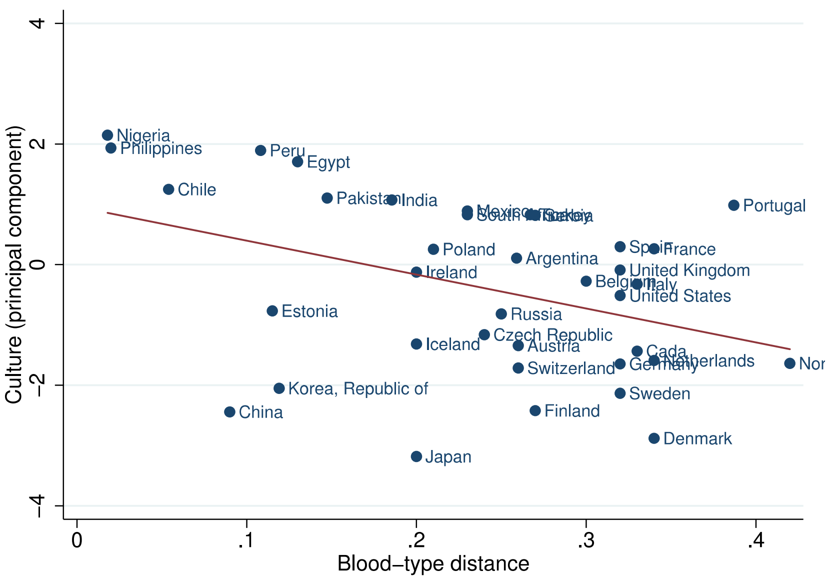

Figure 4.13 The relationship between culture and the Euclidean distance between blood types A and B. "Culture" is the principal component of four variables: family ties, trust, obedience, and uncertainty avoidance.

Table 4.10 Weak instrument diagnostic and tests for underidentification of the instruments used in Tables (4.3), (4.4), (4.5), (4.12).

	Sanderson-Windmeijer F Stat			Sanderson-Windmeijer χ^2 p-val		
	regional	T. gondii	blood	regional	T. gondii	blood
Instrument statistics						
IND	470.10	34.45	448.14	0.000	0.000	0.000
PDI	160.88	13.73	143.27	0.000	0.000	0.000
MAS	53.20	21.08	25.78	0.000	0.000	0.000
UAI	327.97	38.92	17.48	0.000	0.000	0.000
LTO	27.81	38.92	18.87	0.000	0.000	0.000
FAMILY_1	326.76	11.97	102.98	0.000	0.000	0.000
FAMILY_2	84.28	14.79	9.13	0.000	0.000	0.002
FAMILY_3	78.52	22.57	13.10	0.000	0.000	0.000
TRUST	318.60	141.50	32.30	0.000	0.000	0.000
OBEDIENCE	356.10	24.07	12.56	0.000	0.000	0.000
TOLERANCE	92.20	13.01	14.13	0.000	0.000	0.000
WORK	124.49	30.79	41.36	0.000	0.000	0.000
Stock-Yogo critical values						
10 % maximal IV size	16.38	16.38	16.38			
15 % maximal IV size	8.96	8.96	8.96			

Notes: Table reports weak instrument diagnostics. Sanderson-Windmeijer F-tests and Chi-squared-tests are computed as described in Sanderson and Windmeijer (2016). The test extends the weak instrument test for individual regressors proposed by Angrist and Pischke (2009). Critical values refer to Stock and Yogo (2005). The columns labeled "regional", "T. gondii" and "blood" refer to the instrumental variables used in the regressions: Regional culture, prevalence of Toxoplasma gondii, and the Euclidean distance between blood types A and B. A detailed description is provided in Section (4.4.2).

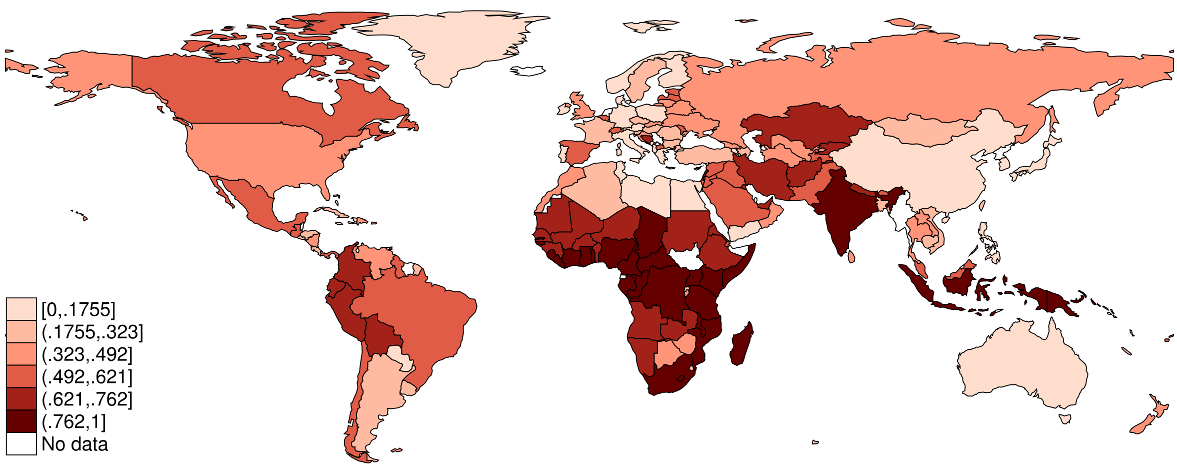

Figure 4.14 The degree of ethnic fractionalization in the world. Data is from Fearon (2003). Selection of the classes refers to the distribution of the variable.

Table 4.11 First-stage results of the regressions based on the instruments used in Tables (4.3), (4.4), (4.5), (4.12).

	Estimated parameters in first-stage		
	regional instruments	Toxoplasma gondii	blood distance
IND	0.810***	-0.413***	151.82***
	(21.68)	(-5.67)	(22.51)
PDI	0.584***	0.232***	-96.56***
	(8.44)	(3.85)	(-13.48)
MAS	-0.863***	-0.081*	-37.74***
	(-7.29)	(-1.71)	(-5.08)
UAI	0.866***	0.417***	40.76***
	(18.11)	(6.07)	(4.18)
LTO	0.435***	-0.501***	45.75***
	(3.80)	(-5.66)	(4.65)
$FAMILY_1$	0.899***	0.103**	-97.86***
	(18.08)	(2.52)	(-17.34)
$FAMILY_2$	0.741***	0.137***	-16.87***
	(9.18)	(3.85)	(-3.02)
$FAMILY_3$	0.595***	0.049***	-8.61**
	(8.86)	(2.60)	(-2.26)
TRUST	0.854***	-0.480***	64.35***
	(17.85)	(-12.99)	(10.01)
OBEDIENCE	0.873***	0.257***	-25.28***
	(18.87)	(4.91)	(-3.29)
TOLERANCE	0.651***	0.102***	31.97***
	(9.60)	(3.54)	(7.04)
WORK	0.816***	0.165***	-43.95***
	(11.16)	(5.55)	(-12.83)

Notes: Table reports first-stage regression results, t statistics in parentheses. A detailed description of the instruments is provided in Section (4.4.2). The underlying 2SLS specification refers to Section (4.4) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.12 The effect of culture on redistribution. Cross-sectional regression results, average of the period 2005-2009. Dependent variable is REDIST.

	OLS estimates			IV estimates		
	isolated effect	distribution controls	institution controls	isolated effect	distribution controls	institution controls
	Panel A: Hofstede Dimensions					
IND	0.247***	0.0948**	0.0639**	0.320***	0.199***	0.193**
	(11.29)	(2.36)	(2.20)	(7.72)	(2.62)	(2.33)
N (R^2)	64 (0.61)	51 (0.79)	51 (0.83)	61 (0.60)	49 (0.78)	49 (0.80)
PDI	-0.191***	-0.0406**	-0.0295	-0.410***	-0.185*	-0.311
	(-5.55)	(-2.07)	(-1.63)	(-4.14)	(-1.82)	(-1.30)
N (R^2)	64 (0.30)	51 (0.87)	51 (0.87)	60 (0.60)	48 (0.73)	48 (0.45)
MAS	0.00290	-0.0175	-0.0200	0.445*	0.117	0.0423
	(0.05)	(-0.61)	(-0.91)	(1.76)	(1.54)	(1.08)
N (R^2)	64 (0.01)	51 (0.76)	51 (0.82)	60 (0.19)	48 (0.66)	48 (0.80)
UAI	-0.00229	0.0132	-0.0488***	-0.0538	-0.00764	-0.0932**
	(-0.05)	(0.46)	(-2.91)	(-0.82)	(-0.28)	(-2.33)
N (R^2)	64 (0.01)	51 (0.76)	51 (0.92)	60 (0.62)	48 (0.78)	48 (0.91)
LTO	0.0316	-0.0448	-0.0190	-0.694	-0.0276	0.0882
	(0.79)	(-1.28)	(-0.61)	(-1.19)	(-0.47)	(0.40)
N (R^2)	64 (0.01)	51 (0.76)	51 (0.82)	52 (0.00)	40 (0.83)	40 (0.72)
	Panel B: Alesina and Giuliano Dimensions					
FAMILY_1	-0.366***	-0.156***	-0.108***	-0.449***	-0.205***	-0.174***
	(-11.46)	(-5.43)	(-2.97)	(-8.75)	(-3.66)	(-2.66)
N (R^2)	72 (0.43)	59 (0.83)	59 (0.86)	72 (0.44)	59 (0.82)	59 (0.85)
FAMILY_2	-0.208***	-0.00447	-0.0247	-0.376***	-0.0545	-0.167
	(-3.04)	(-0.11)	(-0.65)	(-2.64)	(-0.42)	(-1.06)
N (R^2)	72 (0.10)	59 (0.78)	59 (0.84)	72 (0.05)	59 (0.89)	59 (0.80)
FAMILY_3	-0.313***	-0.0362	-0.0400	-0.593**	-0.223	-0.296
	(-2.78)	(-0.60)	(-0.68)	(-2.44)	(-1.22)	(-1.18)
N (R^2)	77 (0.08)	64 (0.84)	64 (0.88)	77 (0.60)	64 (0.73)	64 (0.76)
TRUST	0.222***	0.0991***	0.0708**	0.448***	0.124*	0.131**
	(4.98)	(2.92)	(2.21)	(6.19)	(1.88)	(2.34)
N (R^2)	120 (0.19)	97 (0.77)	97 (0.80)	120 (0.49)	97 (0.75)	97 (0.79)
OBEDIENCE	-0.159***	-0.0155	-0.0186	-0.212***	-0.120*	-0.193*
	(-6.26)	(-0.57)	(-0.71)	(-6.15)	(-1.72)	(-1.90)
N (R^2)	93 (0.20)	74 (0.80)	74 (0.86)	93 (0.18)	74 (0.78)	74 (0.77)
TOLERANCE	0.163*	0.113**	0.0873*	0.624**	0.519**	0.541*
	(1.86)	(2.23)	(1.90)	(2.39)	(2.41)	(1.75)
N (R^2)	93 (0.05)	73 (0.81)	73 (0.83)	93 (0.39)	73 (0.62)	73 (0.60)
WORK	-0.436***	-0.162**	-0.178**	-0.753***	-0.207**	-0.199*
	(-5.46)	(-2.63)	(-2.50)	(-5.31)	(-2.33)	(-1.73)
N (R^2)	73 (0.31)	55 (0.82)	55 (0.85)	70 (0.58)	55 (0.82)	55 (0.86)

Notes: Table reports OLS and IV regression results with Huber-White-robust standard errors. t (OLS) and z (IV) statistics in parentheses. IV regressions use jack-knifed regional cultural values. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.13 Sensitivity analysis of the effect of culture on redistribution. Estimates based on language (pronoun drop) as instrument. Dependent variable is REDIST.

	isolated effect	distribution controls	institution controls	First-stage	SW F-stat (10 % IV size)
	Panel A: Hofstede Dimensions				
IND	0.238***	0.85***	0.156***	44.342***	1754.82
	(23.50)	(7.65)	(5.56)	(41.89)	(16.38)
N (R^2)	570 (0.55)	272 (0.77)	207 (0.82)		
PDI	-0.335***	-0.242***	-0.22***	-31.544***	565.13
	(-18.01)	(-6.43)	(-5.07)	(-23.77)	(16.38)
N (R^2)	570 (0.17)	272 (0.60)	207 (0.70)		
MAS	-25.83	5.135	1.370**	-0.409	0.05
	(-0.22)	(0.71)	(1.72)	(-0.22)	(16.38)
N (R^2)	570 (0.01)	272 (0.01)	207 (0.01)		
UAI	-0.576***	-0.228***	-0.135***	-18.350***	102.09
	(-8.59)	(-4.85)	(-4.97)	(-10.10)	(16.38)
N (R^2)	570 (0.01)	272 (0.34)	207 (0.74)		
LTO	1.073***	0.477***	0.327***	9.847***	24.98
	(5.05)	(2.83)	(3.06)	(5.00)	(16.38)
N (R^2)	570 (0.01)	272 (0.07)	207 (0.19)		
	Panel B: Alesina and Giuliano Dimensions				
FAMILY_1	-0.496***	-0.327***	-0.304***	-21.06***	1297.78
	(-17.94)	(-6.58)	(-5.39)	(-17.26)	(16.38)
N (R^2)	463 (0.38)	219 (0.75)	173 (0.80)		
FAMILY_2	-2.440***	-1.415***	-0.890***	-4.278***	19.14
	(-4.57)	(-2.40)	(-2.87)	(-4.38)	(16.38)
N (R^2)	463 (0.01)	219 (0.01)	173 (0.14)		
FAMILY_3	38.37	-13.43	-5.953	0.2677	0.29
	(0.53)	(-0.97)	(-1.45)	(0.54)	(16.38)
N (R^2)	530 (0.00)	253 (0.00)	197 (0.00)		
TRUST	0.509***	0.323***	0.253***	20.15***	291.33
	(16.12)	(5.70)	(5.17)	(17.07)	(16.38)
N (R^2)	619 (0.55)	299 (0.62)	234 (0.76)		
OBEDIENCE	-0.967***	-2.036	-0.615***	-10.42***	52.24
	(-7.90)	(-1.40)	(-2.73)	(-7.23)	(16.38)
N (R^2)	580 (0.00)	277 (0.01)	214 (0.58)		
TOLERANCE	1.106***	0.925***	1.309***	9.109***	167.66
	(12.16)	(3.57)	(2.03)	(12.95)	(16.38)
N (R^2)	580 (0.21)	277 (0.23)	214 (0.46)		
WORK	-1.594***	-2.325**	-4.975	-6.485***	52.02
	(-8.71)	(-2.42)	(-0.92)	(-7.21)	(16.38)
N (R^2)	495 (0.01)	230 (0.00)	177 (0.00)		

Notes: Table reports IV regression results with Huber-White-robust standard errors, z and t statistics in parentheses. Column labeled "First-stage" gives the results of the first stage with respect to the reduced specification of Column "isolated effect". SW F-stat reports the Sanderson and Windmeijer (2016) weak instrument test, Stock-Yogo critical value of a 10 % IV size in parentheses. See Section (4.4.2) for a detailed description of the employed instrument. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.14 Regional differences in the effect of diversity on redistribution. Dependent variable is REDIST.

	Ethnic (HHI)	Religion (HHI)	Culture (Fearon)	Ethnic (Fearon)
EUROPE	-0.00125***	0.000177	-0.143***	-0.142***
	(-5.83)	(0.96)	(-7.16)	(-4.97)
ASIA	-0.000189*	-0.0000588	-0.0193**	-0.0374***
	(-1.94)	(-0.49)	(-2.07)	(-3.59)
AFRICA	0.0000714*	0.0000397	0.00706*	0.00188
	(1.88)	(0.99)	(1.72)	(0.39)
SOUTH AMERICA	-0.000368***	0.000195**	-0.0344***	-0.0440***
	(-4.14)	(2.09)	(-3.97)	(-5.54)
OCEANIA	-0.00125***	0.000819***	-0.0993***	-0.121***
	(-7.77)	(3.17)	(-5.19)	(-4.18)
NORTH AMERICA	0.000291	0.00248***	0.156	-0.0723
	(0.41)	(17.11)	(0.67)	(-0.70)

Notes: Table reports pooled OLS regression results with Huber-White-robust standard errors based on subsamples that are composed of countries from different continents. t statistics in parentheses. Column "Ethnic (HHI)" and "Religion (HHI)" denote the Herfindahl indices based on ethnic and religious subgroups. "Culture (Fearon)" and "Ethnic (Fearon)" denote the degrees of cultural and ethnic fractionalization as computed by Fearon (2003). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 5

Conclusion

Globalization and inequality are currently two of the most striking phenomena in economics. The aim of this dissertation was to contribute to a comprehensive view on the labor market impacts of globalization and to provide a better understanding of the empirical determinants of governmental redistribution for a broad panel of countries. This chapter briefly summarizes the main findings of the dissertation and concludes with some future research questions which still remain open.

The analysis in Chapter (2) started with the empirical effects of increasing import penetration on manufacturing employment growth in 12 OECD countries between 1996 and 2011. Accounting for various model specifications, different measures of import penetration, and alternative estimation strategies, the results point to a weak positive overall impact of growing trade on manufacturing employment. However, the labor market effects crucially depend on the country of origin of the import penetration variable. While intermediate inputs from China and the new EU member countries are substitutes for manufacturing production in highly developed countries, imports from other EU members act as complements to domestic manufacturing production. Application of a three-level mixed model implies that the hierarchical structure of the data plays only a minor role, while controlling for endogeneity and cyclical influences leaves the results unchanged.

Altogether, globalization has proven to be a main driver of growing economic prosperity in the world, which is why politicians should give support to necessary structural changes rather than impeding them. However, the diverse effects of growing trade on manufacturing employment in highly developed countries emphasize both rising job opportunities for some parts of the labor force and an increasing risk of job losses through globalization for other parts of the population. Thus, demand for social security and redistribution has increased substantially in recent decades. Chapter (3) is therefore concerned with the analysis of the determinants of governmental redistribution. Cross-national inequality datasets that have become available only recently enable empirical investigation of the inequality-redistribution nexus for a broad panel of countries, various sample compositions, and several model specifications. The results suggest a robust link between inequality and redistribution, confirming the Meltzer-Richard hypothesis. The effect, however, is less pronounced in developing economies with less sophisticated political rights, indicating that it is the political channel through which higher inequality translates into more redistribution.

Additionally, this chapter accounts for the shape of the income distribution, emphasizing the decisive role of the middle class, though also approving a negative impact of top incomes. While the former result is in line with the theoretical predictions of the Meltzer-Richard hypothesis, the significant impact of top incomes is due to further channels of influence, e.g. engagement in rent-seeking behavior. Recent research points to the crucial role of perceptions of inequality in the creation of demand for redistribution. However, the findings indicate that perceptions of inequality are often biased, which is why demand for redistribution depends on the perceived level of inequality rather than actual inequality. The Meltzer-Richard effect is even stronger when using perceived inequality measures.

In the next step, Chapter (4) studies the effects of culture and diversity on governmental redistribution for a large sample of countries. The sharp rise in migration in recent years raises questions on whether the cultural differences between natives and migrants are influential in determining the size of the social security system. To disentangle culture from institutions, the analysis employs regional as well as several external instruments, including biological conditions and linguistic differences. The results show a substantial but ambiguous impact of culture on the generosity of the welfare state, with higher levels of redistribution in countries with individualistic attitudes and loose family ties as well as a high prevalence of trust and tolerance. In contrast, redistribution is lower in countries with high levels of power distance and obedience and a prevalent belief that hard work is the key to success. Apart from these direct effects, cultural traits also exert indirect influence on the transmission of inequality on redistribution.

The last part of Chapter (4) investigates the effect of cultural, religious, and ethnic diversity on redistribution. The results suggest a negative link between diversity and the generosity of the welfare state, which is most pronounced with respect to cultural and ethnic fractionalization. Further examinations on this topic illustrate that diversity and redistribution stand in a non-linear relationship, where moderate levels of diversity impede redistribution and higher levels offset the generally negative effect.

Though this dissertation provided some empirical insights into the effects of globalization and the determinants of redistribution, further research is needed since several questions still remain open. In this context, some long-term investigations are necessary to determine whether manufacturing decline is inevitable. Thus far, the literature is fairly divided, with some considering the decline of the manufacturing sector a necessary consequence of sustained development while others view the manufacturing sector as the main (future) engine of long-term growth. In recent years, more and more services have become part of the manufacturing process and have therefore been counted as manufacturing value added, which is to some extent misleading. Future research should attempt to disentangle the growing influence of services in manufacturing. This would provide the opportunity to more clearly assess how countries adjust to globalization.

Future analyses should monitor trends in market inequality. Will it continue to grow? And if so, how will the government react to higher inequality? Is net inequality going to increase or is it being kept down by increasing levels of redistribution? Higher levels of inequality and higher degrees of redistribution, however, may threaten social peace, requiring very prudent policy actions. In addition, theoretical predictions point to an inequality-reducing effect of lower unemployment and more flexible labor market conditions. The empirical results on this topic remain inconclusive, which is why further research on this topic is necessary.

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