Essays on International Trade and Labor Market Outcomes

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1 Preface

This thesis contributes to the understanding of the labor market effects of international trade, with a special focus on the effects on wage inequality in Germany and the USA. There is a broad consensus among economists that the opportunity to engage in international trade of goods and services raises the average living standard in countries. At the same time, the idea that the gains from trade might be unequally distributed across the population and that trade therefore might generate income inequality is not new and dates back at least to Stolper and Samuelson (1941). The labor market provides the main source of income for most households in industrialized countries. It is therefore not surprising that the public debate about the consequences of international trade in countries like Germany and the USA centers around the effects on employment and wages. Motivated by this debate, and motivated by a flourishing academic debate on that topic, this thesis aims to provide novel insights on the link between international trade and labor market outcomes of individuals and households in industrialized countries.

The last decades have seen substantial waves of trade integration between countries. Largely in response to lower tariffs and transport costs, world merchandise trade has increased by more than 7% on average per year between 1980 and 2011 (WTO 2013). With growth rates below 3%, the increase in world merchandise trade was smaller, but not negligible, in more recent years (WTO 2019). An important feature of the rise in world trade is the integration of low-income countries into the world economy, most notably of China. In the course of its transition into a market economy, China experienced rapid productivity growth and became a major exporter of manufacturing goods. Between 1980 and 2018, China's share in world exports increased from 1% to around 13%, making it the number one exporter (WTO 2013; WTO 2019). This trend is mirrored by a surge in imports of Chinese manufacturing goods in many industrialized countries. For example, between 1991 and 2007, U.S. manufacturing imports from China increased by more than 1,100% (Autor et al. 2013). From the perspective of Germany, the country which receives most of the attention in this thesis, not only trade with China but also growing trade with Eastern European countries increased sharply during the last decades.[1] In the course of China's opening towards the world economy and the fall of the Iron Curtain, Germany's exports to and imports from China and Eastern Europe increased by more than 1,000%, much more strongly than trade with other countries.[2] The focus of this thesis on the labor

[1] Throughout this thesis, I define Eastern Europe as the following group of countries: Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, and the former USSR or its succession states Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan.

[2] Data from the Comtrade database reveals that Germany's exports to and imports from China and Eastern Europe as a share of total German exports and imports increased from below 5% in 1990 to around 25% in 2010. This implies that trade with China and Eastern Europe has increased more strongly than trade with the rest of the world.

market effects of trade with China and Eastern Europe is motivated by the dominant role that growing trade with these countries has played during the last decades.

Simultaneously to these developments in the world economy, many industrialized countries experienced profound changes in their labor markets. Using detailed micro data, a large number of studies identify an increase in inequality of gross hourly, daily, weekly, and annual labor earnings in countries like Germany, the USA, and the United Kingdom (e.g. Dustmann et al. 2009; Fuchs-Schuendeln et al. 2011; Acemoglu and Autor 2011; Dustmann et al. 2014; Blundell et al. 2018; Song et al. 2019). In Germany, workers at the upper part of the wage distribution have seen growing real wages, while real wages for workers at the middle of the wage distribution have stagnated and real wages of workers at the bottom of the wage distribution have declined during the 1990s and 2000s (Dustmann et al. 2009; Card et al. 2013).

Part of the rise in wage inequality reflects a growing wage premium for higher education, for example a college or university degree. This so-called college wage premium or skill premium has increased during the last decades despite a widespread expansion of college or university education (Katz and Murphy 1992; Goldin and Katz 2009; Dustmann et al. 2009; Acemoglu and Autor 2011). However, a substantial part of the rise in wage inequality in fact occurred within skill groups. This means that wages became more unequal between workers with the same education level (e.g. Juhn et al. 1993; Lemieux 2006).[3] To be able to understand the rise in so-called residual wage inequality, previous research points to wage differences between workers performing different tasks at their workplace (e.g. Autor et al. 2003; Autor et al. 2008; Acemoglu and Autor 2011) and to wage differences between firms (e.g. Abowd et al. 1999; Egger and Kreickemeier 2012; Card et al. 2013; Helpman et al. 2016; Card et al. 2018). In analyzing the determinants of growing wage inequality, this thesis draws heavily on the recent progress in research concerning the role of tasks and firms and adds new insights to the discussion.

An even more profound way in which labor markets in industrialized countries have changed during the last decades is the shift from the manufacturing to the service sector. In the USA, the employment share of the manufacturing sector has decreased from about 25% in 1960 to below 10% in 2010. The U.S. manufacturing sector lost about 5.7 million jobs between 2000 and 2010 (Baily and Bosworth 2014). A similar trend can be observed in Germany, a country which is still considered as a major manufacturing producer. Manufacturing employment in Germany has decreased by about 20% from 1994 through 2010 (Dauth et al. 2017). The decrease in manufacturing employment partly fuels the simultaneous expansion of the service sector. The descriptive statistics in chapter 3 of this thesis will show that about 15% of manufacturing workers move into the expanding service sec-

[3]For example, Baumgarten (2013, p.204) finds that about one third of the rise in wage inequality in Germany between 1996 and 2007 occurred between skill groups, whereas about two thirds occurred within skill groups. He measures wage inequality as the variance of log daily wages of workers and defines 20 skill groups as all interactions between five age groups and four education groups.

tor over a period of 10 years. The most common explanations for the secular decline in manufacturing employment are labor-saving technological progress in the manufacturing sector and growing manufacturing imports from low-income countries. Understanding the causes and the consequences of the shift of the economy from the manufacturing to the service sector is high up on the agenda of economic research. This thesis aims to contribute to the discussion about the distributional effects of the manufacturing decline. The nexus between growing trade with China and Eastern Europe, manufacturing employment, and wage inequality therefore will be a recurring theme throughout this thesis.

Why should we care about inequality and the underlying causes? One can argue that inequality matters based on fairness considerations. However, there are reasons to care about the level of inequality in a society which go beyond mere fairness considerations. Bourguignon (2015) argues that excessive levels of inequality can have large economic costs. He focuses on two groups of arguments. The first one is based on credit market imperfections. Inequality in income or wealth might translate into inequality in access to credit and this is why potential entrepreneurs might have to give up ideas which are socially valuable just because they lack the necessary collateral. A similar argument can be made for education decisions of talented students in the presence of costly education and credit market imperfections (Bourguignon 2015, p.131f.). The second group of arguments is based on the idea that excessive inequality might harm the social and political stability in a country. To the extent that excessive inequality triggers social tensions or a "populist backlash", it can have adverse economic consequences (Bourguignon 2015, p.133f.). Another reason why the impact of international trade on inequality matters is that redistribution in response to a given trade-related increase in inequality is costly. This is because typical tax-transfer systems with increasing marginal tax rates necessarily distort the market and therefore go along with efficiency losses. This is a point which is made for example by Antràs et al. (2017). They emphasize that trade-induced increases in inequality need to be taken into account when evaluating the welfare gains from international trade.

If it turns out that international trade indeed triggers increased inequality, the answer should not be to curb international trade. Instead, it is vital to design and implement policies which ensure that the whole population participates in the overall gains from trade. This is especially relevant in times of increasing resistance to globalization and protectionist tendencies around the world. However, to be able to design efficient policies, one needs to have a clear picture about the micro-level effects of trade integration. The detailed micro-level perspective in this thesis which takes into account the role of education, tasks performed on the job, firms, industries, and regions for the way in which an individual is affected by trade integration takes one further step into this direction. The main part of this thesis consists of four essays which add to the discussion about the inequality effects of international trade.

The first essay titled "All you need is love? Trade shocks, inequality, and risk sharing between partners" analyzes the effects of growing trade with China and Eastern Europe on labor earnings inequality between individual workers and between households in Germany. This paper points to the importance of households in mitigating the distributional effects of international trade which occur at the individual worker level. The main novel insight of this paper is that a pure worker-level perspective which ignores risk sharing mechanisms at the household level between partners leads to an overstatement of the effects of international trade on labor earnings inequality. This paper is joint work with Katrin Huber, a former doctoral student form the University of Passau, and has been published in the *European Economic Review* in 2019.

The paper uses detailed survey data on individuals and households from the Socioeconomic Panel as well as data on international trade flows from the UN Commodity Trade Database (Comtrade). In a first step, we build on recent research (e.g. Autor et al. 2014; Dauth et al. 2014) and estimate the link between growing exports to and imports from China and Eastern Europe and annual labor earnings and, alternatively, cumulative labor earnings of individuals over several years. These estimates capture the effects of industry-level exports and imports on labor earnings which result from changes in hourly wages as well as changes in hours worked (e.g. due to temporary unemployment) throughout the year. The estimated positive effects of exports on labor earnings stem from higher wages and higher job stability in response to increased demand from abroad. The estimated negative effects of imports on earnings large capture adjustment costs that arise to workers who need to move out of import-exposed industries and experience temporary unemployment and depressed wages.[4]

Based on these estimates, we analyze the contribution of the trade shock to the overall rise in labor earnings inequality in Germany. To illustrate the importance of the household in mitigating the inequality effects, we distinguish between two scenarios. The first scenario focuses on the pure worker-level effects of the trade shock and abstracts from the existence of households in which partners redistribute income. We then compare the results to a scenario with household-level risk sharing in which we allow for redistribution of income between partners. To the extent that partners are differently affected by the trade shock, for example because they work in differently affected industries, income pooling at the household level gives rise to a risk sharing effect that might mitigate the resulting inequality effects. In an extension, we also allow for "active risk sharing" at the household level through endogenous labor supply responses of partners.

[4] It is important to stress that these estimates do not capture the total welfare effects of trade with China and Eastern Europe. Imports of relatively cheap products constitute an important part of the welfare gains from trade integration. The estimates of the effects of imports in this analysis instead capture pure labor market adjustment costs that arise to workers in import-exposed industries. Nevertheless, as the consumption benefits of cheaper imports tend to be more equally distributed across the population than the labor market adjustment costs, these estimates reflect distributional effects.

While the trade shock triggers a rise in labor earnings inequality in all scenarios, it turns out that the estimated inequality effects are up to 42% lower when taking household-level risk sharing mechanisms into account. This result needs to be evaluated against the backdrop of a large recent literature on the distributional effects of international trade which typically focuses on worker-level rather than household level outcomes. The analysis in this paper suggests that a pure focus on worker-level outcomes might give an incomplete picture of the distributional effects of globalization. It also suggests that changes in household structure, for example an increasing prevalence of single-headed households which cannot rely on the risk sharing mechanisms emphasized in this analysis, might alter the distributional effects of a given episode of trade integration.

Partly, the estimated effects of growing imports on earnings in the first essay stem from changes in earnings for workers who leave the manufacturing sector in response to growing imports and move into the expanding service sector. The second essay, titled “Diverging paths: Labor reallocation, sorting, and wage inequality” puts this process under closer scrutiny. The essay emphasizes that structural change in the form of a reallocation of workers from the manufacturing into the service sector goes along with a rise in wage inequality. The essay points to a specific channel through which labor reallocation affects wage inequality, namely an increase in sorting of high-skilled and low-skilled workers across high-paying and low-paying firms.

At the heart of this essay is the robust finding from several countries, including Germany, that some firms pay higher wages than others for similarly skilled workers (e.g. Abowd et al. 1999; Card et al. 2013; Alvarez et al. 2018; Song et al. 2019).[5] This implies that changes in the sorting of workers across high-paying and low-paying firms affects the wage structure in an economy. Two recent studies suggest that the sorting of workers across firms has indeed changed fundamentally during the last decades. In the USA and Germany, high-skilled (low-skilled) workers have become more likely to be employed by high-paying (low-paying) firms. This increase in sorting accounts for about one third of the rise in wage inequality in both countries since the 1990s (Card et al. 2013; Song et al. 2019). Despite its relevance for wage inequality, the causes of the increase in sorting are not yet fully explored.

To analyze the link between trade-induced labor reallocation into the service sector, sorting, and wage inequality, this essay makes use on extensive administrative data on 50% of all West German male employees from 1985 through 2010, combined with trade data from Comtrade and survey data on tasks performed on the job from the BIBB-BAuA employment surveys. In response to growing net manufacturing import exposure from China and Eastern Europe, workers move from the manufacturing into the non-

[5]This literature decomposes log wages of workers into a worker permanent worker component which is assumed to be portable across firms and a firm component. The firm component reflects a wage premium or discount that the firm pays to all its employees. High-paying (low-paying) firms are firms with a particularly high (low) estimated firm component.

manufacturing sector at higher rates. While the initial effect of moving workers out of the manufacturing sector at higher rates is very similar for high-skilled and low-skilled workers, the paths within the service sector diverge. After being initially employed by manufacturing firms paying relatively high wages, highly educated workers performing complex tasks mostly move to high-paying service firms in response to increased import exposure, whereas low-educated workers performing routine and codifiable tasks more often reallocate to low-paying service firms. As a result, sorting by education and tasks increases and so does wage inequality. Through the resulting increase in sorting upon formal education and tasks, labor reallocation causes an increase in the skill premium and in residual wage inequality.

The findings of this essay are not specific to trade-induced labor reallocation. Instead, they carry over to a wide range of shocks and policies which cause a contraction of the manufacturing sector and trigger a reallocation of workers into the service sector. The findings imply that a further decline of manufacturing employment, potentially driven by technological progress, a negative demand shock, or any other cause, might go along with increasing wage inequality in the future. From the perspective of a policymaker who aims to curb the resulting distributional effects, the analysis in this paper suggests a strong focus on the set of skills which enable a worker to take up a job at a high-paying firm in the service sector. In contrast, a mere focus on bringing displaced manufacturing workers into full-time employment in the expanding service sector is not sufficient to fully curb the distributional effects.

What the first and the second essay have in common is that they abstract from the regional dimension. However, an important feature of the rise in wage inequality observed throughout the last decades is its heterogeneity across regions. Moretti (2013) for example illustrates this feature by estimating the college wage premium (CWP) separately by U.S. metropolitan area and year. It turns out that some areas experienced a strong rise in the CWP since the 1980s, whereas other areas experienced no significant increase or even a decrease in the CWP. This finding implies that a relatively small number of regions produce a large part of the aggregate rise in wage inequality. A full understanding of the causes of the rise in aggregate wage inequality therefore requires an understanding of its regional heterogeneity. Motivated by this phenomenon, the third essay, titled "International trade and its heterogeneous effect on the college wage premium across regions", analyzes the extent to which trade with China affected the CWP differently across U.S. commuting zones.

This essay lays out a model along the lines of Costinot and Vogel (2015), in which workers endogenously select into sectors according to their individual comparative advantage. In this model, the CWP in a region can either increase or decrease at a different magnitude, depending on the initial allocation of college and non-college workers into the manufacturing and non-manufacturing sector in the region. Building on the model structure, I then provide an estimate of the effect of China's rise as a major exporter of manufacturing goods on the CWP in U.S. commuting zones. To this end, I draw on data from the U.S. Census for the years 1990 and 2000 and the American Community Survey for the years 2006 and 2007. The results show a large regional heterogeneity, with estimated changes in the CWP ranging from an increase by 4.96 log points to a decrease by 1.27 log points over a period of ten years. These differences are sizable in the light of the mean observed increase in the CWP over ten years which amounts to 5.39 log points.

The previous literature on the regional effects of trade with China focused on regional outcomes such as manufacturing employment, average wages, or welfare within regions (e.g. Autor et al. 2013; Dauth et al. 2014; Balsvik et al. 2015; Acemoglu et al. 2016; Caliendo et al. 2019). In contrast, the effects of trade with China on wage inequality within regions, and in particular the potential regional heterogeneity in the effects on wage inequality, have received much less attention. The novel insight of this paper is that the inequality effects of trade integration might be very different between regions. It therefore suggests that growing international trade has the potential to explain part of the observed regional heterogeneity in the evolution of the CWP.

The first three essays have in common that they focus on a period of rising wage inequality and the extent to which growing trade integration caused the observed changes in the wage structure. During the Great recession from 2007 through 2009, however, wage inequality in Germany temporarily decreased. At the same time, German exporting firms faced a sudden decrease in demand from abroad caused by the crisis. This phenomenon is at the center of the fourth essay, titled "Exporters and wage inequality during the Great Recession - Evidence from Germany". The main result of this paper is that the exporter wage premium, i.e. the wage premium that exporting firms pay relative to non-exporting firms for similarly skilled workers, has decreased at the dawn of the Great recession. This decline explains up to 43% of the drop in residual wage inequality during the Great Recession. This paper is joint work with Hans-Jörg Schmerer (FernUniversität Hagen) and Wolfgang Dauth (University of Würzburg). It has been published in *Economics Letters* in 2015.

In this essay, we use the LIAB, a matched employer-employee dataset, to estimate the exporter wage premium on a yearly basis. Based on the results, we estimate the contribution of the decline in the exporter wage premium to the decline in residual wage inequality using the method proposed by DiNardo et al. (1996) and Lemieux (2002). This essay contributes to an extensive literature which emphasizes the existence of an exporter wage premium. For Germany, Baumgarten (2013) provides evidence on an increase of the exporter wage premium from 1996 through 2007, a period of rising trade integration and increasing wage inequality. The main contribution of our essay is to shed light on the evolution of the exporter wage premium in a context of declining trade flows and the corresponding effect on wage inequality.

The results of this essay are also of interest for the discussion about the robustness of the German labor market during the Great Recession. Moeller (2010) argues that the existence of working time accounts and the opportunity to opt into short time work have created a strong buffering capacity in German firms and this is why firms did not lay off workers at large scale despite the large negative shock. For exporting firms which have been hit most strongly by the crisis, cutting part of their wage premium (e.g. in the form of lower or no bonus payments) might have been a comparatively painless way of reducing labor costs in times of low demand. The decrease in the exporter wage premium therefore might be linked to the so-called "German Job Miracle" (Moeller 2010) during the Great Recession from 2007 to 2009.

Each essay in this thesis provides an independent contribution to the existing literature and has its own abstract, introduction, conclusion, and appendix. The joint bibliography of all essays and this preface can be found at the end of this thesis. The essays published in the *European Economic Review* and in *Economics Letters* have been edited to match the formatting style of this thesis.

2 All you need is love? Trade shocks, inequality, and risk sharing between partners

All you need is love? Trade shocks, inequality, and risk sharing between partners

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A large literature suggests that growing international trade is among the drivers of rising labor earnings inequality within countries. We contribute to this literature by studying the distributional effects of Germany's trade integration with China and Eastern Europe. We provide evidence that the trade shock explains 5-18% of the rise in earnings inequality between individual workers. However, when we take risk sharing between partners into account, we find that the inequality-increasing effect of the trade shock is up to 42% lower. Our results therefore suggest that a pure worker-level perspective which ignores risk sharing might give an incomplete picture of the distributional effects of international trade.

JEL-Classification: D13, F14, F16, J12, J31
Keywords: International trade, Earnings inequality, Risk sharing, Households

2.1 Introduction

During the last decades, inequality in labor earnings has increased in many industrialized countries and this has triggered a vast amount of research on the causes of this phenomenon (OECD 2012).[1] The literature on the causes of increasing wage and earnings inequality has examined for example technological progress (Autor et al. 2003; Autor et al. 2008), changes in the relative supply of skills (Goldin and Katz 2009), institutional factors such as changes in the real value of the minimum wage (DiNardo et al. 1996), and macroeconomic factors such as the inflation rate (Jaentti and Jenkins 2010). International trade is also part of the usual suspects to be blamed for rising inequality. A recent literature suggests that especially the integration of China and Eastern Europe into the world economy had strong and heterogeneous effects on labor market outcomes of workers in high-income countries (e.g. Autor et al. 2013; Autor et al. 2014; Dauth et al. 2014; Dauth et al. 2019a; Keller and Utar 2019; Utar 2018; Harrigan et al. 2016).[2] Pinning down the extent to which this trade shock contributed to rising earnings inequality is of large importance for the public and for policymakers.

In this paper, we analyze the impact of Germany's trade integration with China and Eastern Europe on labor earnings inequality between individual workers and households. We emphasize how risk sharing within households mitigated the resulting distributional effects. This approach is motivated by a large literature in family economics which suggests that household income plays an important role for the consumption possibilities and the welfare of individual household members. The idea that redistribution between household members can insure individuals against negative income shocks dates back at least to Becker (1974). The gains from marriage due to risk sharing can be illustrated in a simple model in which partners face idiosyncratic income shocks and therefore have an incentive to provide mutual insurance (Browning et al. 2014).[3] A trade shock might affect partners differently depending on differences in their characteristics and this might give rise to a substantial risk sharing effect. Ignoring this effect and its heterogeneity along the earnings distribution might lead to an incomplete picture of the distributional effects of international trade.

During our period of analysis, 1993-2008, Germany's trade volume with China and Eastern Europe has increased by almost 800% and the share of these countries in total German exports and imports increased from 5% to 25%. This event coincided with an increase in labor earnings inequality between individuals and households (see Figure 1

[1] See e.g. Acemoglu and Autor (2011) for an overview of inequality trends in the USA, Jenkins (2016) for the UK, and Dustmann et al. (2009) for Germany.

[2] These are of course not the only studies on the link between trade and inequality. See Harrison et al. (2011), Helpman (2017), and Muendler (2017) for extensive overviews of the relevant literature.

[3] Studies which model the allocation of resources within a household as a non-cooperative bargaining process emphasize that resource allocation strongly depends on who earns the income (e.g. Browning et al. 1994; Cherchye et al. 2015). Nevertheless, the results in these studies imply a substantial degree of redistribution on average. See section 2.5.3 of the paper for more details.

in section 2.3). In a worker-level analysis, Dauth et al. (2019a) provide evidence that the trade shock indeed had strong heterogeneous effects on employment and earnings of workers. They do however not aim to quantify the actual contribution of this trade shock to the overall rise in earnings inequality in Germany. Our first main contribution therefore is to quantify how much of the increase in earnings inequality is driven by rising trade with China and Eastern Europe. Our second main contribution is to provide evidence that a pure worker-level perspective that ignores risk sharing between partners might give an incomplete picture of the full distributional consequences of any trade shock in general and this one in particular. We find that the trade shock explains 5-18% of the increase in labor earnings inequality between workers in Germany. Taking the results at face-value, our estimates imply that risk sharing between partners reduced this impact by 17-42%.

More specifically, in our analysis we focus on married and unmarried couples as well as on singles working in dependent employment.[4] We analyze the impact of the trade shock on labor income of workers and households since increasing dispersion of labor income has been identified as the main driver of increasing overall income inequality between workers and households in Germany (*OECD* 2008; Biewen and Juhasz 2012). In a first step, we estimate the distributional effects of the trade shock in a worker-level approach that abstracts from the existence of households in which partners redistribute income. We then compare the results to an approach with household-level risk sharing in which we allow for redistribution of income between partners. In our main specification with household-level risk sharing, we assume that partners within couples share the sum of their earnings equally. Alternatively, we follow the recent literature on allocation of resources within households and assume that the share of household earnings available for consumption to one partner positively depends on her income share or wage share, respectively (e.g. Browning et al. 1994; Lise and Seitz 2011; Browning et al. 2013; Cherchye et al. 2015; Cherchye et al. 2016b; Cherchye et al. 2016a). While the main analysis emphasizes the risk sharing effect that comes from sharing of household income, an extension allows for "active risk sharing" of partners by modeling individual earnings as a function of trade exposure on the partner. In any case, a comparison between the results of the approach without risk sharing and the results of the approach with risk sharing is informative about the extent to which worker-level distributional effects are changed at the household level.

Starting with the worker-level approach without risk sharing, we estimate two complementary specifications. In a short-run fixed effects regression that tightly controls for individual heterogeneity, we relate changes in annual earnings to industry-level trade shocks. In a more medium-run approach, we estimate the impact of the trade shock on cumulative earnings over three years, conditioning on a large set of base year controls. In both specifications, we employ the instrumental variable approach pioneered by Au-

[4] We of course allow for unemployment as an outcome. To capture a representative picture of households, we further also allow households in our sample to contain partners who are initially unemployed.

tor et al. (2014) and adapted to the German context by Dauth et al. (2014) and Dauth et al. (2019a). The results suggest that the trade shock explains 5-18% of the increase in earnings inequality between workers during the sample period. The estimates are robust to a large variety of different specifications and controls for industry-level technological progress.

We then compare these results to the results from the approach with household-level risk sharing, in which we make assumptions on income sharing and redistribution between partners. In line with Blundell et al. (2016) and studies on assortative mating (e.g. Eika et al. 2014; Greenwood et al. 2014), we find that the trade shock on average affected partners within couples similarly. Nevertheless our results provide robust evidence that risk sharing reduced 17-42% of the worker-level distributional effect of the trade shock. Note that the inequality-increasing effect of the trade shock is not mechanically reduced through risk sharing. In the Appendix, we construct a simple example which illustrates that risk sharing might also amplify the distributional effects of a shock, depending on the actual mating structure and the distribution of the trade shock across individuals and households. The main reason is that risk sharing between partners (e.g. through equal sharing of household income) does not only reduce the dispersion of gains and losses from the shock across individuals. It also changes the distribution of initial incomes and the respective position of individuals in the initial income distribution (after redistribution within the household).[5]

In a next step, we study the nature of the risk sharing effect and find that two related channels are at work. First, workers who incurred earnings losses often benefited from partly offsetting positive effects of the trade shock on their partner. We find that couples on average were able to cushion 15% of trade-related earnings losses of one partner via positive effects on the other partner. This share ranges from more than 30% for negative effects on low-earnings workers to about 10% for high-earnings workers. Second, especially low-earnings workers who were not affected by the trade shock indirectly benefited from the gains from trade via positive effects on their partner. Our results suggest that in particular females as well as low-skilled and non-manufacturing workers were able to benefit from risk sharing.

The main analysis treats partners as independent of each other in terms of the effects of the trade shock and their adjustment behavior. It therefore exclusively focuses on the risk sharing effect from sharing of household income and implicitly sharing the effects of the trade shock. This means that the risk sharing effect results from the existing mating stucture. In a final extension, we allow for "active risk sharing" by controlling for trade exposure on the partner in the regressions and modeling the predicted impact of the trade shock as a function of the partner's trade shock. The results are consistent with

[5] In contrast, cross-sectional inequality of e.g. mean household earnings across individuals should be smaller than inequality of individual earnings. Figure 1 illustrates these level differences.

the existence of an added worker effect (Lundberg 1985). The basic conclusion about the mitigating effect of risk sharing remains.

Taking a household perspective is still not very common in the literature that investigates the consequences of growing international trade. Notable exceptions are Autor et al. (2017) who analyze how import competition affects the structure of marriage in the USA and Keller and Utar (2018) who examine the effect of Chinese import competition on the family-market work balance and gender inequality in Denmark. However, to the best of our knowledge, this paper is the first one that analyzes the distributional consequences of within-household risk sharing in the context of a specific shock on the labor market. Our results are complementary to the findings e.g. by Autor et al. (2014), Dauth et al. (2014) and Dauth et al. (2019a) and underscore that a household-level perspective is necessary to capture the full distributional consequences of the trade shock. The results on the distributional effects suggest that intra-household risk sharing from offsetting labor income shocks is a quantitatively important mechanism which is complementary to redistributive policies such as taxation and government transfers. Our analysis also contributes to the literature which studies insurance of households against income shocks (e.g. Blundell et al. 2008). Even though the extent of the risk sharing effect varies depending on the specific shock, the mechanism we illustrate carries over to any shock or policy that has heterogeneous effects across workers and therefore should encourage further research to take into account the household perspective to capture the full range of distributional implications and draw the right policy conclusions.

The rest of this paper is structured as follows. The next section briefly discusses how this paper fits into previous literature. Section 2.3 outlines the data and section 2.4 presents the empirical strategy. In section 2.5, we discuss the results, provide extensions and robustness checks. Finally, section 2.6 concludes.

2.2 Related literature

Our paper builds a bridge between different strands of literature. It is related to research which analyzes the impact of increasing trade with China (and in some cases Eastern Europe) on workers' earnings and on earnings inequality. Autor et al. (2014) examine the impact of Chinese import competition in US manufacturing on workers' earnings and find that workers employed in industries that are strongly exposed to import competition suffer from earnings losses.[6] Several following studies find similar results for other countries, e.g. Balsvik et al. (2015) for Norway, Keller and Utar (2019), Utar (2018) and Ashournia et al. (2014) for Denmark and Nilsson Hakkala and Huttunen (2016) for Finland.[7] Dauth et al.

[6] In terms of methodology, the approach is based on Autor et al. (2013).

[7] In a recent study, Shen and Silva (2018) provide evidence that the labor market impact of Chinese import competition in the USA depends on the position of the exporting industry in the global value chain.

(2014) and Dauth et al. (2019a) perform a similar analysis for Germany, a country which was exposed to substantial import competition from China and Eastern Europe since the 1990s but also benefited from increasing export opportunities to those countries. They also detect a negative labor market impact of import competition but find that this is overcompensated by the positive effect of exports.

Our paper is closely related to these studies and especially to Dauth et al. (2019a) as it uses a similar identification strategy to estimate the effects of Germany's trade integration with China and Eastern Europe on workers' earnings growth. However, we extend their analysis beyond the worker level by providing evidence on the distributional effects of within-household risk sharing in the context of this trade shock. With its family perspective, our paper is also related to Autor et al. (2017) and Keller and Utar (2018) who analyze how import competition affects household and family outcomes in the USA and in Denmark respectively.

We also contribute to the literature on drivers of increasing earnings inequality. In Germany, inequality of labor income, both at the worker and at the household level, has increased in roughly equal magnitude (Fuchs-Schuendeln et al. 2011). The literature has identified technological change, supply shocks and de-unionization (Dustmann et al. 2009) as well as growing international trade (Baumgarten 2013; Dauth et al. 2019a) as the main drivers of wage and earnings inequality between workers in Germany. Concerning the rise in labor income inequality between households, the same factors can be blamed (OECD 2012; Biewen and Juhasz 2012). Additionally, changes in household structure such as the increasing prevalence of single-headed households (Peichl et al. 2012) or increasing assortative matching (Grave and Schmidt 2012) are potential drivers of earnings inequality between households. Our paper contributes to this literature with a careful assessment of whether increasing trade with China and Eastern Europe is as important for household earnings inequality as it is for worker-level inequality. Moreover, we provide evidence on the distributional effects of within-household risk sharing. This is an aspect which remained largely unexplored until now.

Finally, we contribute to a large literature that analyzes the degree to which individuals and households can insure themselves against negative income shocks. The literature has devoted attention on different insurance mechanisms, such as government transfers (Dynarski and Gruber 1997; Blundell et al. 2008) and borrowing and saving (Krueger and Perri 2011; Asdrubali et al. 2015). Our paper is most closely related to studies that investigate within-household insurance from offsetting labor income of partners. Results of these studies have so far been mixed. While Hayashi et al. (1996) and Dynarski and Gruber (1997) do not find evidence for the mechanism, Garcia-Escribano (2004), Asdrubali et al. (2015)[8], and Blundell et al. (2016) argue that offsetting labor income

[8] In a recent contribution, Fehr et al. (2017) emphasize the risk sharing effect of families in the context of changes of pension policies.

plays an important role for intra-household risk sharing. Further evidence in favor of the importance of within-household risk sharing comes from Shore (2010) whose results imply a strong risk sharing effect from offsetting income shocks, especially when the economy is on a downturn. We contribute to this literature with an analysis of the distributional consequences of risk sharing.[9]

2.3 Data

2.3.1 Data on individuals and households

We use worker and household-level data from the German Socio-Economic Panel (SOEP), a longitudinal and representative survey of approximately 11,000 private households in Germany. Interviews take place on a yearly basis since 1984 (East Germany since 1990) and provide a large battery of information on each individual's socio-economic characteristics (e.g. gender, age, migration background, education level), on labor market outcomes (e.g. earnings, industry affiliation), but also on more general household-level characteristics (e.g. number of household members, identifier for partner, region of residence). Most importantly for our purpose, the SOEP offers the possibility to match individuals with their (married and unmarried) partners and to thus exactly determine which individuals live in a shared household.[10] See Wagner et al. (2007) for more information on the SOEP.

In our main analysis, the aim is to compare a pure individual worker-level perspective without risk sharing in the spirit of the previous literature (e.g. Autor et al. 2014; Dauth et al. 2014; Dauth et al. 2019a) to a perspective in which we allow for income sharing and redistribution. To be able to make meaningful comparisons, we make sure that we include exactly the same individuals both in the individual worker analysis in which we abstract from risk sharing and in the analysis where we assume that risk sharing between partners takes place. Therefore, in the case of couples, all the sample restrictions we impose on one partner have to hold simultaneously for the other partner.

In the empirical analysis, we implement two complementary approaches. In a short-run panel approach we relate year-to-year changes in trade exposure to changes in annual earnings and investigate the resulting distributional impact and the degree to which it is affected by risk sharing between partners. In a more medium-run approach, we instead examine the impact of the trade shock on cumulative earnings and the respective earnings inequality over three years.[11] The data requirements differ slightly between these two approaches.

[9] See also the recent contribution by Tominey (2016) which provides evidence on the insurance effect from shorter maternity leave periods in case of paternal employment shocks.

[10] This is the main reason why we do not use the larger IEB dataset from the German Institute of Employment Research (e.g. Dauth et al. 2014). As pointed out by (Baumgarten et al. 2013), one further advantage of the SOEP data as compared to the IEB is that earnings are not top-coded.

[11] For detailed information on the empirical strategy of both approaches, please refer to section 2.4.1.

For the short-run panel approach, we construct an unbalanced panel of manufacturing and non-manufacturing workers from 1993 through 2008.[12] For the medium-run approach, we split the sample into four intervals, each of them containing four years: 1993-1996, 1997-2000, 2001-2004 and 2005-2008. We denote the first year of each interval z as the base year z_0. Within these intervals, the four-year panels are balanced, i.e. we only keep individuals who are observed in all four years respectively. Following Dauth et al. (2019a), we restrict our analysis to workers aged between 16 and 64 and working in dependent employment, excluding self-employed individuals, civil servants, pensioners, and individuals in education and military service. Even though the trade shock mainly affected the manufacturing sector, including the non-manufacturing sector is important for two reasons. First, transitions from manufacturing into non-manufacturing play an important role for workers affected by the trade shock (Autor et al. 2014). Second, in almost 40% of all couples in our sample, one partner works in manufacturing, while the other partner works in non-manufacturing. Our household-level perspective would therefore lose representativeness if we dropped non-manufacturing workers.

Previous studies have shown that transitions into temporary unemployment constitute an important channel through which a trade shock affects workers' annual earnings Autor et al. (2014), Dauth et al. (2014), and Dauth et al. (2019a). To capture these effects, we follow the previous literature and allow for unemployment or part time work during the sample period. This also makes sure that we capture the large share of couples in the sample (about 40%) where one partner works full time and the other partner does not. In our baseline specification for the short run (medium run), we drop couples where at least one partner is unemployed or non-employed in the first period of observation (in the base year of the respective interval).[13] As this restriction might however bias the sample composition substantially towards couples where both partners are active in the labor market, we keep couples in which one or even both partners are unemployed in the first period of observation (in the base year) in an extended specification. We assign a trade shock of zero to those individuals.

We allow workers in our sample to be either singles (with or without children) or live in a shared household with their partner (married or unmarried, with or without children). In the short-run approach, we allow the marital status to change over time to capture possible changes of the mating or family structure, e.g. changes in the prevalence of single-headed households (Peichl et al. 2012), which might be partly due to the trade shock (Autor et al. 2017). In the medium run, we condition on a dummy for being in a single-headed household in the base year z_0 and therefore allow only for changes of the mating structure between the 4-year intervals, but keep it constant within this period.

[12] We start with 1993 because this is the first year in which all variables are available and harmonized between East and West Germany.

[13] The reason for this is that the industry variable we need to assign the trade shock is completely missing in case of unemployment in the first period of observation (the base year).

Combining the information on the average monthly income in each year and the information on the number of months the individual received this average amount, we compute gross annual labor income for each worker. We cannot use net income because our data does not contain enough information to precisely derive each individual's tax class. We therefore cannot capture (possibly mitigating) effects of taxation which might be different depending on the household structure. In the extended specification that considers individuals who are non employed in the base year, instead of assuming zero earnings for unemployed individuals, we use the gross annual amount of unemployment benefits and reliefs the individuals received. In cases where individuals received both regular income and benefits during the year, we add these two sources of income in order to get the outcome variable "earnings". We convert income and benefits from DM to EUR for years prior to 2001 and deflate them according to the consumer price index (base year 2010) provided by the German Federal Statistical Office. For the medium-run approach we cumulate earnings (and benefits) over the respective three years after the base year. To make sure that our results are not driven by outliers, we drop workers whose earnings in any year are more than 50 (12) times larger than in the base year in the short-run (medium-run) approach.

2.3.2 Data on international trade flows

Based on the 2-digit industry information in the SOEP, we merge individual-level data with data on exports and imports from the United Nations Commodity Trade Statistics Database (Comtrade). This database contains annual statistics on commodity trade of more than 170 countries. We convert the trade flows into Euros of 2010 using the exchange rates of the German Bundesbank. With help of the correspondence between the SITC rev.3 product codes and NACE codes provided by the UN Statistics Division, we then aggregate the product-level trade flows to trade flows at the 2-digit industry level. For the short-run approach, we follow Dauth et al. (2019a) and compute the degree to which a 2-digit industry j is directly exposed to import competition and export opportunities with respect to China and Eastern Europe[14] in year t:

$$IM_{jt}^{Direct,SR} = \frac{Imports_{jt}^{E+C \to G}}{WageSum_{j(t-1)}} \times 100 \tag{1}$$

$$EX_{jt}^{Direct,SR} = \frac{Exports_{jt}^{G \to E+C}}{WageSum_{j(t-1)}} \times 100 \tag{2}$$

where $Imports_{jt}^{E+C \to G}$ and $Exports_{jt}^{G \to E+C}$ denote industry j's imports from and exports to China and Eastern Europe in year t. We normalize the trade flows by the lagged

[14] Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, and the former USSR or its succession states Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan.

industry wage sum $WageSum_{j(t-1)}$ to control for size differences between industries as well as differences in the importance of exports and imports across industries.[15][16]

In the medium-run approach, we follow Autor et al. (2014) more closely. Trade exposure on industry j during interval z is computed in the following way:

$$\Delta IM_{jz}^{Direct,MR} = \frac{\Delta Imports_{jz}^{E+C \to G}}{WageSum_{j(z_0)}} \times 100 \tag{3}$$

$$\Delta EX_{jz}^{Direct,MR} = \frac{\Delta Exports_{jz}^{G \to E+C}}{WageSum_{j(z_0)}} \times 100 \tag{4}$$

where $\Delta Imports_{jz}^{E+C \to G}$ and $\Delta Exports_{jz}^{G \to E+C}$ denote the change in imports from and exports to China and Eastern Europe in industry j during interval z. We normalize the value by the industry's wage bill in the base year z_0.

As the trade shock is a shock on the German manufacturing sector (Dauth et al. 2014), we obtain the direct trade exposure measures for 22 2-digit manufacturing industries. To capture the extent to which export and import shocks are transmitted along the value chain to intermediate goods suppliers, we follow Acemoglu et al. (2016) and compute indirect import (export) exposure of an industry as the weighted average of the import (export) exposures faced by the industry's downstream purchasers. For the short-run approach, indirect exposures therefore are computed in the following way (analogously in the medium-run approach):

$$IM_{jt}^{Indirect,SR} = \sum_k \omega_{jk} IM_{kt}^{Direct,SR} \tag{5}$$

$$EX_{jt}^{Indirect,SR} = \sum_k \omega_{jk} EX_{kt}^{Direct,SR} \tag{6}$$

where ω_{jk} is the share of industry j's sales that is used as inputs by the downstream purchasing industry k in 1994. The necessary information can be extracted from input-output tables provided by the German Statistical Office.[17]

[15] The wage sums are computed as the number of workers employed in industry j at time $(t-1)$ times their daily wage. We are grateful to Wolfgang Dauth for providing the data to us.

[16] To reduce the risk that changing labour-capital-intensities mechanically influence our trade exposure measures, we alternatively normalize the trade flows by the wage bill from the first year (1993) of our observation period. This implies that we control only for time-constant size differences between industries and that changes in labor- or capital-intensity over time should not have an impact on our trade exposure measures. The results are qualitatively and quantitatively very similar to those obtained in Table 2, panel (a) and are available upon request.

[17] Acemoglu et al. (2016) show that indirect exposure from downstream purchasers has a significant impact, whereas indirect exposure from upstream suppliers has not. We therefore only include the former.

Total export exposure and import exposure results as the sum of the direct and indirect exposure measures and will be used as explanatory variables EX_{jt} and IM_{jt} in our empirical specification in the short-run approach (analogously for the medium-run approach):

$$IM_{jt} = IM_{jt}^{Direct,SR} + IM_{jt}^{Indirect,SR} \tag{7}$$

$$EX_{jt} = EX_{jt}^{Direct,SR} + EX_{jt}^{Indirect,SR} \tag{8}$$

We end up with trade exposure measures for 22 manufacturing industries (computed as direct plus indirect trade exposure) and 34 non-manufacturing industries (consisting only of the indirect trade exposure). Note that trade exposure measures for the short run are computed in levels and not in changes. This has to do with the fact that in the short-run approach we estimate regressions with individual fixed effects that exploit changes in these levels over time for a given individual. See section 2.4.1 for a detailed explanation. Table A1 in Appendix A provides a list of the industries that were most affected by increasing trade with China and Eastern Europe. While some industries such as manufacturing of office machinery were affected strongly by both increasing export and import exposure, others such as manufacturing of leather and furniture (basic metals and motor vehicles) were affected almost exclusively by increasing import (export) exposure.

2.3.3 Descriptives

Table 1 gives an overview of the resulting samples for the baseline specification without those unemployed in the first period (in the base year). Applying all the restrictions and keeping observations where all relevant variables are non-missing, we end up with 58,931 worker-year and 37,779 household-year observations from 6,678 different households in the short-run approach.[18] Panel (a) of the table shows a considerable dispersion in individual labor earnings. For each worker-year observation, we compute normalized earnings as annual earnings divided by earnings in the first year of observation. The mean value of 133.48 indicates that workers on average experience earnings gains as compared to the first year of observation. For the median worker, however, earnings remain roughly at their base year level. A look at the changes in trade exposure is worthwhile because the numbers illustrate a large heterogeneity in the degree to which the trade shock affected workers. On average, export exposure (import exposure) increased by 1.57 (1.25) percentage points per year for workers in the sample. However, while some workers experienced large increases in trade exposure of around ten percentage points, trade exposure for other workers even declined. Figure A1 in the Appendix further illustrates the large variation in trade

[18] Note that we drop the last year (2008) in the short-run approach because for this year we cannot compute a change in trade exposure.

exposure across workers. While the 95th percentile of export (import) exposure in a given year increases strongly and steadily during our sample period, trade exposure for workers in the 5th percentile remains largely unchanged. We will exploit this variation in our empirical strategy in section 2.4.

Table 1: General Descriptives

	Mean	Median	p95	p05	Obs
(a) Short Run					
Annual Earnings	25,416	24,108	57,396	0	58,931
100 x Normalized Earnings	133.48	101.36	329.85	0	58,931
Manufacturing	0.29	0	1	0	58,931
Single	0.44	0	1	0	58,931
Female	0.50	0	1	0	58,931
High-Skilled	0.25	0	1	0	58,931
Δ Import Exposure (ΔIM_{jt})	1.25	0.13	9.80	-2.79	58,931
Δ Export Exposure (ΔEX_{jt})	1.57	0.13	12.39	-2.55	58,931
(b) Medium Run					
Cumulative Earnings	83,372	77,928	174,132	11,976	9,529
100 x Normalized Earnings	312.99	304.93	518.54	114.45	9,529
Manufacturing	0.30	0	1	0	9,529
Single	0.47	0	1	0	9,529
Female	0.50	1	1	0	9,523
High-skilled	0.26	0	1	0	9,529
Δ Import Exposure (ΔIM_{jz})	3.11	0.48	12.02	0.00	9,529
Δ Export Exposure (ΔEX_{jz})	4.21	0.52	18.87	0.00	9,529

Notes: Data preparation as explained in section 2.3. In panel (a), normalized earnings are computed as annual earnings relative to base year earnings (i.e. the first year of observation). Δ Import Exposure (Δ Export Exposure) reflects the change in import (export) exposure for a given worker between t and $t+1$. Note that exposures can change also due to workers switching between industries. In panel (b), normalized earnings are computed as cumulative earnings relative to base year earnings. Changes in trade exposure are computed based on a worker's industry affiliation in the base year. See section 2.4.1 for more details. We define workers with ISCED>4 as being high-skilled. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Panel (b) gives an overview of the resulting sample for the medium-run approach. The large attrition rates substantially reduce the sample size as compared to the short-run approach. We end up with 9,529 worker-year observations and 6,419 household-year observations from 4,155 different households. Dispersion in cumulative and normalized earnings,[19] as well as in trade exposures can be confirmed for this longer-run perspective.

Figure 1 takes a closer look at the evolution of earnings inequality in our short-run sample (without those unemployed in the base year). In this figure, we display four different measures of labor earnings inequality: The Gini of annual worker earnings, the Gini of average annual household earnings excluding children, the Gini of equivalized annual household earnings[20] excluding children, and the Gini of equivalized household earnings including children. In line with other studies (Dustmann et al. 2009; Fuchs-Schuendeln et al. 2011; Grabka et al. 2015) which analyze the evolution of earnings inequality in Germany, the figure provides evidence that earnings inequality has increased during the sample period. This illustrates that the phenomenon of increasing earnings inequality is not restricted to inequality between individuals but also applies to inequality between households. However, in this figure it is not possible to deduce anything about the differential effects of the trade shock at hand on individual- and household-level inequality. This is because there is a large number of drivers of inequality, and each one of these drivers might influence individual-level inequality differently from household-level inequality.

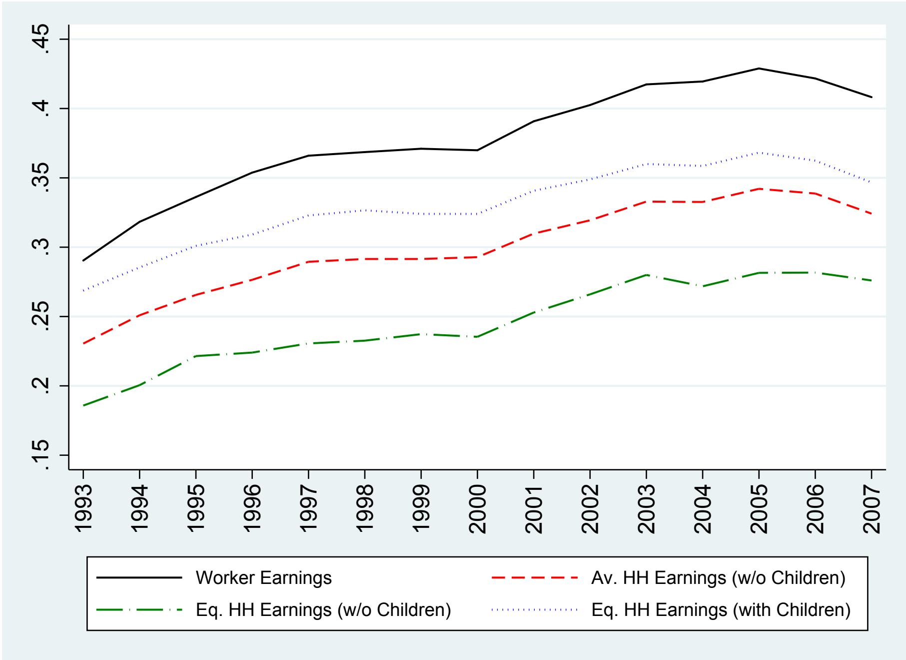
2.4 Empirical strategy

Our empirical strategy consists of three parts. In a first step, we estimate the impact of the trade shock on individual workers' earnings growth. Note, however, that the estimation strategy is not our main contribution as we largely follow Autor et al. (2014) as well as Dauth et al. (2014) and Dauth et al. (2019a). We then use these estimates to compute the predicted impact on earnings and earnings inequality between workers. We refer to the results in which we abstract from redistribution of income between partners as the worker-level results without risk sharing. Finally, in a third step, we explain how we translate the worker-level effects without risk sharing into effects with household-level risk sharing by making assumptions on how partners share and redistribute income. We compare the results of the approach without risk sharing to those of the approach with risk sharing to analyze the extent to which risk sharing between partners changes the distributional effects of the trade shock. We refer to *risk sharing* as a situation in which partners are differently affected by the trade shock, such that their household-level impact (after redistribution) differs from their worker-level impact. This implies that for every couple, there is one partner who benefits from risk sharing and one partner who loses from risk sharing. We have benefits from risk sharing for a negatively affected individual with a partner who is less negatively or positively affected, for an unaffected individual whose partner is positively affected or for a positively affected individual whose partner is even

[19] Normalized earnings in this case are defined as cumulative earnings divided by base year earnings.

[20] The needs of a household do not increase proportionally if the number of household members increases. Equivalized household earnings therefore account for economies of scale in consumption of goods like for instance electricity. We use the OECD scale or Oxford scale, which assigns a value of one to the first household member, 0.7 to each additional adult and 0.5 to each child.

Figure 1: Earnings Inequality in Germany



Notes: Figure displays the evolution of the Gini coefficient of workers' labor earnings, average household labor earnings (without children), and equivalized household labor earnings (with or without children). Earnings are equivalized using the OECD scale that attributes a value of one to the first household member, 0.7 to the second adult and 0.5 to each child. Data source: *SOEP v28*

more positively affected. The flip side of this coin is that the respective partner in all these cases loses from risk sharing. The reason for this broad definition is that all of these three cases have implications on the difference between the worker-level and household-level impact on inequality of a given shock - and this is what we are ultimately interested in. In section 2.5.4, we will differentiate between different types of risk sharing. As we are interested in the distributional implications of risk sharing, we especially care about where in the earnings distribution individuals who benefit from more positive effects on their partner are located.

In our empirical analysis, we examine the distributional consequences of risk sharing in the context of a trade shock whose effect we allow to vary across industries and education levels. We consider these two dimensions as the most important ones for several reasons. If workers are partly sector-specific, either because they select into industries based on their individual comparative advantage (Costinot and Vogel 2010; Grossman et al. 2017) or because they accumulate sector-specific human capital (Neal 1995), industry affiliation should be an important indicator for the labor market outcome. Workers who are laid off from import-competing sectors lose their industry-specific human capital and have to switch to an industry in which they have a comparative disadvantage and this might go along with lower earnings. Moreover, if the labor market is beset by search frictions or if it takes time for the worker to acquire new skills, reallocating to a different industry might go along with temporary unemployment and consequently a decrease in earnings. Note that an increase in industry-level imports and the subsequent reallocation of workers might not necessarily be exclusively driven by increased competition in the final goods market but might also capture increased offshoring and its labor market impact. On the side of export-oriented industries, in contrast, there are plausible reasons to assume that the increase in foreign demand goes along with higher job-stability or higher wages (Egger and Kreickemeier 2012).

In addition to industry, we focus on education because one can expect that there is a strong interaction between the industry-level trade shock and the skill level of a worker. First, to the extent that more skilled workers have more general knowledge or acquire new knowledge more easily than less skilled workers, the above mentioned negative effects of import competition might differ between more and less skilled workers. Second, to the extent that more skilled workers differ from less skilled workers in the characteristics that make them vulnerable to offshoring (e.g. routine vs. non-routine tasks), they are differently affected by industry-level imports. Third, and finally, if more skilled workers have a comparative advantage in export-oriented industries (see e.g. Costinot and Vogel 2010), they should benefit relatively more in terms of wages from an increase in export exposure or a decrease in import exposure due to industry-switching. Education of course can only be an imperfect measure of a worker's skill level (and also the degree of offshorability). We believe, however, that this variable captures a substantial degree in the heterogeneity of skills across workers.

It should be noted that there is not a lot of scope for risk sharing against aggregate regional shocks because partners tend to be employed in the same local labor market. Compared to Autor et al. (2013) and Dauth et al. (2014), we do thus not exploit the variation in trade exposure over local labour markets but concentrate on the individual-level analysis using variation in trade exposure between different industries. The main reason is that we are interested in the distributional effects of the trade shock (mainly within local labor markets) and therefore exploit the large variation in trade exposure across industries. In the papers mentioned above, the region-level impact is a weighted average of these industry-level impacts.

As pointed out in section 2.3, we conduct a short-run and a medium-run analysis. These two approaches are complementary both in terms of the identification strategy and in terms of the outcome variable of interest. In the short-run approach, we examine the effects of annual changes in trade exposure on annual earnings growth. The advantage of this approach is that it allows to tightly control for individual heterogeneity and time-variant shocks on regions with the help of individual and region $\times$ year fixed effects. Due to the relatively large sample size, the coefficients of interest can be estimated with substantial precision. The benefits of this approach come at the cost of potential bias from endogenous worker mobility in response to the trade shock. Moreover, one might argue that from a welfare perspective, it is more interesting to look at effects of the trade shock on earnings over a longer time horizon since annual fluctuations in earnings can be cushioned more easily than changes in cumulative earnings over several years. Therefore, we implement also a medium-run analysis. In this approach, we examine the impact of changes in trade exposure on cumulative earnings over three years. This approach mitigates the concern of bias from endogenous mobility as trade exposure is fixed at the base year level. While including individual fixed effects in this approach would not leave enough variation to be exploited, it allows to condition on a large variety of base year individual, household, employer, and industry characteristics. Sample size in this approach, however, is substantially smaller and the effects therefore are estimated with less precision.[21]

2.4.1 Worker-level impact on earnings and inequality

Regression short run. To analyze the effect of the trade shock on workers' annual earnings growth, we make use of the panel structure in our sample and estimate the following empirical specification:[22]

$$Y_{isjrt} = \beta_{1s} \times IM_{jt} + \beta_{2s} \times EX_{jt} + \alpha X'_{isjrt} + \gamma_i + \delta_{tr} + \delta_J + \epsilon_{isjrt} \tag{9}$$

Y_{isjrt} denotes annual earnings (plus unemployment benefits in the extended specification) of individual i, with education level s, working in 2-digit industry j in federal state r in period t relative to i's earnings (plus unemployment benefits in the extended specification) in the base year, i.e. the first year the individual is observed in our dataset. We call this variable normalized annual earnings and multiply it with 100.[23] As compared to the conventional approach of taking logs, this normalization is robust to zero earnings in a given year.[24] We include the two main explanatory variables IM_{jt} and EX_{jt} as levels and our fixed effects approach exploits changes in trade exposure over time for a given worker. Since we allow workers to switch between industries (possibly in response to the trade shock), a worker's export or import exposure can change either because she remains in the same industry and trade exposure of that industry changes between t and $t + 1$, or because she switches to a different industry which is subject to a different trade exposure

[21] Given our quite small sample size, we have to deviate from Autor et al. (2014) and Dauth et al. (2019a), who estimate the medium-run effects for a time interval of at least 10 years. Instead, we split our sample period into four four-year intervals (one base year and three years in which the outcome is measured).

[22] See Baumgarten et al. (2013) and Dauth et al. (2019a) for a closely related panel approach.

[23] This normalization implies that we measure the impact on earnings growth.

[24] Autor et al. (2014) normalize earnings by average pre-shock earnings over several pre-shock years. In our data the first year with reliable information on East Germany is 1993 and we therefore cannot take an average over several pre-shock periods. We instead follow Dauth et al. (2019a) and Dauth et al. (2018) and normalize by base-year earnings.

between t and $t+1$.[25] As this comes at the cost of potential bias from endogenous mobility, we also carry out a complementary medium-run analysis that is less sensitive to this issue. X'_{isjrt} includes age and age squared of the worker.

We include individual worker fixed effects γ_i and thereby control for time-constant differences between workers, such as differences in unobserved ability or other characteristics related to initial earnings. Additionally, we control for year-specific shocks on regional labor markets by adding year $\times$ federal state fixed effects (δ_{tr}). This fixed effect accounts e.g. for the fact that Eastern and Western German regions still differ in many respects and are specialized in different industries that are subject to different time-varying shocks. Finally, to account for time-constant heterogeneity between different industries, e.g. in terms of capital intensity, we include 1-digit industry fixed effects (δ_J) and thereby only compare individuals employed in the same 1-digit industry. We estimate equation (9) separately for different education levels s, namely low-skilled workers (ISCED 1-4) and high-skilled workers (ISCED 5-6).

Although the fixed effects can control for unobserved time-constant confounding factors, the estimation might still give rise to bias due to industry-level time-varying demand and productivity shocks that are correlated with the trade measures and have an impact on individual earnings growth. We thus apply the IV-strategy pioneered by Autor et al. (2013) and Autor et al. (2014) and adapted to the German context by Dauth et al. (2014) and instrument the trade exposures by the respective exposures of a group of other countries, namely Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom. The idea is that growth of Chinese and Eastern European exports and imports is driven mainly by rapid productivity growth, resulting from capital accumulation, migration to rural areas and improvement in infrastructure (Naughton 2007; Hsieh and Klenow 2009; Burda and Severgnini 2009). As discussed in for example Autor et al. (2014) and Dauth et al. (2014), besides the fact that the instrument should have explanatory power, the validity of this approach hinges especially on the exclusion restriction, saying that trade shocks on other countries must not have any direct or indirect impact on workers' earnings other than through the rise of China and Eastern Europe. To avoid that unobserved demand and supply shocks in Germany and in the instrument countries are too similar to remove the bias in the estimate, the instrument countries are neither direct neighbours of Germany nor members of the European Monetary Union or of the United States of America. This reduces the likelihood that a change in trade exposure of the instrument countries directly affects German workers. If however an instrument country's change in import or export behaviour also affects demand or supply in Germany,

[25] We allow for industry-switching because this constitutes an important channel for workers to adjust to the trade shock (Autor et al. 2014; Dauth et al. 2019a). We measure the extent to which a worker is exposed to trade based on an industry variable which is missing in case of unemployment. In this case, in the short-run approach, we follow Dauth et al. (2019a) and assign the last observed industry affiliation to the individual.

some risk of getting a bias in the estimated effects remains.[26] However, our basic results remain unchanged when we rely exclusively on the fixed effects specification.

In our baseline specification, we estimate equation (9) using only individuals who (and whose partners) are employed in the first period of observation in order to have a clear industry affiliation for the assignment of the trade shock. We do not consider unemployment benefits and reliefs, in case of unemployment in periods after the base year, earnings are assumed to be equal to zero. In the extended specification, we allow for unemployment and non-employment also in the first period of observation. The respective individuals get assigned a trade shock of zero. Moreover, in the extended specification, we consider unemployment benefits and reliefs as an additional source of income. Individuals who report zero labor earnings and benefits/reliefs in the base year cannot be included into the regression because in this case relative earnings are not defined. For the inequality analysis, however, we can again include these individuals in the sample.

Regression medium run. In the medium-run approach, we estimate the following specification, which is in the spirit of Autor et al. (2014):

$$Y_{isjrz} = \beta_{1s} \times \Delta IM_{jz} + \beta_{2s} \times \Delta EX_{jz} + \alpha X'_{isjrz} + \delta_{zr} + \delta_J + \epsilon_{isjrz} \tag{10}$$

where z denotes the respective four-year interval (93-96, 97-00, 01-04, 05-08). Y_{isjrz} denotes cumulative earnings over years two to four of the respective interval relative to earnings in the base year z_0 (=year one) of individual i, with education level s, employed in industry j in region r in the base year of interval z. We call this variable normalized cumulative earnings and multiply it with 100. It is being regressed on the changes in export and import exposure as defined in section 2.3. Note that the trade exposure measures are based in individual i's base year industry and therefore are insensitive to industry-switching of worker i during years two to four. The approach thereby limits the potential for bias from endogenous worker mobility in response to the trade shock. 1-digit industry fixed effects are kept in the regression. Instead of controlling for year-specific shocks in federal states we now include interval × federal state fixed effects. Additionally, this specification allows to condition the effects on a large battery of base year controls X'_{isjrz}, namely: age and age squared, gender, log base year earnings and its interaction with gender, and dummy variables for being in a single-headed household, having children in the household, being fulltime-employed, being employed by a company with more than 20 employees, being a manager or professional, and a dummy for carrying out simple tasks at work. The latter variable might be an important control for technological progress. However, this can only be an imperfect measure for the degree to which a job

[26] Concerning the instrument, we simply replace German exports/imports in industry j by the sum of exports/imports of the instrument countries in industry j in the numerator. In the denominator, we keep the lagged industry wage sum.

is vulnerable to technological change as the degree of routineness or the codifiability of tasks might be important as well. Therefore, to further mitigate concerns about bias from technological progress, we control for industry-level changes in gross fixed capital formation of information and communication technology using data from the EUKlems database in a robustness check. Analogously to the short-run approach, we instrument the trade exposure measures with the respective trade exposures of other high-income countries and cluster standard errors at the industry × (base) year level.[27]

The main analysis treats partners as independent of each other in terms of the effects of the trade shock and their adjustment behaviour. It therefore exclusively focuses on the risk sharing effect from sharing of household income and implicitly sharing the effects of the trade shock. This means that the risk sharing effect results from the existing mating structure. In a final extension (see section 2.5.5), we allow for "active risk sharing" by controlling for trade exposure on the partner in the regressions and modelling the predicted impact of the trade shock as a function of the partner's trade shock.

Predicted impact on workers' earnings. Based on the resulting point estimates, we compute the predicted impact of the trade shock on annual earnings of every worker in every year in the short-run approach. In the medium-run approach, we compute the predicted impact on cumulative earnings for every worker in every interval.

In the short-run regression, the coefficient $\hat{\beta}_{1s}$ ($\hat{\beta}_{2s}$) reflects the estimated change in normalized earnings of individual i with education level s between t and $t+1$ (in percentage points) that is induced by a change in import (export) exposure by one percentage point between t and $t+1$. We therefore can compute the predicted impact on normalized earnings for every worker in every year by multiplying the respective coefficients with the observed changes in trade exposure ΔIM_{jt} and ΔEX_{jt} on a given worker in a given year. Note that industry j can change between t and $t+1$ due to workers switching between industries. For simplicity of notation, we simply keep index j:

$$(\frac{\widehat{E_{isjr,t+1}}}{E_{isjr,0}} - \frac{E_{isjr,t}}{E_{isjr,0}}) \times 100 = \Delta IM_{jt} \times \hat{\beta}_{1s} + \Delta EX_{jt} \times \hat{\beta}_{2s} \tag{11}$$

The left-hand side of this equation is the predicted impact of the trade shock on normalized earnings of worker i in year t. It consists of her base year earnings $E_{isjr,0}$, her earnings in year t ($E_{isjr,t}$), and $\widehat{E_{isjr,t+1}}$ which reflects her predicted earnings in year $t+1$ if the trade shock had happened as observed in the data and everything else had stayed constant. These earnings result from the standard ceteris-paribus interpretation of the regression coefficients. The predicted impact on normalized earnings is a function of the

[27] Following Dauth et al. (2019a), we cluster standard errors at the industry × (base) year level. This increases the number of clusters but does not allow for serial correlation within industries. We thus also estimate both the medium- and the short-run regressions clustering only at the 2-digit-industry level. The results for the short run do not change, the medium-run results become even stronger in terms of statistical significance. Results can be obtained upon request.

observed changes in trade exposure (ΔIM_{jt} and ΔEX_{jt}) and the estimated regression coefficients which differ by education level s. Note that $\widehat{E_{isjr,t+1}}$ is the only unknown in this equation. We can solve for $\widehat{E_{isjr,t+1}} - E_{isjr,t}$, which reflects the predicted change in earnings due to the trade shock. We call this difference $\widehat{Impact}^{SR}_{isjr,t}$:

$$\widehat{Impact}^{SR}_{isjr,t} = (\Delta IM_{jt} \times \hat{\beta}_{1s} + \Delta EX_{jt} \times \hat{\beta}_{2s}) \times E_{isjr,0} \times \frac{1}{100} \tag{12}$$

Put simply, the predicted impact on earnings is a function of the worker's trade shock as well as his education level. The predicted impact of the trade shock on cumulative earnings in interval z in the medium-run approach can be computed analogously:

$$\widehat{Impact}^{MR}_{isjr,z} = (\Delta IM_{jz} \times \hat{\beta}_{1s} + \Delta EX_{jz} \times \hat{\beta}_{2s}) \times E_{isjr,z_0} \times \frac{1}{100} \tag{13}$$

Predicted impact on earnings inequality. To analyze the distributional effects of the trade shock, we perform a counterfactual exercise in the spirit of the decomposition literature in labor economics (e.g. Lemieux 2002). Consider first the short-run approach. Taking actual earnings in year t of every worker in t and adding $\widehat{Impact}^{SR}_{isjr,t}$ yields counterfactual earnings of the respective workers in $t+1$ if the trade shock had happened between t and $t+1$ as observed in the data and everything else had stayed constant. The result is also a counterfactual earnings distribution in $t+1$. Comparing this distribution to the actual distribution in t, for example using the Gini coefficient, yields an estimate of the impact of the trade shock on earnings inequality between t and $t+1$.

Consider now the medium-run approach. Taking actual cumulative earnings in interval z and subtracting $\widehat{Impact}^{MR}_{isjr,z}$ yields counterfactual cumulative earnings in z in absence of the trade shock. Comparing the two resulting distributions yields an estimate of the impact of the trade shock on cumulative earnings. Note that the exercise in case of the medium-run approach differs slightly from the exercise in the short-run approach (subtracting instead of adding the predicted impact) due to the differences in the estimation approach. The general idea, however, is exactly the same. To obtain standard errors for the estimates of the predicted impact, in both approaches, we pool all years/intervals and perform 200 bootstrap replications, clustered at the household level.

2.4.2 Risk sharing versus no risk sharing

The explanations so far in this section were related to the estimation of the impact of the trade shock on individual workers' earnings and earnings inequality between workers. The main goal of the empirical exercise is to compare this worker-level perspective, which is in the spirit of the previous literature (Autor et al. 2014; Dauth et al. 2014; Dauth et al. 2019a), to a perspective with household-level risk sharing. Note that the term *household-level perspective* does not mean that we aggregate up our dataset to the household level and then perform the analysis at the household level. Instead, we make assumptions on how partners split and redistribute income and then work with the respective earnings after redistribution. In the baseline scenario, we assume that partners in married and unmarried couples split the sum of their labor income equally. Consider a couple in which the husband earns 20,000 EUR in a given year and the wife earns 30,000 EUR (the same logic applies to cumulative earnings in the medium-run approach). In the baseline scenario, we attribute household-level earnings of 25,000 EUR to both partners, i.e. we assume that the wife redistributes 5,000 EUR to the husband.

Further assume that the husband has a worker-level impact of the trade shock of -300 EUR, which reduces his individual earnings to 19,700 EUR, whereas the wife has a worker-level impact of +500 EUR, which raises her individual earnings to 20,500 EUR. With equal sharing, the worker-level impact of -300 EUR (+500 EUR) on the husband (wife) translates into a household-level impact of +100 EUR on the husband (wife). The distributional effect of the trade shock with household-level risk sharing is then computed analogously to the procedure explained above for the individual worker level. We go beyond the baseline scenario and perform several different extensions and robustness checks (e.g. change the sharing rule). See section 2.5.3 for details.

Note that risk sharing does not mechanically reduce the inequality-increasing impact of the trade shock. In fact, the distributional impact with risk sharing can even be larger than the respective effect without risk sharing. The reason is that risk sharing between partners (e.g. through equal sharing of household income) does not only reduce the dispersion of gains and losses from the shock across individuals. It also changes the distribution of initial incomes and the respective position of individuals in the initial income distribution (after redistribution within the household). To illustrate this important point more formally, in Appendix B, we construct a simple example with four individuals and three different mating structures.

2.5 Results

2.5.1 The impact on workers' earnings growth

We first estimate the impact of the trade shock on normalized earnings using the specifications in equations (9) (short run) and (10) (medium run) for the baseline version without those who are unemployed in the base year and without unemployment benefits. Regression results for the extended version, which are very similar to those of the baseline version, can be found in Table A2 in Appendix A. Panel (a) in Table 2 displays the short-run results. Both the pure fixed effects and the IV estimates suggest that industry-level trade exposure has a statistically significant effect on workers' annual earnings growth.[28] The results suggest that workers in export-oriented industries experienced an increase in

[28]See Table A3 in Appendix A for the detailed first stage results.

annual earnings growth. The positive effect can be due to increasing wages in export-oriented sectors (Schank et al. 2007; Egger and Kreickemeier 2012; Baumgarten 2013) or increasing job-stability as compared to a scenario without exports (Dauth et al. 2014). Workers in import-competing industries, in contrast, experienced a significant negative effect on annual earnings growth. This effect can be due to real wage cuts, temporary unemployment, or decreasing hours of work (Autor et al. 2014; Dauth et al. 2014; Dauth et al. 2019a). All in all, our results are in line with evidence from previous studies (e.g. Autor et al. 2014; Dauth et al. 2014; Dauth et al. 2019a).

A look at the IV estimates suggests that both the positive effects of export exposure and the negative effects of import exposure are slightly larger for high-skilled workers than for low-skilled workers. However, the pattern is reversed for the pure FE estimates. As the IV estimates yield more conservative results in the inequality analysis, we will use the IV estimates to compute the predicted impact on earnings in the main specification. As a robustness check, however, we also use the FE estimates and show that the results are qualitatively unchanged.

Panel (b) of Table 2 offers a look at the medium-run results. Overall, the pattern which is present in the short-run results can be confirmed in the medium-run results. The main difference is that the point estimates are estimated with substantially less precision due to the smaller sample. While the point estimates are statistically significant in columns (1) and (2) where we employ the whole sample, the standard errors become substantially larger in columns (3)-(6) where we split the sample across skill groups. The first stage F-statistic for export exposure lies well above the rule-of-thumb value of 10. The instrument for import exposure could be stronger (F-statistic varies between 4.8 and 7.2), however, with a single instrument for each endogenous variable, we estimate a just-identified 2SLS and our IV estimates are thus median-unbiased and less vulnerable to weak instrument problems (Angrist and Pischke 2009). Moreover, the Cragg-Donald Wald F-statistic lies above 500 in all specifications and is thus well beyond the respective critical values in Stock and Yogo (2005). Overall, given that these two complementary specifications yield a very similar pattern, we conclude that there is a robust impact of the trade shock on workers' earnings growth.

Table 2: Effects of Trade Shock on Workers' Earnings Growth

(a) Short Run

Norm. annual earnings ×100	**Whole Sample** FE	**Whole Sample** IV	**Low-skilled** FE	**Low-skilled** IV	**High-skilled** FE	**High-skilled** IV
EX_{jt}	0.3972***	0.3969***	0.4603***	0.2672***	0.2771**	0.3951**
	(0.0886)	(0.1070)	(0.0768)	(0.1025)	(0.1195)	(0.1689)
IM_{jt}	-0.1328***	-0.1543***	-0.1914***	-0.1257**	-0.1030**	-0.1741**
	(0.0499)	(0.0520)	(0.0366)	(0.0502)	(0.0514)	(0.0775)
R2	0.74	0.74	0.73	0.73	0.85	0.85
1st F (EX_{jt})	-	168.34	-	215.01	-	144.28
1st F (IM_{jt})	-	272.85	-	671.29	-	533.50
Obs.	58,931	58,931	44,159	44,159	14,772	14,772

(b) Medium Run

Norm. cum. earnings ×100	**Whole Sample** OLS	**Whole Sample** IV	**Low-skilled** OLS	**Low-skilled** IV	**High-skilled** OLS	**High-skilled** IV
ΔEX_{jz}	0.8296***	1.6028**	0.9979***	1.5532**	0.5345	1.9249**
	(0.2080)	(0.6452)	(0.2622)	(0.6214)	(0.3312)	(0.9512)
ΔIM_{jz}	-0.3679**	-0.4055*	-0.4671**	-0.3798	-0.2784	-0.6421
	(0.1602)	(0.2419)	(0.2142)	(0.4236)	(0.2679)	(0.4952)
R2	0.14	0.14	0.16	0.16	0.11	0.11
1st F (EX_{jz})	-	19.41	-	17.27	-	22.64
1st F (IM_{jz})	-	4.91	-	4.83	-	7.16
Obs.	9,529	9,529	7,052	7,052	2,477	2,477

Notes: The table shows the estimated coefficients from equations (9) and (10), baseline specification without unemployed in the first period and without unemployment benefits. Panel (a): All estimates include individual, year × federal state and 1-digit industry fixed effects. Further controls include age and age squared. Panel (b): All estimates include base year × federal state and 1-digit industry fixed effects. Further base year controls include age, age squared, gender, a dummy for being in a single headed household, log(earnings), log(earnings) × gender, a dummy for being employed in a large company (>20 employees), a dummy for being a manager or professional, a dummy for carrying out simple tasks at work, a dummy for having children, a dummy for being fulltime employed in the base year. Standard errors clustered by 2-digit industry × (base) year in parentheses. We define individuals with ISCED<5 as being low-skilled and those with ISCED>4 as being high-skilled. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Table 3 offers a look at the magnitude of these estimates. Employing the method explained in section 2.4.1 and using the IV estimates separated by skill group (columns

(4) and (6) in Table 2, we compute the predicted impact on annual earnings in the short-run approach and on cumulative earnings in the medium-run approach. The first line of panel (a) gives a descriptive overview of the estimates for $\widehat{Impact}^{SR}_{isjr,t}$ for every worker-year observation in the sample. It turns out that the positive effects of exports overcompensated the negative effects of imports as workers on average gained about 88 Euros per year from the trade shock. However, positive and negative effects were unequally distributed across the population. A look at the 95th and 5th percentile of the predicted impact shows that the predicted impact ranges from a gain of almost 700 Euros to a loss of around 140 Euros.

Line 2 of panel (a) displays summary statistics for the impact with household-level risk sharing.[29] While the mean predicted impact naturally is unchanged, the dispersion of the trade shock is different if we consider household-level risk sharing. A look at the standard deviation suggests that the dispersion of effects on average is smaller with household-level redistribution and this already gives first evidence in favor of the existence of a risk sharing effect within households. However, this is not true uniformly across the whole distribution, as the 5th percentile of the shock with risk sharing is more negative than the corresponding 5th percentile at the worker level. This might appear if workers who are affected negatively by the trade shock have a partner who is even more negatively affected. In the 95th percentile, workers who individually benefit to a great extent from the trade shock can have a partner who is less positively or even negatively affected. This is the reason why for the 95th percentile, if partners are assumed to split gains and losses from the trade shock equally, the worker-level effect is larger than the impact considering household-level risk sharing.

Panel (b) shows the medium-run predicted impact. It turns out that the positive predicted impact of the trade shock in the medium-run approach is larger than in the short-run approach. Line 1 of panel (b) suggests that workers on average gained 1,887.88 EUR over three years due to the trade shock, which corresponds to more than 600 EUR per year. Again, the effects are highly unevenly dispersed across the sample population. A possible explanation for the higher magnitude of the effects in the medium-run approach is that it can capture effects of the trade shock which are being "washed out" in the short-run panel approach which exploits only year-to-year changes in trade exposure. To the extent that some of the effects (e.g. wage increases or higher job stability) do not fully play out in the first year of increasing trade exposure but rather take several years, these effects are underrepresented in the short-run approach. Analogously to panel (a), line 2 of panel (b) illustrates the effects with household-level risk sharing in the medium-run approach.

Another notable finding in Table 3 is that the share of individuals with a negative

[29] As explained in section 2.4.2, taking the average of both partners' predicted impact corresponds to equal sharing of total household income. In the robustness section, we will relax this assumption.

predicted impact is higher in the scenario with risk sharing. This is driven by individuals who experience small positive effects from the trade shock, but have a partner who experiences a larger negative impact. Even though the number of those cases is small in our sample, this finding further emphasizes the virtue of a household perspective. Despite the mitigating impact of risk sharing concerning the overall earnings distribution (see the following section), the number of "losers" in absolute terms is larger if risk sharing is taken into account. Especially in the context of a discussion about "winners" and "losers" from globalization, this result is highly relevant and illustrates that a pure worker-level analysis might underestimate the number of "losers" from a shock or policy.

Table 3: Predicted Impact on Earnings - Summary Statistics

Pred. Impact	Mean	Median	S.D.	p95	p05	Obs	<0 (%)
(a) Short Run							
w/o risk sharing	88.47	4.14	672.52	690.27	-139.47	58,931	13.64
with risk sharing	88.47	9.52	543.58	653.41	-190.11	58,931	15.91
(b) Medium Run							
w/o risk sharing	1,887.88	163.51	4,846.90	10,118.80	0.51	9,529	2.40
with risk sharing	1,887.88	336.55	4,162.91	9,135.73	0.77	9,529	2.72

Notes: The first line refers to $\widehat{Impact}^{SR}_{isjr,t}$, i.e. the predicted impact without risk sharing in the short run (see equation 12). The second line refers to the respective values with risk sharing (assuming that household income is split equally between partners. Analogously, line 3 displays summary statistics for $\widehat{Impact}^{MR}_{isjr,z}$ (equation 13) and line 4 displays the respective values with risk sharing. Predicted impact is computed using the IV-estimates differentiated by skill group from Table 2. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

2.5.2 Risk sharing and the distributional effects of the trade shock

The extent to which the impact on individuals without risk sharing differs from the impact with risk sharing depends on the degree to which partners are differently affected by the trade shock. In the most extreme case where the impact of the trade shock is exactly the same for both partners (i.e. the regression coefficient of predicted impacts in Table 4 is equal to one), the impact without risk sharing corresponds to the impact with risk sharing. This does not necessarily imply that the distributional effects do not differ between these two scenarios as the distribution of initial incomes differs between scenarios and this has an impact on how a given shock influences inequality.

Table 4 nevertheless takes a first descriptive look at risk sharing by examining the correlation between partners of export exposure, import exposure, the dummy variable for being high-skilled and the predicted impact. The "correlation" we depict here is the regression coefficient resulting from a simple bivariate regression of for example an individual's export exposure on the partner's export exposure.

Table 4: Correlation between Partners

(a) Short Run

Dep. Var.:	ΔEX_{jt}	ΔIM_{jt}	High Education	Pred. Impact	Obs.
Whole Sample	0.0613***	0.0577***	0.3153***	0.0249***	33,110
	(0.0055)	(0.0055)	(0.0052)	(0.0055)	
Different Industry	0.0250***	0.0218***	0.2827***	-0.0059	28,186
	(0.0059)	(0.0059)	(0.0057)	(0.0059)	
Different Education	0.0501***	0.0554***	-1.0000	0.0270***	9,108
	(0.0105)	(0.0105)	-	(0.0105)	
Diff Ind. and Ed.	0.0044	0.0025	-1.0000	-0.0106	7,888
	(0.0112)	(0.0116)	-	(0.0112)	

(b) Medium Run

Dep. Var.:	ΔEX_{jz}	ΔIM_{jz}	High Education	Pred. Impact	Obs.
Whole Sample	0.1222***	0.0922***	0.3360***	0.0461***	5,029
	(0.0140)	(0.0141)	(0.0133)	(0.0141)	
Different Industry	-0.0082	0.0054	0.3085***	-0.0310**	4,242
	(0.0154)	(0.0154)	(0.0146)	(0.0154)	
Different Education	0.0891***	0.0699**	-1.0000	0.0487**	1,344
	(0.0272)	(0.0272)	-	(0.0273)	
Diff Ind. and Ed.	-0.0839***	-0.0273	-1.0000	-0.0474	1,145
	(0.0295)	(0.0296)	-	(0.0296)	

Notes: The first column in panel (a) denotes the coefficient and standard error of a regression of an individual's export exposure on his/her partner's export exposure. Columns 2-4 show the results of an analogous regression with import exposure, a dummy for high education, and the predicted impact. "Different Industry" refers to partners that are employed in a different 2-digit industry. "Different Education" refers to partners that do not have the same education level (low versus high education). In panel (b) we display the same results for the medium-run approach. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

The first line in panel (a) of Table 4 illustrates that partners on average are employed in similarly affected industries and that there is a highly significant correlation in education levels between partners. Even though the correlations we find are highly significant, they are far from perfect. This is not surprising: We allow the effect of the trade shock to vary across industries and skill groups and 85% (25%) of workers are employed in a different industry (have a different education level) as their partner. The positive correlation in these characteristics translates into a positive correlation in terms of the predicted impact on earnings.

When we restrict the sample on couples where partners work in a different 2-digit industry in line 2, the correlation of changes in trade exposure remains significant but drops considerably. Interestingly, the correlation of education levels also decreases slightly. The correlation of the predicted impact becomes statistically insignificant. Restricting on couples where partners have a different education level (line 3) also reduces the correlation in trade exposures, but to a smaller extent. Surprisingly, the correlation of the predicted impact in column 4 does not decrease. Finally, the correlations drop most when we apply both restrictions in line 4. This pattern is qualitatively similar when we look at the correlations in the medium-run approach in panel (b). Overall, these descriptives suggest that a risk sharing effect might be at work - especially when partners are employed in different industries and/or have a different education level.

To analyze the degree to which this corresponds to assortative mating, we compare these estimates to a scenario of random mating. To this end, we rematch partners within years/intervals randomly (keeping singles as singles) and compute the respective correlations. Repeating this 10,000 times, we obtain an estimate for the expected correlations under random mating. Appendix A shows the respective kernel density plots for the baseline short-run approach in Figure A2. It turns out that our sample exhibits significant levels of assortative mating in terms of trade exposure and education levels. Take for example the correlation in import exposures which is 0.0577 in our sample (see panel (b)). Under random mating, the correlations center around zero and are never larger than 0.042. A comparison of the dispersion of mean household earnings across individuals in our sample ($100 \times$ Gini = 30.795) to the respective levels of inequality under random mating suggests that the actual mating structure in our sample significantly reinforces inequality in the cross section: $100 \times$ Gini under random mating is significantly below 30.795 along the whole distribution, with a mean of 30.63. In other words, we also find assortative mating in terms of annual earnings. These findings are in line with studies that document significant assortative mating (e.g. Eika et al. 2014; Greenwood et al. 2014).

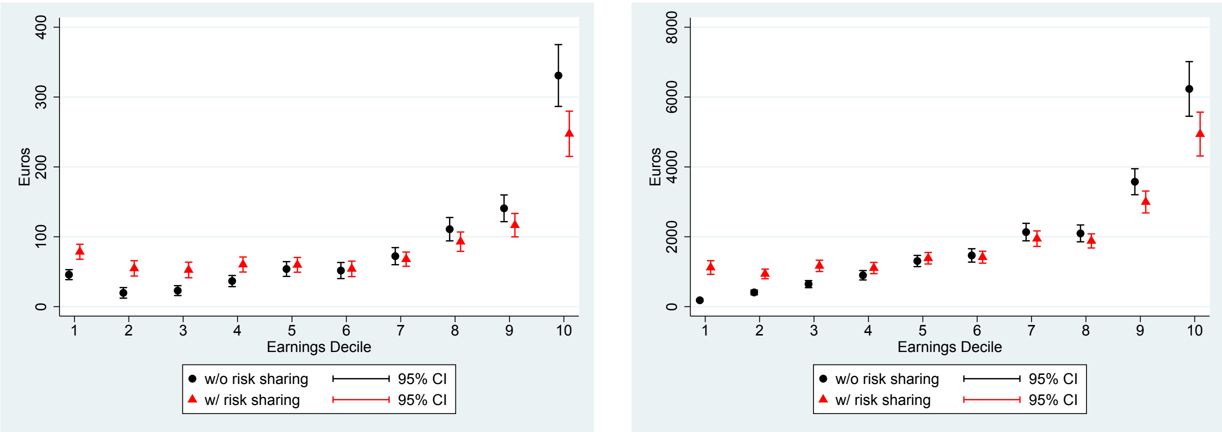
Figure 2 provides a visual representation of the distributional effect of the trade shock as well as the relevance of risk sharing between partners. In panel (a), we order all worker-year observations in our sample according to individual annual earnings and divide the sample into ten earnings deciles. For every decile, we display the mean predicted impact with and without risk sharing. Panel (b) analogously displays the respective values for the medium-run approach.

Panel (a) provides evidence on the inequality-increasing impact of the trade shock, both at the worker level (without risk sharing) and with household-level risk sharing (assuming that household earnings are equally shared). The mean worker-level effect for the lowest deciles is below 50 Euros, whereas it is above 300 Euros for the highest deciles. A comparison between the estimates without risk sharing and those with risk sharing suggests that the inequality-increasing effect is lower with household-level risk sharing. Workers in the lowest deciles on average benefit from larger positive effects at the household level. The opposite is true for the highest earnings deciles. The pattern we detect is very similar in panel (b) for the medium-run approach. All in all, the results in Figure 2 provide first suggestive evidence that the effect on inequality with household-level risk sharing is smaller than the worker-level effect without risk sharing.

Figure 2: Predicted Impact along the Earnings Distribution

(a) Short Run

(b) Medium Run



Notes: Workers are ordered according to their annual earnings in panel (a) and according to their cumulated earnings in panel (b). They are then grouped into ten deciles. For every decile, we display the average impact without risk sharing and the impact with household-level risk sharing. The worker-level impact stems from equations (9)(short run) and (10)(medium run), baseline specification without benefits. The impact with household-level risk sharing is the average of both partners' predicted impact in case of couples. In case of singles the impacts with and without household-level risk sharing are identical. Confidence intervals result from 200 bootstrap replications, clustered at the household level. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

The figure, however, only displays mean effects for every decile and thereby ignores the distribution of effects within deciles. Second, the figure displays the effects in absolute levels and not relative to annual earnings. For these reasons, we go one step further and conduct the inequality analysis outlined in section 2.4.2, using the Gini coefficient, a commonly used measure of inequality which takes into account the effect in relation to annual earnings. To compare the method used in Figure 2 with the Gini coefficient, consider a scenario where all workers gain the same amount from the trade shock. From the absolute numbers displayed in Figure 2 , we would conclude that there is no impact on inequality. The Gini coefficient, in contrast, would decrease (i.e. less inequality) because the impact relative to earnings of low-earnings workers is larger than the impact relative to earnings of high-earnings workers.

In Table 5, we report the results of the procedure outlined in section 2.4.1 and 2.4.2.

Table 5 confirms the inequality-increasing effect of the trade shock at the worker level. In this table, we show the estimates for the short- and the medium-run approach. In addition to the baseline specification in which we restrict the sample to couples in which both partners are employed in the first year of observation, we provide an extended specification in which we also include couples in which at least one partner is unemployed or non-employed in the base year. The respective individuals get assigned a trade shock of zero. In this specification, we additionally consider income from benefits and reliefs. The respective regression results (analogously to the regression results for the baseline sample in Table 2) can be found in Appendix A, Table A2.

Table 5: Predicted Impact on Earnings Inequality

Pred. Impact	**Short Run**		**Medium Run**	
	Baseline	Extended	Baseline	Extended
Without Risk Sharing	0.0407***	0.0521***	0.2460***	0.2961***
	(0.0054)	(0.0049)	(0.0324)	(0.0273)
% of Total Increase	4.9	12.7	15.0	18.3
With Risk Sharing	0.0310***	0.0431***	0.1438***	0.1898***
	(0.0060)	(0.0058)	(0.0347)	(0.0297)
% of Total Increase	4.4	6.7	11.6	12.1
Difference	0.0097***	0.0090***	0.1022***	0.1064***
	(0.0034)	(0.0028)	(0.0173)	(0.0150)
% of Impact w/o Risk Sharing	23.8	17.3	41.5	35.9
Observations	58,931	78,808	9,529	12,195

Notes: Table displays the predicted impact of the trade shock on inequality of workers' earnings and of average household earnings as explained in sections 2.4.1 and 2.4.2. Inequality is measured by the Gini index ×100. The first two columns (short run) look at year-to-year changes, the medium-run results show changes over the respective four year interval. "Total Increase" refers to the average annual increase in earnings inequality for the short run, see Figure 1. For the medium run, total increase is defined as the mean increase in inequality of cumulative earnings over the four intervals. *Baseline* restricts on both partners being employed in the base year. *Extended* allows for non-employment in the base year and additionally includes income from unemployment benefits. Standard errors in parentheses result from 200 bootstrap replications, clustered at the household level. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Consider first the estimates from the short-run approach. According to the estimates, which are highly statistically significant, the trade shock on average increased the Gini coefficient of individual annual earnings (i.e. without risk sharing) by 0.000407 per year. When we set this in relation to the average increase in overall inequality per year (see Figure 1), we find that the trade shock explains about 5% of the increase in the Gini coefficient of worker earnings between 1993 and 2007.

We then compare the estimated effect without risk sharing to the respective effect that emerges if we take risk sharing between partners into account. Again, the estimated impact is highly statistically significant. A comparison to the estimated worker-level impact without risk sharing reveals that the impact with household-level risk sharing is smaller, both in absolute terms and in terms of its contribution to overall inequality.[30] The difference between worker and household level is highly statistically significant. According to the estimates, the impact with household-level risk sharing is almost 24% smaller than the respective impact without risk sharing. The second column confirms this result for the extended specification. In this specification, the contribution of the trade shock to overall inequality is slightly higher (12.7 and 6.7 % respectively), the difference between the results with and without risk sharing in contrast decreases to 17.3%.

Columns 3 and 4 of Table 5 show the results for the medium-run approach. A look at the estimates without risk sharing suggests that the trade shock explains 15% (18.3%) of the total increase of inequality in cumulative individual earnings.[31] Taking risk sharing into account, this contribution decreases by 41.5% (35.9%). The mitigating effect we detect in the medium-run approach therefore are even larger than those in the short run-approach.

In this specific case, a pure worker-level perspective would thus overestimate the inequality-increasing impact of Germany's trade integration with China and Eastern Europe. The difference between the results with and without household-level risk sharing is even larger when using the fixed effects (short run) or OLS (medium-run) estimates instead of the IV estimates. See Table A4 in Appendix A. Before we turn to the underlying drivers of the difference between worker-level results and results with household-level risk sharing in section 2.5.4, we now provide several robustness checks and extensions to further confirm the results.

2.5.3 Robustness and extensions

Controlling for technological progress. In the medium-run analysis, we include a dummy variable which indicates whether the worker performs simple tasks at work. The information is drawn from a variable stating the employee's occupational position and the respective task requirement which consists of simple duties ("Simple Tasks" = 1) or (highly) qualified (e.g. executives, scientists, technical draftsmen) or managerial duties.[32] To the extent that simple tasks are more substitutable by capital than other tasks, this

[30] For the estimates with household-level risk sharing, we use the average annual increase in inequality between households, see Figure 1 for the Gini.

[31] In the medium-run, "total increase" is defined as the difference in inequality of cumulative earnings between the fourth and the first interval, divided by three. This corresponds to the mean increase in inequality of cumulative earnings over the four intervals.

[32] As in our sample, this variable has almost no variation within workers over time (only if both occupation and task requirement changes), we do not include it in the short-run fixed effects approach.

variable serves as a control for the vulnerability of a job to technological progress. However, we are aware that this can only be an imperfect control for technological progress, as other characteristics of a job such as the degree of routineness or the codifiability might play an even larger role. Therefore, to further mitigate concerns of a bias from technological progress both in the short- and in the medium-run approach, we collected data from the EUKlems database.

More specifically, we use data on gross fixed capital formation of information and communication technology (ICT). For each interval of our medium-run approach, we compute the industry-level change in gross fixed capital formation of ICT, relative to the industry wage bill in the base year. We thereby obtain measures for ICT exposure at the level of 31 industries.[33] This measure is similar to Dauth et al. (2017). As an alternative, instead of the change during the interval, we consider the cumulative gross fixed capital formation relative to the base year wage bill.

Table 6 shows the results of including both the ICT variables (in values per 10,000 employees) and the dummy for simple tasks (which is however also present in the main specifications). As the industry "*Computer And Related Activities*" (NACE code = 72) has experienced an extremely huge change in gross fixed capital formation of ICT, we drop this outlier in Table 6. This does not considerably affect the estimates for import and export exposure.[34] As compared to the results without controlling for technological change (column (1)), the point estimates for export and import exposure are slightly lower when including ΔICT or $Sum\ ICT$, but still considerable and highly statistically significant. The decrease in the point estimates seems to be driven almost entirely by low-skilled workers.

As expected, the task measure and the change in ICT investment seem to have a significant impact on labor market outcomes of workers. To gauge the magnitude of the controls, consider the difference between a worker at the 75th percentile and a worker at the 25th percentile of normalized cumulative earnings, which amounts to roughly 62 percentage points. Taking the estimates for the whole sample in panel (a), the dummy for performing simple tasks explains $14/62 = 22.5\%$ of this difference.[35] Comparing a worker at the 75th percentile to a worker at the 25th percentile to ICT exposure, the estimates imply a difference in normalized cumulative earnings of 2.04 (2.90) percentage points, using the point estimate for ΔICT ($SumICT$) in panel (a).

[33] Some 2-digit NACE codes have to be combined to match the EUKlems industry codes.

[34] The results including NACE code 72 are available upon request.

[35] Panel (c) suggests a positive impact of performing simple tasks for high-skilled workers. However, the dummy is one only for around 5% of high-skilled workers. We therefore prefer not to take the estimates separated by skill group at face value.

Table 6: Medium-Run Effect of Trade Shock - Controlling for Technological Progress

Norm. cum. earnings ×100	(1)	(2)	(3)
(a) Whole sample (N=9,406)			
ΔEX_{jz}	1.6150**	1.5645**	1.5133**
	(0.6416)	(0.6246)	(0.6348)
ΔIM_{jz}	-0.4052*	-0.3366	-0.32023
	(0.2402)	(0.2415)	(0.2508)
Simple Tasks	-13.8246***	-13.9045***	-13.8784***
	(5.2015)	(5.2173)	(5.2105)
Δ ICT		341.9148***	
		(90.2607)	
Sum ICT			48.7229***
			(17.7943)
R2	0.14	0.14	0.14
(b) Low-Skilled (N=6,993)			
ΔEX_{jz}	1.5680**	1.5169**	1.4817**
ΔIM_{jz}	-0.3725	-0.2893	-0.2904
Simple Tasks	-18.3380***	-18.4117***	-18.3652***
Δ ICT		348.4023***	
Sum ICT			39.1759*
R2	0.16	0.16	0.16
(c) High-Skilled (N=2,413)			
ΔEX_{jz}	1.9333**	1.8816**	1.8131*
ΔIM_{jz}	-0.6538	-0.6145	-0.5763
Simple Tasks	14.2755	14.2121	14.0208
Δ ICT		329.4944**	
Sum ICT			68.3544**
R2	0.11	0.11	0.11

Notes: Description analogous to Table 2, panel (b). Additional controls: ΔICT : change in gross fixed capital formation of ICT per 10,000 workers within each interval, Sum ICT: sum of gross fixed capital formation per 10,000 workers over the four years respectively. All trade exposure measures are instrumented. Panels (b) and (c) omit standard errors for better visibility. NACE= 72 excluded. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office, EUKlems.

The positive point estimate of the ICT estimates is well in line with the findings in Dauth et al. (2017). To check whether the impact of industry-level investment of ICT differs between workers performing different types of tasks, we additionally estimate a specification in which we interact the ICT variable (ΔICT or $Sum\ ICT$) with the dummy variable for performing simple tasks. The estimates for import and export exposure remain qualitatively and quantitatively unaffected (see Table A5, Appendix A). As expected, the interactions have a negative sign, i.e. workers performing simple tasks are less positively affected by ICT investment than other workers. All in all, our results remain qualitatively unchanged, although the point estimates hint at a certain influence of technological change.

Table 7: Predicted Impact on Earnings Inequality - Controlling for Technological Progress

Pred. Impact	**Short Run**		**Medium Run**	
	Baseline	Extended	Baseline	Extended
Without Risk Sharing	0.0350***	0.0378***	0.2373***	0.2609***
	(0.0051)	(0.0046)	(0.0319)	(0.0269)
% of Total Increase	4.2	9.2	14.5	16.1
With Risk Sharing	0.0250***	0.0289***	0.1348***	0.1580***
	(0.0057)	(0.0054)	(0.0342)	(0.0292)
% of Total Increase	3.6	4.5	10.9	10.1
Difference	0.0100***	0.0090***	0.1025***	0.1029***
	(0.0034)	(0.0027)	(0.0173)	(0.0148)
% of Impact w/o Risk Sharing	28.6	23.8	43.2	39.4
Observations	58,931	78,806	9,529	12,195

Notes: Table displays the predicted impact of the trade shock on inequality of workers' earnings and of average household earnings as explained in sections 2.4.1 and 2.4.2. Inequality is measured by the Gini index $\times 100$. Values are based on the skill-group specific coefficients of Table 6 (medium run) and Table A6 (short run). "Total Increase" refers to the average annual increase in earnings inequality for the short run, see Figure 1. For the medium run, total increase is defined as the mean increase in inequality of cumulative earnings over the four intervals. *Baseline* restricts on both partners being employed in the base year. *Extended* allows for non-employment in the base year and additionally includes income from unemployment benefits. Standard errors in parentheses result from 200 bootstrap replications, clustered at the household level. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office, EUKlems.

The estimates for the short-run approach including the levels of ICT investment normalized by the lagged wage bill are very similar and can be found in Table A6 in Appendix A. Note that the short-run estimates do not include the dummy for simple tasks as it has almost no year-to-year variation within workers. The respective results for the main inequality analysis using the coefficients from Tables 6 and A6 can be found in the following Table 7. The results are still very similar to our main specification.

Equivalized household income including children. In the main specification, we ignore the existence of children and simply divide the sum of both partners' labor earnings by two. Since children partly consume household labor income but do not contribute to it in the form of own labor income, ignoring children might give an incomplete picture of the distributional effects of the trade shock. Moreover, the needs of a household do not grow proportionally with each additional household member due to increasing returns to scale in consumption, i.e. dividing total income by two might underestimate the true consumption possibilities of both partners. In a robustness check, therefore, we take both children and increasing returns to scale into account and compute equivalized household earnings (including children) for each partner. We use the OECD scale which assigns a value of one to the first household member, 0.7 to the second one, and 0.5 to each child. Consider again the example in which the husband earns 20,000 EUR in a given year and the wife earns 30,000 EUR. In this case, we would assign household-level earnings of 50,000 EUR/1.7=29,411.76 EUR to each partner if the couples had no child and 50,000 EUR/2.7=18,518.52 EUR if they had two children. Assuming that the impact on the husband's earnings is -300 EUR, while the impact on the wife's earnings is +500 EUR, we would attribute a household-level impact of 50,200 EUR/1.7 - 50,000 EUR/1.7 = 117.65 EUR to each partner if the couple had no children and 50,200 EUR/2.7 - 50,000 EUR/2.7 = 74.07 EUR if the couple had two children.

Table 8 shows the results of the inequality analysis when we use equivalized household income, including children. Since this modification only concerns household earnings, the worker-level results remain unchanged. Most importantly, both the conclusions concerning the distributional impact of the trade shock as well as the difference between worker-level results and results with household-level risk sharing remain qualitatively unchanged.

Table 8: Predicted Impact on Earnings Inequality - Equivalized HH income including children

Pred. Impact	Short Run		Medium Run	
	Baseline	Extended	Baseline	Extended
Without Risk Sharing	0.0407***	0.0521***	0.2460***	0.2961***
	(0.0054)	(0.0049)	(0.0324)	(0.0273)
% of Total Increase	4.9	12.7	15.0	18.3
With Risk Sharing	0.0252***	0.0356***	0.1380***	0.1726***
	(0.0058)	(0.0057)	(0.0347)	(0.0298)
% of Total Increase	3.6	6.5	8.4	11.0
Difference	0.0155***	0.0165***	0.1080***	0.1236***
	(0.0039)	(0.0035)	(0.0218)	(0.0194)
% of Impact w/o Risk Sharing	38.1	31.7	43.9	41.7
Observations	58,931	78,808	9,529	12,195

Notes: Table displays the predicted impact of the trade shock on inequality of workers' earnings and of average household earnings as explained in sections 2.4.1 and 2.4.2. Inequality is measured by the Gini index $\times 100$. The first two columns (short run) look at year-to-year changes, the medium-run results show changes over the respective four year interval. "Total Increase" refers to the average annual increase in earnings inequality for the short run, see Figure 1. For the medium run, total increase is defined as the mean increase in inequality of cumulative earnings over the intervals in the sample. *Baseline* restricts on both partners being employed in the base year. *Extended* allows for non-employment in the base year and additionally includes income from unemployment benefits. Standard errors in parentheses result from 200 bootstrap replications, clustered at the household level. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Changing the sharing rule. There is a growing literature on the allocation of resources between partners which argues that partners do not necessarily share household income equally. This literature models the allocation of resources within the household as a non-cooperative bargaining process and illustrates that the consumption share of one partner (or the share of household earnings the partner can consume) increases with her income share or wage share (Browning et al. 1994; Lise and Seitz 2011; Browning et al. 2013; Cherchye et al. 2015; Cherchye et al. 2016b; Cherchye et al. 2016a). Modeling intra-household bargaining over resources and structurally estimating the respective parameters is beyond the scope of this paper. Instead, we change the sharing rule such that it reflects the idea that the consumption share of one individual increases with her income share within the household. Cherchye et al. (2015) estimate the female resource share (i.e. the share of household income that is controlled by the female partner) as a function of the female/male wage ratio. Their estimates yield a female resource share of around 25% in cases where the female/male wage ratio is 0.18, a resource share of around

50% for a wage ratio of 1, and a resource share of around 0.75 in cases where the wage ratio is above 3. Our goal is to implement a corresponding sharing rule for annual income shares (we do not observe hourly or daily wages in our sample) which matches these three moments. To this end, we attribute a weight of 75% to an individual's own income and 25% to the partner's income (as compared to 50%-50% in the case of equal sharing). In the example from above, household-level earnings of the husband were 0.75*20,000 EUR + 0.25*30,000 EUR = 22,500 EUR and his household-level impact would amount to 0.75*(-300 EUR)+0.25*500 EUR = 100 EUR.

Table 9: Predicted Impact on Earnings Inequality - Incomplete Sharing

Pred. Impact	**Short Run**		**Medium Run**	
	Baseline	Extended	Baseline	Extended
Without Risk Sharing	0.0407***	0.0521***	0.2460***	0.2961***
	(0.0054)	(0.0049)	(0.0324)	(0.0273)
% of Total Increase	4.9	12.7	15.0	18.3
With Risk Sharing	0.0310***	0.0413***	0.1644***	0.2297***
	(0.0054)	(0.0051)	(0.0323)	(0.0273)
% of Total Increase	3.8	7.4	9.5	12.4
Difference	0.0097***	0.0108***	0.0816***	0.0664***
	(0.0024)	(0.0020)	(0.0123)	(0.0092)
% of Impact w/o Risk Sharing	22.6	20.7	33.2	22.4
Observations	58,931	78,808	9,529	12,195

Notes: Table displays the predicted impact of the trade shock on inequality of workers' earnings and of the weighted (75-25) average household earnings as explained in sections 2.4.1 and 2.4.2. Inequality is measured by the Gini index $\times 100$. The first two columns (short run) look at year-to-year changes, the medium-run results show changes over the respective four-year interval. "Total Increase" refers to the average annual increase in earnings inequality for the short run, see Figure 1. For the medium run, total increase is defined as the mean increase in inequality of cumulative earnings over the intervals in the sample. *Baseline* restricts on both partners being employed in the base year. *Extended* allows for non-employment in the base year and additionally includes income from unemployment benefits. Standard errors in parentheses result from 200 bootstrap replications, clustered at the household level. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

In Table 9, we perform the inequality analysis with the new sharing rule. The worker-level results are unchanged because the sharing rule only concerns allocation of money at the household level. All in all, the results remain strikingly robust to changing the sharing rule. As before, the inequality-increasing impact of the trade shock is substantially smaller at the household than at the worker level. Not surprisingly, the difference between worker and household level becomes slightly smaller as redistribution of gains and losses from the trade shock now is restricted. The results suggest that the inequality-increasing effect with household-level risk sharing is 22.6-33.2% smaller than at the worker level.

2.5.4 A closer look at risk sharing

Types of risk sharing. The difference between the worker-level effect and the effect with household-level risk sharing we observed in the previous sections can have various reasons. Take the lowest earnings deciles which benefit at the household level as compared to the worker level. This difference can be driven by workers who are negatively affected and have a partner who experiences a positive effect and thereby (partly) offsets the negative effect. Alternatively, the difference can be driven by workers who individually are not affected (or almost not) by the trade shock, but have a partner who experiences a positive impact. In both cases, income pooling and sharing would lead to positive spillovers that make the impact with household-level risk sharing on these workers more positive than the worker-level impact. Finally, the difference in the deciles which lose at the household level could be due to the mirror image of the two cases, i.e. due to the prevalence of workers who individually experience a positive effect but have a partner that incurs earnings losses or is not affected.

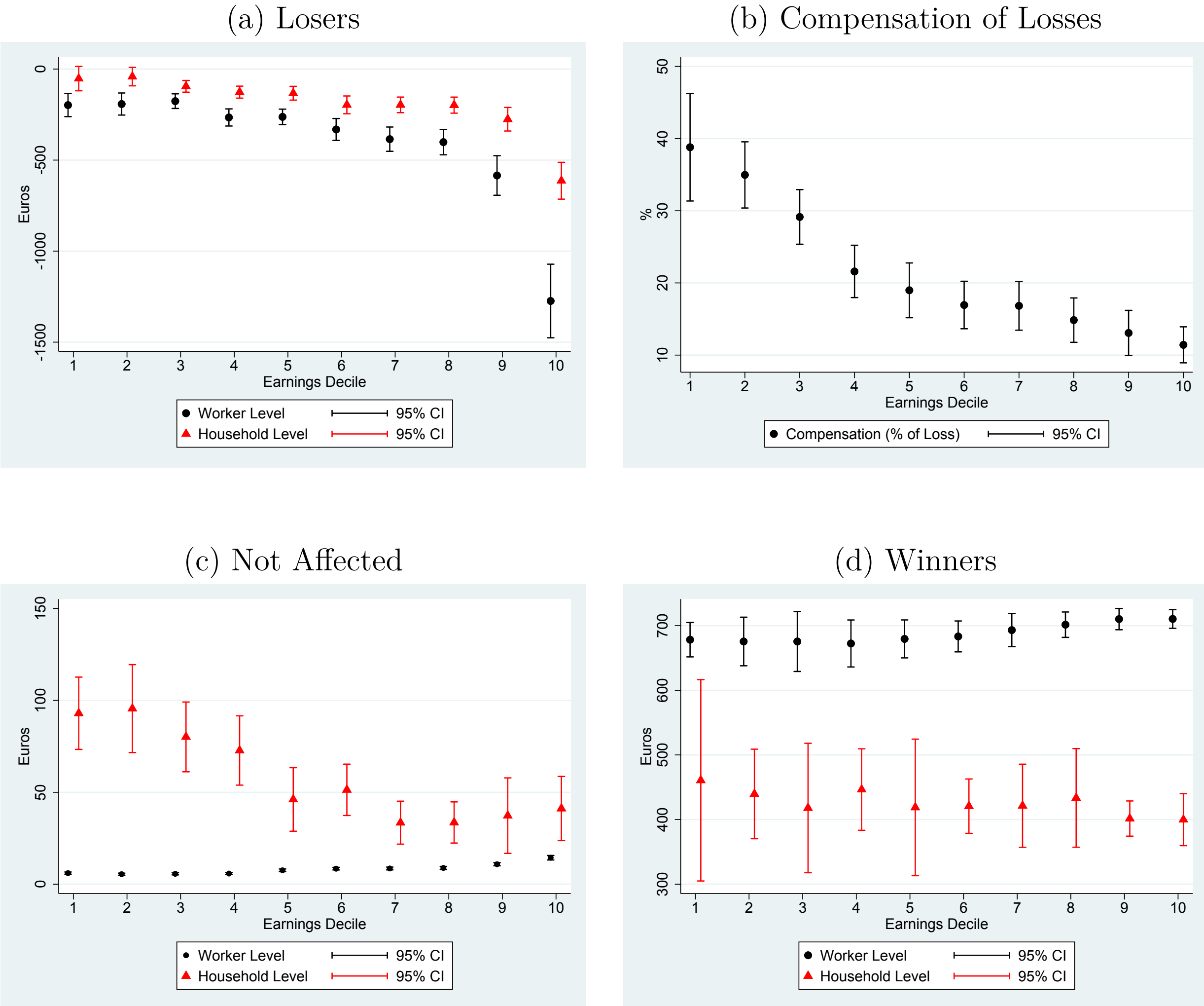
In Figure 3, we focus on couples in the short-run approach (the results from the medium-run approach are very similar and are available upon request) and differentiate between these three effects by alternatively restricting the sample on workers who experience a negative predicted impact (panels (a) and (b)), on workers who are not directly affected by the trade shock (panel (c)) and workers who experience large individual gains (panel (d)). The figure in total suggests that the risk sharing effect is driven both by compensation of losses and positive spillovers on workers who are not directly affected by the trade shock. A look at panel (a) suggests that across the whole earnings distribution, workers who experience a negative effect on average benefit from more positive effects on their partners. The difference between worker and household level in absolute terms is larger for losers at the top of the earnings distribution who incur larger losses than their low-earnings counterpart. In panel (b), we display the average share of the loss that is compensated by an offsetting positive effect on the partner. For a given worker, this share can either be zero if the partner also experiences a negative impact, or 100 if the positive effect on the partner is larger than the own negative impact. The panel suggests that compensation is largest for low-earnings workers where more than 30% of earnings losses are compensated by offsetting gains.[36]

In panel (c), we restrict on workers with a predicted impact between -50 Euros and +50 Euros, i.e. on workers who individually are not or only marginally affected by the trade

[36] This is of course partly mechanical, as low-earnings workers have lower losses in absolute terms and can therefore be compensated more easily than high-earnings workers who also have higher losses in absolute terms.

shock. We then compare for each decile the worker-level effect (which is by construction roughly equal across all deciles) to the effect with household-level risk sharing. While all unaffected workers on average benefit from positive spillovers, these are largest for low-earnings workers. Therefore, positive spillovers on unaffected workers seem to be a channel that drives the difference between the worker and the household level.

Figure 3: Types of Risk Sharing



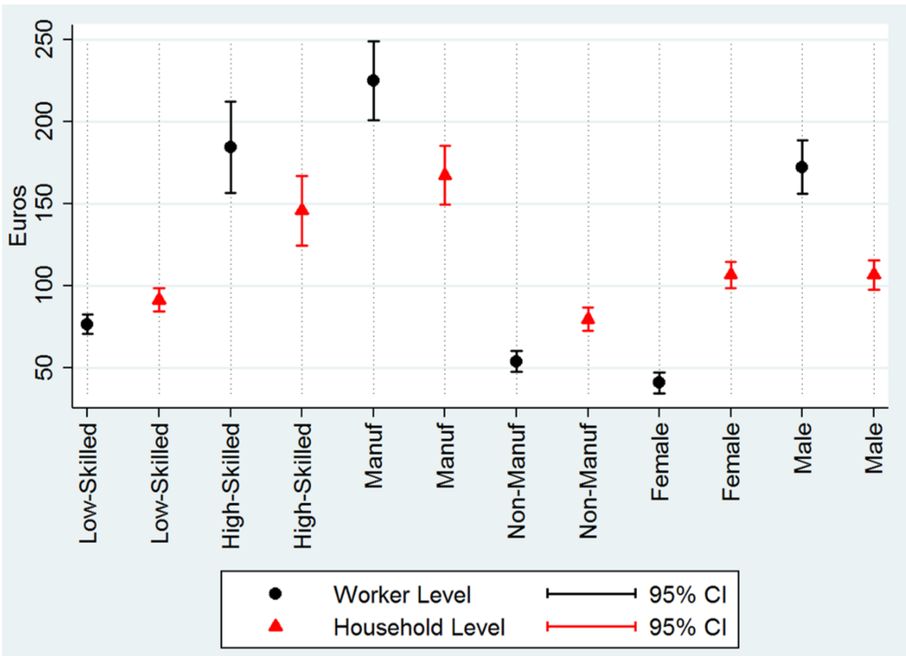
Notes: Panel (a) restricts the sample on worker-year observations with a negative predicted impact. Panel (b) displays the share of their loss that can be compensated by an offsetting positive effect on the partners. This share ranges between 0 and 100%. Panel (c) restricts the sample on worker-firm observations with a predicted impact between -50 Euros and 50 Euros. Panel (d) restricts the sample on worker-firm observations with a predicted impact between 500 Euros and 1,000 Euros. All estimates result from the short-run panel approach, baseline specification without benefits. Confidence intervals result from 200 bootstrap replications, clustered at the household level. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

In panel (d), we restrict our attention to workers who experience a large positive impact between 500 and 1,000 Euros. Again, by construction, the worker-level impact is roughly equal across all deciles. Interestingly, conditional on being a "winner", the extent of redistribution at the household level on average is roughly equal across the whole earnings distribution. This suggests that the difference between worker and household level in terms of inequality is not driven by the fact that "winners" at the top of the earnings distribution have more negatively affected partners than those at the bottom.

Who benefits from risk sharing? The results so far suggest that especially low-earnings workers benefit from more positive effects on their partners and this drives the difference between worker and household level in terms of inequality. In the following, we shed further light on who exactly benefits from risk sharing by differentiating between different groups of workers: low-skilled vs. high-skilled, manufacturing vs. non-manufacturing, and female vs. male.

In Figure 4, we plot the difference between the worker-level impact and the impact with household-level risk sharing for these categories in the short-run approach (the results from the medium-run approach are very similar and are available upon request). As expected, the worker-level impact of the trade shock is on average more positive on high-skilled workers than on low-skilled workers. Additionally, manufacturing workers are more positively affected than non-manufacturing workers and males are more positively affected than females. A comparison between worker and household level suggests that especially low-skilled workers as well as non-manufacturing and female workers on average benefit from the risk sharing effect. In contrast, high-skilled workers as well as manufacturing and male workers on average serve as an insurance for their partners.

Figure 4: Who benefits from Risk Sharing?



Notes: The figure displays the predicted impact for different groups of workers. All estimates result from the short-run panel approach, baseline specification without benefits. Confidence intervals result from 200 bootstrap replications, clustered at the household level. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

2.5.5 Active risk sharing

In the main analysis, we treat partners as independent of each other in terms of the effects of the trade shock and their adjustment behavior. By assuming that partners share total household income, the risk sharing effect we capture is essentially driven by differences in characteristics between partners, or in other words, the mating structure. However, one could imagine that partners engage in “active risk sharing”, for example by increasing their labor supply in response to a negative shock on their partner or by decreasing their labor supply in response to a positive shock on the partner. This mechanism is often called “added worker effect” (Lundberg 1985). Again, note that the aggregate distributional effects of this type of risk sharing a priori are unclear. For example, if high-income individuals who suffer from import competition have a high-income partner who cushions part of the loss by further increasing his/her labor supply, the added worker effect, ceteris paribus, counteracts a decrease in earnings inequality at the household level. The same is true in case of a positively affected low-earnings worker who decreases his/her labor supply in response to a positive shock on a high-income partner.

We employ the medium-run approach since offsetting reactions of partners tend to happen with a time lag and the shock must have a significant impact on lifetime earnings in order to trigger reactions of partners (Lundberg 1985; Maloney 1991; Stephens 2002). As compared to equation (10), we add the respective partner’s export and import exposures as additional control variables.[37] Table 10 provides the regression results.[38] First, the estimated coefficients of the own trade exposure measures remain virtually unchanged. Second, the results hint at significant reactions to partner’s trade exposure. Low export exposure and high import exposure on the partner seems to have a positive effect on normalized earnings of individuals. Analogously, the results imply lower normalized earnings for individuals whose partners are positively affected, either through high export exposure, or low import exposure, or both. The results indicate that the (partly) offsetting reactions (especially to import competition on the partner), are stronger for high-skilled individuals. This result is in line with the findings in (Stephens 2002).

[37] To be able to keep singles in the analysis, we attribute the respective mean export and import exposures of the interval to singles.

[38] Regression results for the extended specification are qualitatively similar and are available upon request.

Table 10: Medium-Run Effects of Trade Shock - Active Risk Sharing (Baseline)

Norm. cum. earnings ×100	**Whole Sample** OLS	IV	**Low-skilled** OLS	IV	**High-skilled** OLS	IV
ΔEX_{jz}	0.8358***	1.6168**	0.9961***	1.5649**	0.5704*	1.9603**
	(0.2106)	(0.6549)	(0.2654)	(0.6306)	(0.3356)	(0.9642)
ΔIM_{jz}	-0.3680**	-0.4113*	-0.4568**	-0.3772	-0.2958	-0.6609
	(0.1613)	(0.2437)	(0.2133)	(0.4232)	(0.2698)	(0.5024)
$\Delta PartnerEX_{kz}$	-0.5222**	-0.5309**	-0.5604*	-0.5577*	-0.6824**	-0.7625***
	(0.2210)	(0.2191)	(0.3261)	(0.3236)	(0.3199)	(0.2908)
$\Delta PartnerIM_{kz}$	0.0846	0.0835	0.0221	0.0094	0.4223	0.4679*
	(0.2301)	(0.2274)	(0.3170)	(0.3096)	(0.2798)	(0.2568)
R2	0.14	0.14	0.16	0.16	0.11	0.11
Observations	9,529	9,529	7,052	7,052	2,477	2,477

Notes: The table shows the estimated coefficients from equation (10), additionally controlling for the trade exposures of the partner, baseline specification without unemployed in the base year and unemployment benefits. Industry $k = j$ or $k \neq j$. Singles get assigned the average trade exposure in the respective interval as partner exposure. All estimates include base year × federal state and 1-digit industry fixed effects. Further base year controls include age, age squared, gender, a dummy for being in a single headed household, log(earnings), log(earnings) × gender, a dummy for being employed in a large company (>20 employees), a dummy for being a manager or professional, a dummy for carrying out simple tasks at work, a dummy for having children, a dummy for being fulltime employed in the base year. Standard errors clustered by 2-digit industry × (base) year in parentheses. We define individuals with ISCED<5 as being low-skilled and those with ISCED>4 as being high-skilled. Data sources: SOEPv28(2012), COMTRADE, German Federal Statistical Office.

Analogously to equation (13), it is possible to consider trade exposure on the partner for the individual predicted impact on earnings and for the distributional impact.[39] Table 11 shows the results of the inequality analysis. The effects without risk sharing remain unchanged by construction. For the effects with risk sharing, we assume equal splitting of household income and consider the regression estimates from table 10. The mitigating impact of risk sharing becomes slightly smaller, but is still sizable. The effect is smaller than in the main analysis without active risk sharing because offsetting responses by partners seem to be stronger for high-skilled individuals. This is true especially for the offsetting response to import competition on the partner.

[39] Not surprisingly, regressing the individual predicted impact on the partner's predicted impact in the scenario of active risk sharing yields a negative coefficient of -0.2775 (as compared to +0.0461 without active risk sharing, see Table 4).

Table 11: Predicted Impact on Earnings Inequality, Active Risk Sharing

Pred. Impact	**Medium Run**	
	Baseline	Extended
	(1)	(2)
Without Risk Sharing	0.2460***	0.2961***
	(0.0324)	(0.0273)
% of Total Increase	15.0	18.3
With Risk Sharing	0.1794***	0.1957***
	(0.0321)	(0.0268)
% of Total Increase	14.5	12.5
Difference	0.0666***	0.1005***
	(0.0176)	(0.0152)
% of Impact w/o Risk Sharing	27.1	33.9
Observations	9,529	12,195

Notes: Table displays the predicted impact of the trade shock on inequality of workers' earnings and of average household earnings as explained in section 2.4.1 and 2.4.2. The results with risk sharing consider the estimates in table 10 for *baseline* and the estimates of the same regression of the *extended* version (upon request). Inequality is measured by the Gini index ×100. *Baseline* restricts to employment in the base year, *extended* allows for unemployment in the base year and takes unemployment benefits into account. "Total increase" is defined as the mean increase in inequality of cumulative earnings over the four intervals. Standard errors in parentheses result from 200 bootstrap replications, clustered at the household level. Data sources: SOEPv28(2012), COMTRADE, German Federal Statistical Office.

2.6 Conclusion

To the best of our knowledge, this is the first study which investigates the distributional consequences of intra-household risk sharing in the context of a shock on the labor market. We exploit a large trade shock on the German economy that affected workers' labor market outcomes and thereby triggered an increase in earnings inequality between workers. Our results suggest that there are substantial differences between the worker and the household level, both in terms of the distributional impact and in terms of who benefited and who lost from the trade shock. More specifically, the fact that the trade shock did not affect all partners within couples similarly gave rise to a substantial risk sharing effect which reduced the worker-level impact on earnings inequality by up to 42%. Moreover, a substantial share of workers who individually benefited from the trade shock turned into losers at the household level because their partner was strongly negatively affected. Overall, our results provide evidence that a household-level perspective is vital to capture the full range of a shock which has heterogeneous effects across individuals.

Even though the extent of risk sharing might vary depending on the specific situation, the mechanism we illustrate carries over to every shock or policy which has heterogeneous effects across workers. The degree of risk sharing crucially depends on the mating structure with respect to the relevant characteristics. Changes in assortative mating as observed in different countries (e.g. Eika et al. 2014) therefore might have implications for the stabilizing role of families documented in this paper. Examining the degree to which changes in assortative mating influence the potential for intra-household risk sharing therefore constitutes an interesting avenue for future research. Finally, analyzing offsetting labor supply reactions of partners and the distributional implications in more detail might be a fruitful way to proceed.

2.7 Appendix A - Figures and tables

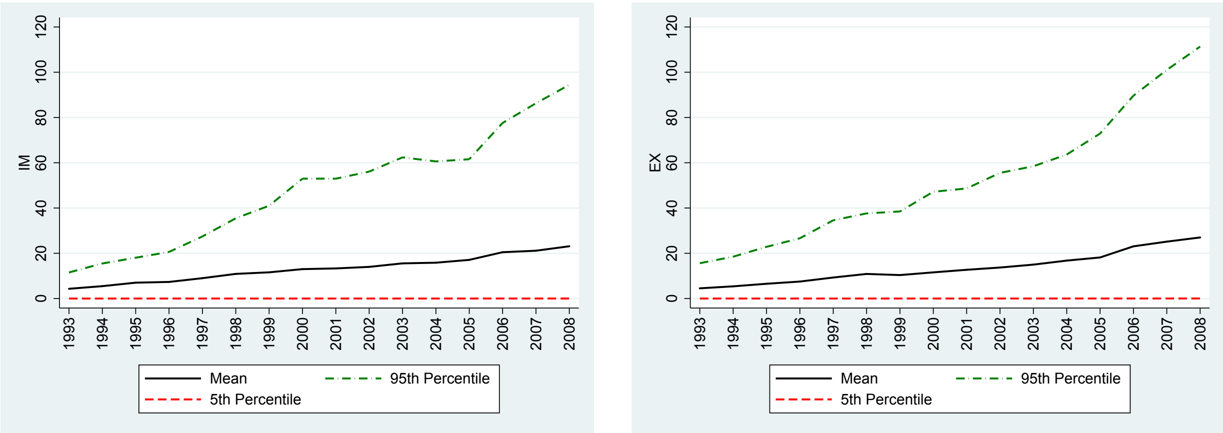
Table A1: Most Affected 2-Digit Industries (1993-2008)

Industry	ΔEX_{jt}	Industry	ΔIM_{jt}
Textiles (17)	196.03	Office Machinery (30)	456.54
Office machinery (30)	133.90	Textiles (17)	400.13
Basic metals (2)	104.70	Leather (19)	189.24
Motor vehicles (34)	89.35	Furniture (36)	176.40
Chemicals (24)	88.72	Radio and Television (32)	137.92

Notes: The table shows the five industries most affected by export exposure and import exposure, respectively. The numbers reflect the change in export (import) exposure from 1993 through 2008. Exposure measures are computed as explained in section 2.3. Industry codes in brackets. Data sources: COMTRADE, German Federal Statistical Office.

Figure A1: Variation in Trade Exposure across Workers

(a) Import Exposure (b) Export Exposure



Notes: The figure displays mean export (import) exposure across all workers in a given year as well as the respective 95th and 5th percentile. Exposure measures are computed as explained in section 2.3. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Table A2: Effects of Trade Shock - With Unemployment Benefits

(a) Short Run

Norm. annual earnings ×100	**Whole Sample** FE	**Whole Sample** IV	**Low-skilled** FE	**Low-skilled** IV	**High-skilled** FE	**High-skilled** IV
EX_{jt}	0.3486***	0.3550***	0.3659***	0.2119*	0.3344***	0.4556***
	(0.0819)	(0.1013)	(0.0815)	(0.1130)	(0.1190)	(0.1629)
IM_{jt}	-0.1127**	-0.1271**	-0.1479***	-0.0884	-0.1670***	-0.2317**
	(0.0454)	(0.0516)	(0.0390)	(0.0542)	(0.0605)	(0.0906)
R2	0.73	0.73	0.71	0.71	0.81	0.81
1st F (EX_{jt})	-	226.62	-	207.14	-	174.12
1st F (IM_{jt})	-	703.99	-	627.63	-	525.98
Observations	68,655	68,655	51,727	51,727	16,921	16,921

(b) Medium Run

Norm. cum. earnings ×100	**Whole Sample** OLS	**Whole Sample** IV	**Low-skilled** OLS	**Low-skilled** IV	**High-skilled** OLS	**High-skilled** IV
ΔEX_{jz}	0.8254***	1.4089***	0.9069***	1.2639***	0.7155***	1.9654**
	(0.1691)	(0.4885)	(0.2038)	(0.4500)	(0.2647)	(0.8166)
ΔIM_{jz}	-0.2582*	-0.3530*	-0.2814	-0.2659	-0.3058	-0.7600
	(0.1355)	(0.1995)	(0.1925)	(0.3268)	(0.2075)	(0.5354)
R2	0.16	0.16	0.19	0.19	0.11	0.11
1st F (EX_{jz})	-	22.41	-	20.23	-	23.90
1st F (IM_{jz})	-	5.14	-	5.32	-	7.77
Observations	11,143	11,143	8,201	8,201	2,942	2,942

Notes: The table shows the estimated coefficients from equations (9) and (10). The outcome variable contains both labor income and income from unemployment benefits and reliefs. Individuals who have neither labor income nor income from benefits in the base year are excluded. Panel (a): All estimates include individual, year × federal state and 1-digit industry fixed effects. Further controls include age and age squared. Panel (b): All estimates include base year × federal state and 1-digit industry fixed effects. Further base year controls include age, age squared, gender, a dummy for being in a single headed household, log(earnings), log(earnings) × gender, a dummy for being employed in a large company (>20 employees), a dummy for being a manager or professional, a dummy for carrying out simple tasks at work, a dummy for having children, a dummy for being fulltime employed in the base year. Standard errors clustered by 2-digit industry × (base) year in parentheses. We define individuals with ISCED<5 as being low-skilled and those with ISCED>4 as being high-skilled. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Table A3: First Stages of IV Estimates - Baseline Specification

(a) Short Run

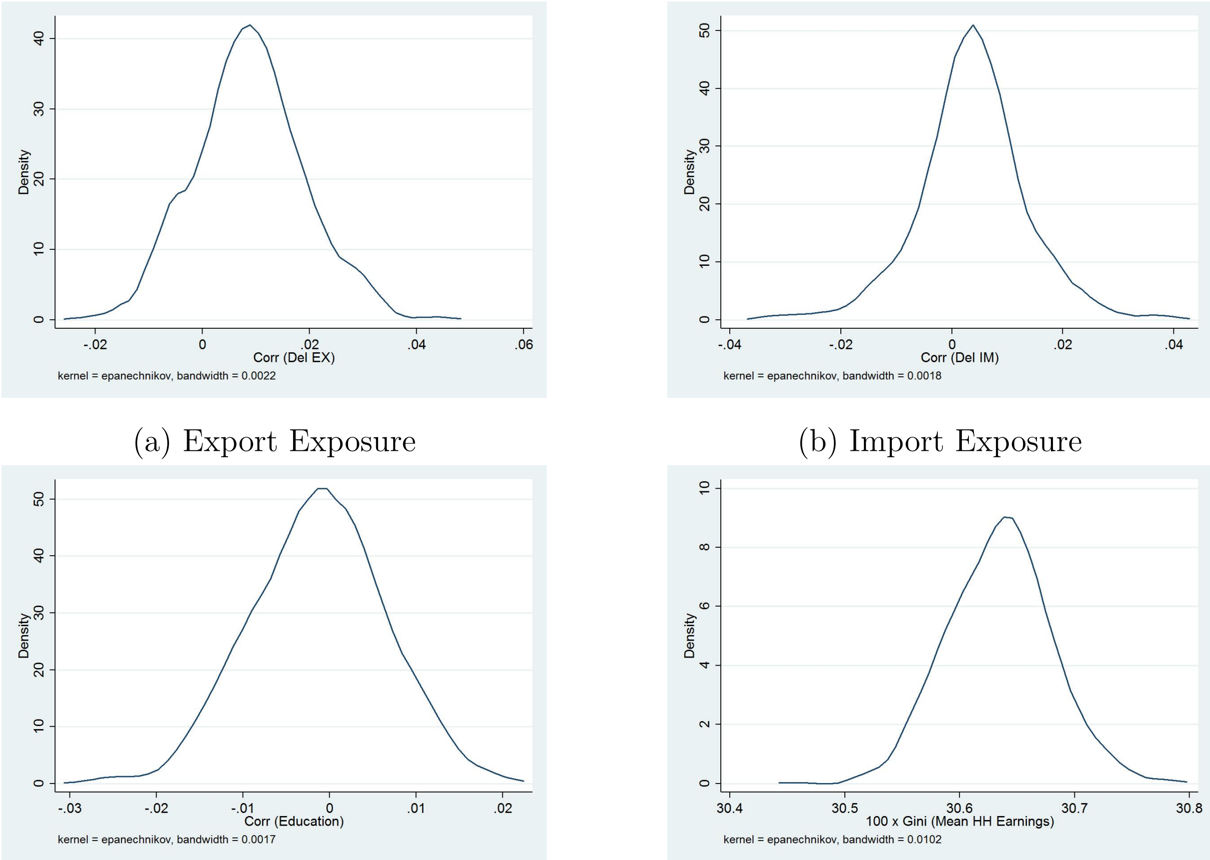
	Whole Sample		**Low-skilled**		**High-skilled**	
	EX_{jt}	IM_{jt}	EX_{jt}	IM_{jt}	EX_{jt}	IM_{jt}
EX_{jt} (Instr.)	0.5030***	0.2252***	0.5120***	0.2359***	0.4632***	0.1994***
	(0.0340)	(0.0254)	(0.03416)	(0.0256)	(0.0374)	(0.0272)
IM_{jt} (Instr.)	0.0626***	0.2809***	0.0620***	0.2817***	0.0648***	0.2766***
	(0.0061)	(0.0076)	(0.0059)	(0.0074)	(0.0085)	(0.0094)
F-statistic	217.44	700.11	215.01	671.29	144.28	533.50
Observations	58,931	58,931	44,159	44,159	14,772	14,772

(b) Medium Run

	Whole Sample		**Low-skilled**		**High-skilled**	
	ΔEX_{jz}	ΔIM_{jz}	ΔEX_{jz}	ΔIM_{jz}	ΔEX_{jz}	ΔIM_{jz}
ΔEX_{jz} (Instr.)	0.4322***	0.1507	0.4294***	0.1445	0.4324***	0.1705
	(0.0711)	(0.1227)	(0.0734)	(0.1229)	(0.0733)	(0.1325)
ΔIM_{jz} (Instr.)	-0.0210*	0.1410**	-0.0223*	0.1178**	-0.0175	0.2058**
	(0.0116)	(0.0610)	(0.0116)	(0.0464)	(0.0139)	(0.0941)
F-statistic	19.41	4.91	17.27	4.83	22.64	7.16
Observations	9,529	9,529	7,052	7,052	2,477	2,477

Notes: First stage regression corresponding to Table 2. See section 2.3 for definition of export and import exposures as well as their instruments. Instrument group: Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom. Standard errors are clustered on 2-digit industry × (base) year in parentheses. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Figure A2: Correlations under Random Mating



(a) Export Exposure

(b) Import Exposure

(c) Education

(d) Inequality of Mean HH Earnings

Notes: Kernel density plots from a simulation that matches partners using a random number within a given year in the baseline short-run sample. Singles are kept as singles. 10,000 replications.

Table A4: Predicted Impact on Earnings Inequality - Using FE / OLS Estimates

Pred. Impact	**Short Run**		**Medium Run**	
	Baseline	Extended	Baseline	Extended
Without Risk Sharing	0.0210***	0.0338***	0.0549***	0.1054***
	(0.0064)	(0.0049)	(0.0134)	(0.0127)
% of Total Increase	2.5	12.0	3.3	6.5
With Risk Sharing	0.0041	0.0177***	-0.0002	0.0480***
	(0.0072)	(0.0058)	(0.0144)	(0.0137)
% of Total Increase	0.6	2.7	-1.2	3.1
Difference	0.0169***	-0.0935***	0.0551***	0.0574***
	(0.0050)	(0.0239)	(0.0092)	(0.0077)
% of Impact w/o Risk Sharing	80.5	12.0	100.4	54.5
Observations	58,931	78,806	9,529	12,195

Notes: Table displays the predicted impact of the trade shock on inequality of workers' earnings and of average household earnings as explained in sections 2.4.1 and 2.4.2. Inequality is measured by the Gini index $\times 100$. The first two columns (short run) look at year-to-year changes, the medium run results show changes over the respective four year interval. Calculations based on the FE (short-run) and OLS (medium run) estimates of Table 2. "Total Increase" refers to the average annual increase in earnings inequality for the short run, see Figure 1. For the medium run, total increase is defined as the mean increase in cumulative earnings inequality over the intervals. *Baseline* restricts to workers who are employed in the base year. *Extended* allows for unemployment in the base year and takes unemployment benefits into account. Standard errors in parentheses result from 200 bootstrap replications, clustered at the household level. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office.

Table A5: Medium-Run Effect of Trade Shock - Technological Progress & Simple Tasks

Norm. cum.	**Whole Sample**				
earnings ×100	(1)	(2)	(3)	(4)	(5)
EX_{jz}	1.6150**	1.5645**	1.5660**	1.5133**	1.5140**
	(0.6416)	(0.6246)	(0.6253)	(0.6348)	(0.6348)
IM_{jz}	-0.4052*	-0.3366	-0.3373	-0.3202	-0.3185
	(0.2402)	(0.2415)	(0.2415)	(0.2508)	(0.2505)
Simple Tasks	-13.8246***	-13.9045***	-13.9307***	-13.8784***	-9.6664
	(5.2015)	(5.2173)	(5.2141)	(5.2105)	(6.0500)
Δ ICT		341.9148***	349.2270***		
		(90.2607)	(85.5055)		
Simple × Δ ICT			-49.7507		
			(253.1489)		
Sum ICT				48.7229***	55.3233***
				(17.7943)	(17.0147)
Simple × Sum ICT					-41.8851*
					(22.5467)
R2	0.14	0.14	0.14	0.14	0.14
Observations	9,406	9,406	9,406	9,406	9,406

Notes: Description analogous to Table 2, panel (b). Additional controls: ΔICT : change in gross fixed capital formation of ICT per 10,000 workers within each interval, Sum ICT: sum of gross fixed capital formation per 10,000 workers over the four years respectively. All trade exposure measures are instrumented. NACE= 72 excluded. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office, EUKlems.

Table A6: Short-Run Effect of Trade Shock - Controlling for Technological Progress

Norm. annual	**Whole Sample**		**Low-skilled**		**High-skilled**	
earnings ×100	(1)	(2)	(3)	(4)	(5)	(6)
EX_{jt}	0.4118***	0.4007***	0.2831***	0.2786***	0.3747**	0.3604**
	(0.1075)	(0.1079)	(0.1025)	(0.1028)	(0.1653)	(0.1656)
IM_{jt}	-0.1624***	-0.1572***	-0.1353***	-0.1332***	-0.1679**	-0.1618**
	(0.0532)	(0.0532)	(0.0509)	(0.0509)	(0.0787)	(0.0788)
ICT		143.6684**		52.7591		312.1996
		(69.0102)		(61.8420)		(214.2555)
R2	0.74	0.74	0.73	0.73	0.85	0.85
Observations	58,203	58,203	43,818	43,818	14,385	14,385

Notes: Description analogous to Table 2, panel (a). Additional controls: *ICT*: gross fixed capital formation of ICT per 10,000 workers per year. All trade exposure measures are instrumented. NACE= 72 excluded. Data sources: *SOEP v28*, COMTRADE, German Federal Statistical Office, EUKlems.

2.8 Appendix B - Mechanics of risk sharing

In the cross-section (i.e. looking at annual earnings or cumulative earnings over several years), inequality of average household earnings across individuals should always be smaller than inequality of individual earnings. However, if we look at the impact of a given shock on inequality, this is not the case. In fact, the inequality-increasing impact of a shock can in principle be larger in the scenario with risk sharing (e.g. equal sharing of household income) than in the scenario without risk sharing. To illustrate this point, we provide a simple example in which we have four individuals (a, b, c and d) with different initial incomes and a different predicted impact on earnings.

Table B1 shows a situation without any risk sharing (i.e. a pure worker-level perspective). The table shows that the Gini index, in response to the trade shock, increased by 0.00344, i.e. we observe an increase in inequality due to the trade shock. We now contrast this result to the result we get if we assume that these four individuals form two households and engage in risk sharing. We consider all three possible mating structures. In Table B2, we assume that individuals a and b form a household and individuals c and d form a household. Moreover, we suppose that partners engage in risk sharing at the household level and divide income equally between household members. This results in pre-shock income of $(50,000 + 40,000)/2 = 45,000$ EUR for individuals in household 1 (HH 1) and in $(30,000 + 10,000)/2 = 20,000$ EUR for individuals in household 2 (HH 2). The impact of the trade shock is also shared at the household level, i.e. both individual b and individual d benefit from the positive effect on their partners. In this scenario, income inequality increases only by 0.00012. Consequently, risk sharing reduces the inequality-increasing effect of the trade shock.

In Table B3, we change the mating structure such that individuals a and c are paired into a household, and individuals b and d are paired into a household. Again, the trade shock increases inequality and now, most importantly to make our point, the Gini increases by 0.00666. This increase is stronger than in the first scenario without any risk sharing. This example therefore shows that risk sharing does not mechanically reduce the inequality-increasing impact of a shock. For the sake of completeness, we show the last possible mating structure in Table B4. In this example, the constellation of partners is such that the trade shock decreases inequality after risk sharing, i.e. the Gini is reduced by 0.00441.

How is it possible that the inequality-increasing impact is reinforced by risk sharing? The reason is that risk sharing between partners (e.g. through equal sharing of household income), does not only change the distribution gains and losses from the shock across individuals. It also changes the distribution of initial incomes. Consider first the distribution of gains and losses in the example from above. In the scenario without risk sharing, the largest gain amounts to 1,000 (individual a) and the largest loss amounts to -500 (individual b). Looking at all possible mating structures, the largest gain with risk sharing is 650 (individuals a and c in mating structure 2) and the largest loss is -300 (individuals b and d in mating structure 2). As this example illustrates, risk sharing decreases the dispersion of gains and losses across individuals and this should, ceteris paribus, mitigate the inequality-increasing effect of the trade shock. However, risk sharing might also change the relative position of individuals in the distribution of incomes (after redistribution). Individual b has a relatively high initial income of 40,000. Without risk sharing, b loses 500 due to the shock and, all other things equal, this works towards a decrease in inequality. If b forms a couple with a low-income individual like d (mating structure 2), in the scenario with risk sharing, it suddenly belongs to the lower tail of the earnings distribution. Therefore, all other things equal, the loss of 500 would work towards an increase in inequality. Finally, note that all commonly used measures of inequality (Gini, Theil, etc.) are relative measures of inequality. If all incomes increase proportionally, e.g. by 10%, the share of every household in aggregate income is unaffected and therefore inequality is unaffected. If, in contrast, the rich households benefit relatively more than the poor households, inequality increases. Consider a high-income person z (income = 100) who is subject to a positive impact (impact = 50). If she has a partner with the same individual income (income = 100) and the same impact (impact = 50), z's earnings (with equal sharing) increase by 50%. In contrast, if z is matched to a low-income partner (income = 50) with the same impact (impact = 50), her earnings (with equal sharing) increase by 66%[40].

To sum up, the distribution of impacts across individuals interacts with the mating structure in a complex way. Finding out whether inequality increases by more or by less due to risk sharing between partners, as well as finding out the magnitude of the difference, is an empirical question.

[40] $\frac{(150+150)*0.5}{(100+100)*0.5} = 1.5 \Rightarrow$ increase by 50%, $\frac{(150+100)*0.5}{(100+50)*0.5} = 1.6667 \Rightarrow$ increase by 66%

Table B1: Without risk sharing

	Initial Income	Impact of Trade Shock	Income after Trade Shock	
	(1)	(2)	(3)	(4)
Individual				
a	50,000	1,000	51,000	
b	40,000	-500	39,500	
c	30,000	300	30,300	
d	10,000	-100	9,900	
				Difference:
Gini	0.25		0.25344	**0.00344**
Theil	0.12044		0.12311	**0.00267**
Sd of log	0.71371		0.72227	**0.00856**

Notes: Income and impact of trade shock are displayed in EUR. The lower part of the table shows the results of different inequality measures for the respective income distribution. In column (4), the differences between the inequality measures for initial income and income after the trade shock are displayed.

Table B2: With risk sharing - mating structure 1

		Before Sharing		After Sharing			
		Initial Income	Impact of Trade Shock	Income	Impact of Trade Shock	Income after Trade Shock	
		(1)	(2)	(3)	(4)	(5)	(6)
	Individual						
HH 1	**a**	50,000	1,000	45,000	250	45,250	
	b	40,000	-500	45,000	250	45,250	
HH 2	**c**	30,000	300	20,000	100	20,100	
	d	10,000	-100	20,000	100	20,100	
							Diff.:
			Gini	0.19231		0.19243	**0.00012**
			Theil	0.07591		0.076	**0.00009**
			Sd of log	0.46819		0.46851	**0.00032**

Notes: Income and impact of trade shock are displayed in EUR. Columns (1) and (2) show each individual's initial income and her impact of the trade shock before any risk sharing takes place. In column (3) - (5) we assume that individuals split income equally and redistribute gains and losses from the trade shock at the household level. The lower part of the table shows the results of different inequality measures for the respective income distribution. In column (6), the differences between the inequality measures of column (5) and column (3) are displayed.

Table B3: With risk sharing - mating structure 2

		Before Sharing		**After Sharing**			
		Initial Income	**Impact of Trade Shock**	**Income**	**Impact of Trade Shock**	**Income after Trade Shock**	
		(1)	(2)	(3)	(4)	(5)	(6)
	Individual						
HH 1	**a**	50,000	1,000	40,000	650	40,650	
	c	30,000	300	40,000	650	40,650	
HH 2	**b**	40,000	-500	25,000	-300	24,700	
	d	10,000	-100	25,000	-300	24,700	
							Diff.:
			Gini	0.11538		0.12204	**0.00666**
			Theil	0.02687		0.03009	**0.00322**
			Sd of log	0.27136		0.28763	**0.01627**

Notes: Income and impact of trade shock are displayed in EUR. Columns (1) and (2) show each individual's initial income and her impact of the trade shock before any risk sharing takes place. In column (3) - (5) we assume that individuals split income equally and redistribute gains and losses from the trade shock at the household level. The lower part of the table shows the results of different inequality measures for the respective income distribution. In column (6), the differences between the inequality measures of column (5) and column (3) are displayed.

Table B4: With risk sharing - mating structure 3

		Before Sharing		**After Sharing**			
		Initial Income	**Impact of Trade Shock**	**Income**	**Impact of Trade Shock**	**Income after Trade Shock**	
		(1)	(2)	(3)	(4)	(5)	(6)
	Individual						
HH 1	**a**	50,000	1,000	30,000	450	30,450	
	d	10,000	-100	30,000	450	30,450	
HH 2	**b**	40,000	-500	35,000	-100	34,900	
	c	30,000	300	35,000	-100	34,900	
							Diff.:
			Gini	0.03846		0.03405	**-0.00441**
			Theil	0.00296		0.00232	**-0.00064**
			Sd of log	0.089		0.07875	**-0.01025**

Notes: Income and impact of trade shock are displayed in EUR. Columns (1) and (2) show each individual's initial income and her impact of the trade shock before any risk sharing takes place. In column (3) - (5) we assume that individuals split income equally and redistribute gains and losses from the trade shock at the household level. The lower part of the table shows the results of different inequality measures for the respective income distribution. In column (6), the differences between the inequality measures of column (5) and column (3) are displayed.

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3 Diverging paths: Labor reallocation, sorting, and wage inequality

Diverging paths: Labor reallocation, sorting, and wage inequality

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This paper provides evidence that labor reallocation from the manufacturing into the non-manufacturing sector causes an increase in sorting of high-skilled (low-skilled) workers into high-paying (low-paying) firms and thereby triggers a rise in wage inequality. I use data on 50% of all West German male employees and exploit industry-level variation in trade-induced labor reallocation into the non-manufacturing sector, stemming from Germany's trade integration with China and Eastern Europe. The results suggest that labor reallocation into the non-manufacturing sector causes an increase in sorting because low-educated workers performing routine and codifiable tasks are less likely to move to high-paying service firms than more skilled workers. These results are not specific to trade-induced labor reallocation, but carry over to any shock or policy which causes a contraction of the manufacturing sector and labor reallocation into the service sector. A back-of-the-envelope calculation suggests that total observed labor reallocation into the non-manufacturing sector explains at least 30% of the rise in sorting and 10% of the rise in wage inequality between 1990 and 2010 in Germany.

JEL-Classification: J31, J62, F14
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3.1 Introduction

Wage inequality has increased substantially in the USA, Germany, and other industrialized countries during the last decades (e.g. Dustmann et al. 2009; Acemoglu and Autor 2011; Antonczyk et al. 2018). To fully understand the causes of this phenomenon, it is crucial to understand the role that firms play for the wage structure. The idea that some firms pay higher wages than others for similarly skilled workers has a long tradition in the economic literature (e.g. Slichter 1950; Dickens and Katz 1987; Krueger and Summers 1988). Existing firm-specific wage premiums contribute to the overall wage dispersion in different countries (e.g. Card et al. 2013; Card et al. 2018; Alvarez et al. 2018; Song et al. 2019).[1]

In the presence of firm-specific wage premiums, changes in sorting of workers across high-paying and low-paying firms affect wage inequality. Indeed, recent evidence suggests that the allocation of workers across firms has changed fundamentally during the last decades. In the USA and Germany, high-skilled (low-skilled) workers have become more likely to be employed by high-paying (low-paying) firms. This increase in sorting accounts for about one third of the rise in wage inequality in both countries (Card et al. 2013; Song et al. 2019). Despite its relevance for wage inequality, the causes of the increase in sorting are not yet fully explored.

This paper analyzes the impact of structural change, in the form of labor reallocation from the manufacturing into the non-manufacturing sector, on sorting, and the resulting effect on wage inequality. Structural change is a salient feature in many industrialized countries. In Germany, manufacturing employment has decreased by about 20% from 1994 through 2014 (Dauth et al. 2017). Partly, the decline in manufacturing employment and the simultaneous expansion of the service sector have been fueled by labor mobility between sectors. A common explanation for the secular decline in manufacturing employment is labor-saving technological progress in the manufacturing sector (Herrendorf et al. 2014).[2] Understanding the distributional effects of decreasing manufacturing employment is especially relevant as manufacturing employment might further decline due to technological progress or other reasons in the future.

How can labor reallocation cause an increase in sorting? In a first step, I make use of data on 50% of all West German male employees from 1985 through 2010 to provide two novel descriptive findings which suggest a channel through which labor reallocation affects sorting. To this end, I build on Abowd et al. (1999) and decompose log wages of

[1] Building on Abowd et al. (1999), these studies control for observable and unobservable differences in workforce composition across firms and obtain measures of a proportional wage premium or discount which the firm pays to all its employees. See section 3.2 for more details.

[2] Other potential explanations are rising income levels paired with non-homothetic preferences over manufacturing and service goods (Herrendorf et al. 2014) and rising import competition from low-wage countries (e.g. Autor et al. 2013; Pierce and Schott 2016). See Herrendorf et al. (2014) for a more detailed overview of the trends in structural change and potential causes.

workers into a permanent worker component which is assumed to be portable across firms and a firm component. The firm component reflects a wage premium or discount that the firm pays to all its employees.

First, I provide evidence that estimated firm wage premiums differ between the manufacturing and the non-manufacturing sector. The manufacturing sector offers comparatively high wage premiums, potentially because of the strong role that unions play in this sector.[3] The non-manufacturing sector, in contrast, contains a segment of firms paying wage premiums that are comparable to those in the manufacturing sector, and a segment of firms paying substantially lower wage premiums. Partly, the dispersion within the non-manufacturing sector reflects a divide between high-end service industries like financial intermediation and low-wage service industries such as industrial cleaning. Firm wage premiums, however, also differ across firms within industries.

The second main descriptive finding suggests that manufacturing workers with low formal education performing routine and codifiable tasks have lower access to high-paying non-manufacturing firms than more skilled manufacturing workers.[4] Potential reasons are inherent differences in the skill requirements between high-paying and low-paying non-manufacturing firms or skill-biased technological change in high-paying non-manufacturing industries or firms. As low-skilled and high-skilled manufacturing workers tend to be employed by firms paying similar wage premiums, this implies that a contraction of the manufacturing sector which triggers labor reallocation into the non-manufacturing sector causes an increase in sorting and wage inequality. Importantly, in this case, sorting and wage inequality increase even if high-skilled and low-skilled workers are equally likely to move into the non-manufacturing sector in response to a given shock or policy.

In the main empirical analysis, I then isolate a shock which generates labor mobility from the manufacturing into the non-manufacturing sector for all skill groups. I exploit industry-level variation in labor reallocation from the manufacturing into the non-manufacturing sector, stemming from Germany's trade integration with China and Eastern Europe. Triggered to a large extent by China's transformation into a market economy and the fall of the Iron Curtain, Germany's exports to and imports from China and Eastern Europe increased by more than 1,000% between 1990 and 2010. This trade shock played out differently across manufacturing industries and thereby created variation in involuntary labor reallocation into the non-manufacturing sector. Workers employed in import-exposed industries experience increasing rates of displacement at their initial firm. In the light of the overall contraction of the manufacturing sector, moving into the non-manufacturing sector is the most viable path for displaced workers. Growing imports

[3]See for example Hirsch and Mueller (2018) who find that German firms bound by collective bargaining agreements and firms with a works council pay higher wage premiums on average.

[4]High-paying firms are firms whose estimated firm wage premium is in the upper tercile in the whole economy in a given year. Analogously, low-paying firms are firms in the lowest tercile.

therefore accelerate the ongoing process of labor reallocation by moving workers into the non-manufacturing sector at higher rates. Growing export opportunities, in contrast, constitute a positive demand shock on the industry and translate into increased job stability for workers employed in these industries. Rising exports therefore slow down the process of labor reallocation by retaining manufacturing jobs.[5] In the main empirical analysis, I focus on worker mobility from the manufacturing into the non-manufacturing sector over a period of ten years and exploit variation in increasing net import exposure across manufacturing industries over time, conditional on a variety of controls at the worker, firm, industry, and region level.

As expected, the results suggest that workers initially employed in manufacturing industries that experience a higher increase in net import exposure face a higher probability of leaving the initial industry, which translates into a higher probability of moving into the expanding service sector. Consistent with the idea that growing import competition constitutes a negative demand shock on the whole industry, this effect is identical across skill groups.

In contrast, the allocation to high-paying and low-paying non-manufacturing firms differs substantially across skill groups. The results provide robust evidence that high-skilled and low-skilled workers initially employed in manufacturing firms paying similar wage premiums sort into firms paying different wage premiums within the non-manufacturing sector. Highly educated workers performing complex tasks mostly move to high-wage non-manufacturing firms and thereby curb the resulting loss in firm wage premiums and wages. Low-educated workers performing routine and codifiable tasks more often reallocate to low-wage non-manufacturing firms and therefore experience a loss in firm wage premiums and wages, relative to more skilled workers. Through the resulting increase in sorting upon formal education and tasks, labor reallocation causes an increase in the skill premium and in residual wage inequality. The effects are the result of sorting between and within non-manufacturing industries. High-skilled workers are better able to reallocate into high-paying service industries, especially in the business services industry, and more often move to the highest-paying firms within the respective service industry.

Overall, the results provide evidence that the rise in sorting documented by Card et al. (2013) and Song et al. (2019) for Germany and the USA is strongly related to labor reallocation from the manufacturing into the non-manufacturing sector. These results are not specific to trade-induced labor reallocation. They carry over to any shock or policy which causes a contraction of the manufacturing sector and thereby triggers labor mobility into the non-manufacturing sector. Importantly, the results suggest that sorting and wage inequality increase even if a given shock causes higher mobility into the non-manufacturing

[5]The previous literature provides strong evidence in favor of the accelerating and decelerating effects of trade with China and Eastern Europe on labor reallocation (e.g. Autor et al. 2014; Dauth et al. 2014; Dauth et al. 2017; Dauth et al. 2019a; Utar 2018). The literature, however, does not focus on sorting of workers across high-paying and low-paying firms within the non-manufacturing sector.

sector to the same extent for all skill groups. The most conservative back-of-the-envelope calculation suggests that total observed labor reallocation from the manufacturing into the non-manufacturing sector and the resulting relative loss of firm wage premiums for low-wage workers explains at least 30% of the rise in sorting and 10% of the rise in wage inequality between 1990 and 2010.

The findings imply that a further decline of manufacturing employment, potentially driven by technological progress, a negative demand shock, or any other cause, might go along with increasing wage inequality in the future. From the perspective of a policymaker who aims to curb the resulting distributional effects, the analysis in this paper suggests a strong focus on the set of skills which enable a worker to take up a high-paying job in the service sector. In contrast, a mere focus on bringing displaced manufacturing workers into full-time employment in the expanding service sector is not sufficient to fully curb the distributional effects.

This paper is related to Goldschmidt and Schmieder (2017) who provide evidence that high-paying firms have increasingly outsourced workers in low-wage occupations to low-wage business service firms (domestic outsourcing), contributing to the rise in sorting and wage inequality in Germany. To the extent that domestic outsourcing is performed by manufacturing firms, it also involves labor reallocation from manufacturing into non-manufacturing. In Goldschmidt and Schmieder (2017), this reallocation causes a rise in sorting because a selected group of low-skilled workers are moved into low-wage service firms, whereas more skilled workers remain employed in the manufacturing firm. In contrast, this paper provides evidence that sorting increases even if the initial shock triggering structural change in the form of labor mobility is homogeneous across skill groups. The results in this paper therefore speak to structural change more generally and carry over to all shocks or policies which trigger a contraction of manufacturing industries and thereby induce labor reallocation into non-manufacturing.

The previous literature offers globalization and technological progress as potential drivers of increased sorting. A number of studies emphasize the effects of technological progress on sorting in the context of complementarities between skills and technologies (Acemoglu 1999; Kremer and Maskin 1996; Håkanson et al. 2015). Globalization can affect sorting as it allows firms to decrease the range of tasks performed within the firm through outsourcing (Feenstra and Hanson 1996; Grossman and Rossi-Hansberg 2008) and as it allows high-skilled workers to match with foreign high-skilled workers rather than with domestic low-skilled workers (Kremer and Maskin 2006). The previous empirical literature on the impact of international trade on sorting across high-paying and low-paying firms focuses on sorting within industries or sectors (Davidson et al. 2014; Baziki et al. 2016; Borrs and Knauth 2016).[6] This paper, in contrast, provides evidence

[6]More generally, research along the lines of Melitz (2003) focuses on the effects of trade on the intra-industry reallocation of economic activity towards the most productive firms and the resulting effects

on a systematic link between trade-induced labor reallocation into the non-manufacturing sector on economy-wide sorting and wage inequality. As most of the low-paying firms in the economy are non-manufacturing firms, a focus on within-industry or within-sector sorting potentially understates the overall effects on sorting and wage inequality

The paper also contributes to the literature on the distributional effects across workers of imports from China and in some cases Eastern Europe (Autor et al. 2014; Dauth et al. 2014; Ashournia et al. 2014; Nilsson Hakkala and Huttunen 2016; Dix-Carneiro and Kovak 2017a; Utar 2018; Dauth et al. 2019a; Keller and Utar 2019; Huber and Winkler 2019). This literature typically focuses on the effects of import exposure on cumulative earnings or employment over several years and thereby potentially captures purely transitional effects, for example coming from temporary unemployment or temporarily depressed wages, and more long-run effects which persist in the new equilibrium after the economy has adjusted. The relative magnitude of these two types of effects are not yet fully explored. This paper provides evidence on a mechanism through which distributional effects persist in the medium-run and long-run, even after workers of all skill levels have moved out of import-exposed industries and found full-time employment in non-manufacturing. In particular, this paper suggests that bringing trade-displaced workers into full-time employment in the service sector is not sufficient to fully curb the resulting distributional effects.[7] By emphasizing long-run distributional effects of import exposure, the paper is related to the literature about the long-lasting effects of job loss on workers' earnings (e.g. Jacobson et al. 1993).

Studies with more structural approaches estimate sizable adjustment costs arising to workers who move between sectors (e.g. Lee and Wolpin 2006; Artuc et al. 2010; Dix-Carneiro 2014). The results in this paper suggest that the degree of adjustment costs that arise for a worker who reallocates into the non-manufacturing sector is intimately related to the ability of moving into high-paying firms, both between and within non-manufacturing industries. By emphasizing the role that tasks performed on the job play for the ability to reallocate to high-paying firms, the paper contributes to a growing literature which documents the important role that tasks performed at the workplace play for the distributional effects of technological progress and globalization (e.g. Autor et al. 2003; Spitz-Oener 2006; Autor et al. 2008; Gathmann and Schoenberg 2010; Becker et al. 2013; Goos et al. 2014; Hummels et al. 2014; Ebenstein et al. 2014; Becker and Muendler 2015).

on within-industry wage inequality (e.g. Helpman et al. 2010; Egger and Kreickemeier 2012; Krishna et al. 2014; Egger et al. 2016; Helpman et al. 2016). See Helpman (2017) or Muendler (2017) for more extensive overviews of the literature.

[7] Dauth et al. (2019a) provide evidence for Germany that more skilled workers garner higher cumulative earnings in the non-manufacturing sector than less skilled workers, in response to growing import competition. However, this difference can be driven by faster reallocation and lower temporary unemployment (i.e. transitional effects) and do not necessarily reflect higher wages conditional on employment in the non-manufacturing sector.

With its focus on structural change and wage inequality, the paper is related to Cravino and Sotelo (2019) who analyze the effects of trade-induced structural change on the skill premium in a quantitative trade model. Buera and Kaboski (2012) theoretically and empirically analyze the link between the rise in skill-intensive service industries and the rise in the skill premium. These studies do not focus on worker-firm sorting and its effects on the skill premium. The results in this paper are consistent with their finding that structural change raises the skill premium. Finally, the paper is also related to Dauth et al. (2019b) who analyze the role of agglomeration effects for within-city sorting of workers across firms.

3.2 Data and AKM estimation

3.2.1 Main data sources

The main data source in this paper is the Employee History Dataset (BeH, V.09.05.00), provided by the Institute for Employment Research in Nuremberg, Germany. The BeH contains information on all German workers subject to social security contributions. It is based on employers' notifications to the social security insurance and therefore is highly reliable. The dataset contains information on workers' wages, industry-affiliation, location, and a large battery of socio-economic variables on a daily basis. Crucially for the question in this paper, the data allow to follow workers over time as they move between firms[8], between and within industries, sectors, occupations, and regions. I make use of a 50% random sample of all West German male full-time employees in the BeH. I impute missing and inconsistent education data with the help of Fitzenberger et al. (2005)'s approach. Since wages are right-censored at the contribution ceiling to social security, I impute censored wages using the procedure described in Card et al. (2013).[9]

The data on exports and imports stem from the United Nations Commodity Trade Database (Comtrade). This database provides annual statistics on commodity trade of more than 170 countries. I convert the trade flows into Euros of 2010 using the exchange rates of the German Bundesbank. With help of the correspondence between the SITC rev.3 product codes and NACE codes provided by the UN Statistics Division, I then aggregate the product-level trade flows to trade flows at the 3-digit industry level. I then match them to the BeH with the help of the industry identifier.

Finally, I use data from the BIBB/BAuA Employment Surveys. These surveys are carried out by the German Federal Institute for Vocational Training and the Institute for Employment Research. They contain a random sample of about one tenth of a percent of

[8] I use the terms "firm" and "establishment" interchangeably. With the datasets used in this paper, I observe establishments and cannot determine to which firm a given establishment belongs. The same is true for the analysis in Card et al. (2013).

[9] The data do not allow to observe workers who are unemployed, self-employed, or employed in the public sector as civil servants.

the German labor force in a given year. The surveys provide information about workplace characteristics and requirements that I use to construct measures for tasks performed at the workplace.

3.2.2 AKM estimation

The wage decomposition pioneered by Abowd et al. (1999) and applied to the German context by Card et al. (2013) forms the basis of the analysis in this paper. I carry out the wage decomposition separately for five six-year intervals: 1985-1990, 1990-1995, 1995-2000, 2000-2005, and 2005-2010. Following Card et al. (2013), I select the worker-firm observation with the highest cumulative earnings among all full-time worker-firm observations within a given year. The resulting sample consists of 30-35 million observations in each interval. I estimate the following "AKM regression" separately for each interval:

$$y_{i\tau} = \alpha_i + \psi_{J(i\tau)} + x'_{i\tau}\beta + r_{i\tau} \tag{1}$$

In this equation, $y_{i\tau}$ denotes the log daily wage of worker i in year τ. α_i reflects the worker component of the wage. It captures all time-invariant observable and unobservable worker characteristics that influence his wage and is assumed to be portable across employers. It captures the effects of formal education as most of the workers in the sample have already completed their education. It also captures time-invariant effects of the worker's occupation and tasks performed on the job as well as time-invariant unobservables like motivation and unobserved ability.

$J(i\tau)$ is a function that gives the identity of firm j that employs worker i in year τ. ψ_j can be interpreted as a proportional wage premium or wage discount that firm j pays to its employees, i.e. all workers for which $J(i\tau) = j$. A potential explanation for the existence of these wage premiums and the resulting deviation from the law of one price for skill is rent sharing. The results of several studies for different countries suggest that rent sharing indeed is an important explanation. For example, in line with the idea of rent sharing, Card et al. (2018) find that more productive Portuguese firms pay higher wage premiums on average. This result is consistent with a link between the productivity dispersion across firms and the wage dispersion found in the previous literature (e.g. Faggio et al. 2010; Barth et al. 2016). Using German data, Hirsch and Mueller (2018) find that firms bound by collective bargaining agreements and firms with a works council pay higher wage premiums, conditional on productivity. While this paper is largely agnostic about the underlying causes of firm wage premiums, the results are consistent with rent sharing being an important factor.[10]

[10] A further potential explanation is that firms pay wage premiums of different size to compensate workers for differences in non-wage job characteristics (e.g. Mas and Pallais 2017). While I cannot rule of that some changes in wage premiums are compensated by non-wage characteristics, the focus in this paper on comparatively large changes in wage premiums makes it unlikely that non-wage characteristics

$x'_{i\tau}$ is a vector of control variables that includes year dummies and a quadratic and cubic term in age fully interacted with education dummies as in Card et al. (2013). Finally, $r_{i\tau}$ is the error term, for which I assume mean zero and orthogonality to worker and firm effects, conditional on the control variables. This empirical specification closely follows Card et al. (2013).[11] Appendix 3.9 provides more details on the estimation of equation 1.

Terciles. In parts of the main empirical analysis, I group all firms in the sample in a given year (manufacturing and non-manufacturing) into three terciles, based on the estimated firm wage premiums $\hat{\psi}_j$: high-wage, medium-wage, and low-wage firms. I do this separately for three years: 1990, 2000, and 2010. These years correspond to the start and end dates of the two intervals 1990-2000 and 2000-2010 for which I carry out the main analysis. To group firms into terciles in 1990 (2000, 2010), I use the estimated firm wage premiums from interval 1985-1990 (1995-2000, 2005-2010).

A potential concern in the estimation of equation 1 is measurement error of the estimated firm wage premiums (Andrews et al. 2008). By using the tercile of the firm by which a worker is employed as an outcome variable in the main analysis, I allow for a substantial degree of measurement error in the estimated firm wage premium. A potential downside of this strategy is that it discards differences in firm wage premiums within terciles. Therefore, I also employ the estimated firm wage premium directly as an outcome. Analogously to the procedure for firms, I rank workers into three terciles based on their estimated worker component $\hat{\alpha}_i$: high-wage, medium-wage, and low-wage workers.

3.3 Descriptives on labor reallocation and sorting

3.3.1 Aggregate trends

Figure 1 illustrates that the rise in wage inequality and the increase in labor market sorting in Germany coincided with a decline in the manufacturing employment share. The blue lines in figure 1 show that wage inequality, as measured by the variance of log daily wages for male full-time employed workers, increased by about 13 log points between the first and the last interval.[12] The red lines show that the increase in sorting accounts for around one third of the rise in wage inequality. More specifically, based on the estimation of equation 1, one can apply a variance decomposition to give a descriptive overview of the role of worker and firm components as well as the role of sorting for the rise in wage inequality. The part of the variance of log wages which is driven by sorting in

provide a full compensation for the estimated effects.

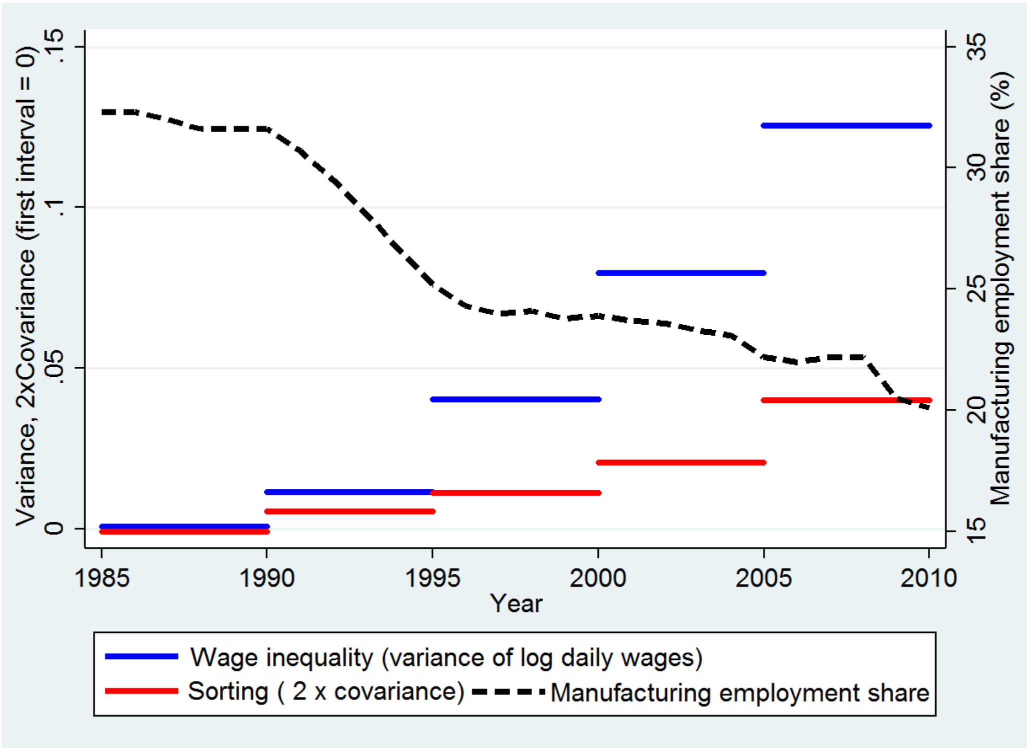
[11] For the purpose of this paper, I choose slightly different time intervals for the decomposition than Card et al. (2013). Another difference is that I employ a 50% sample, whereas Card et al. (2013) have access to the full universe of West German employees. The results of the variance decomposition are very similar to those in Card et al. (2013). I am grateful to Linda Borrs and Florian Knauth for sharing their Matlab code for the decomposition.

[12] In this figure, I pool all observations in a given 6-year-interval. Alternatively, figure D1 in the appendix shows the same trend by plotting various annual wage percentiles over time.

a given interval is $2cov(\hat{\alpha}_i, \hat{\phi}_{J(i\tau)})$.[13] The increase of the covariance over time suggests that high-skilled workers have become relatively more likely to be employed by high-paying firms. This result is consistent with the findings by Card et al. (2013) for Germany. In a recent study, Song et al. (2019) provide results of similar magnitude for the USA.

Finally, figure 1 plots the evolution of the manufacturing employment share in Germany over time. This share has decreased from about 33% in 1985 to about 20% in 2010. The manufacturing sector has also contracted in absolute terms. Dauth et al. (2017) report that total manufacturing employment has decreased by about 20% from 1994 through 2014. Figure D2 in the appendix illustrates that other countries experienced very similar decreases in the manufacturing employment share.

Figure 1: Wage inequality, sorting, and structural change



Notes: The dashed line depicts the manufacturing employment share in Germany in a given year. See figure D2 for a cross-country comparison. The blue lines depict the level of wage inequality, as measured by the variance of log daily wages of full-time employed workers in a given interval, as a deviation from the level of wage inequality in the first interval 1985-1990. The red lines depict the level of sorting, as measured by twice the covariance between estimated worker components and firm wage premiums in a given interval, as a deviation from the level of sorting in the first interval 1985-1990. See section 3.2 for a more detailed explanation of the data preparation and wage decomposition. Data sources: BeH and U.S. Bureau of Labour Statistics.

[13] The total variance decomposition reads as follows: $var(\hat{y}_{i\tau}) = var(\hat{\alpha}_i) + var(\hat{\phi}_{J(i\tau)}) + var(\hat{\beta x'}_{i\tau}) + 2cov(\hat{\alpha}_i, \hat{\phi}_{J(i\tau)}) + 2cov(\hat{\alpha}_i, \hat{\beta x'}_{i\tau}) + 2cov(\hat{\phi}_{J(i\tau)},, \hat{\beta x'}_{i\tau}) + var(\hat{r}_{i\tau})$. See appendix 3.9 for more details.

3.3.2 Descriptives on potential channels

Differences between sectors. The first main descriptive finding is that the absolute size and the dispersion of firm wage premiums differ between the manufacturing and the non-manufacturing sector. Figure 2 plots the employment-weighted distribution of estimated firm wage premiums in 1990 and 2000, separately by sector. First, it shows that estimated firm wage premiums on average are higher in the manufacturing sector. In 1990, the difference in the employment-weighted average firm wage premium between the manufacturing and the non-manufacturing sector amounts to ten log points. A plausible explanation for the difference in levels across sectors is the higher collective bargaining density in manufacturing, illustrated for example by Oberfichtner and Schnabel (2018). Hirsch and Mueller (2018) provide evidence that German firms bound by collective bargaining agreements and firms with a works council pay higher wage premiums on average.

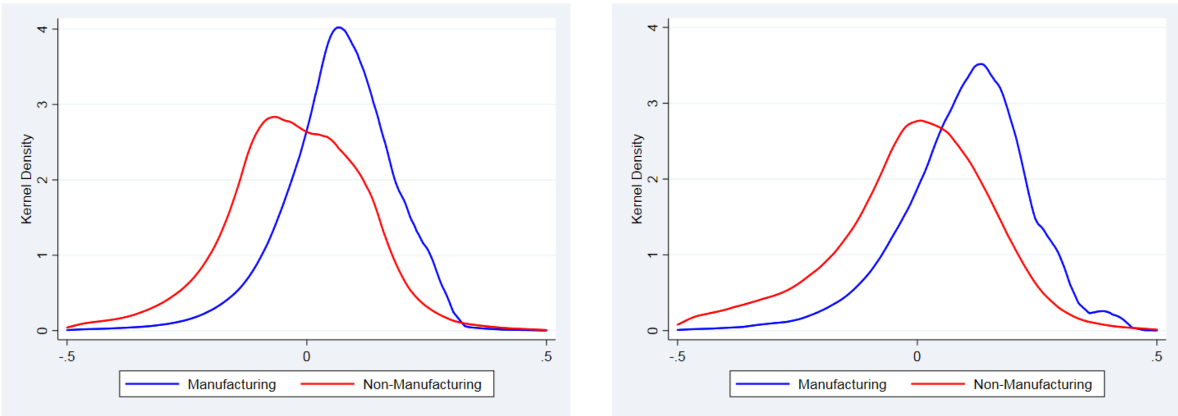
Additionally, figure 2 illustrates that the distribution of firm wage premiums in the non-manufacturing sector is larger than in the manufacturing sector. In particular, the upper part of the distribution within the non-manufacturing sector overlaps with parts of the distribution in the manufacturing sector. This means that the non-manufacturing sector contains a segment of high-paying firms which offer wage premiums that are comparable to or higher than in the average manufacturing firm. However, it also contains a segment of low-paying firms which offer substantially lower wage premiums than in manufacturing. Partly, the dispersion within non-manufacturing reflects a divide between high-end service industries and low-skill service industries. For example, in 1990, the mean firm wage premium in a service industry like financial intermediation (0.10) is slightly higher than in the average manufacturing firm (0.07). In contrast, the mean wage premium in the hotel industry (-0.28) is substantially lower. Table D1 in the appendix provides a list of mean firm wage premiums in selected industries. It is, however, important to note that firm wage premiums also vary substantially within industries, as reflected by the high standard deviations in table D1.[14]

Overall figure 2 illustrates the large heterogeneity in estimated firm wage premiums. The mean firm wage premium within the upper tercile in the economy in 1990 is about 50 (20) log points higher than the mean wage premium in the lower (middle) tercile. For comparison, the wage gap between a worker at the 75th and a worker at the 25th percentile in the raw data in 1990 (2000) amounts 43 (50) log points. Mobility between firms located at different part of the distribution of firm wage premiums therefore corresponds to substantial mobility in the overall earnings distribution.

[14] The pattern which is illustrated by figure 2 is robust across time. Figure D3 shows the same result for the year 2010.

Figure 2: Firm wage premiums: manufacturing vs. non-manufacturing

(a) 1990 (b) 2000



Notes: The figure depicts the employment-weighted distribution of estimated firm wage premiums in 1990 and 2000, separately for the manufacturing and the non-manufacturing sector. Multiply the numbers on the horizontal axis by 100 to obtain log points. See section 3.2 for a more detailed explanation of the data preparation and wage decomposition.

Access to high-paying non-manufacturing firms. The second main descriptive result suggests that low-skilled manufacturing workers have less access to high-paying non-manufacturing firms than high-skilled manufacturing workers. In what follows, I focus on manufacturing workers aged 20-50 in 1990 or 2000 (the base years t) in full-time employment and follow these workers over a period of ten years. With these restrictions, I end up with two intervals (1990-2000, 2000-2010) that contain a total of 3,369,473 worker-base year observations.[15] Based on the estimated worker components, I group workers into three terciles, separately for both base years: high-wage, medium-wage, and low-wage workers.

Panel (a) of figure 3 shows that high-wage, medium-wage, and low-wage workers differ in terms of observable characteristics. High-wage workers on average have a higher level of formal education than medium-wage and low-wage workers. Panel (a) of figure 3 also shows that the worker groups differ in terms of the tasks they perform on the job. Low-wage workers on average perform more routine-intensive and codifiable tasks than medium-wage and high-wage workers. The variables for the tasks content of work are based on the worker's occupation.[16]

Finally, panel (a) of figure 3 suggests that high-wage, medium-wage, and low-wage manufacturing workers on average are employed in firms that pay similar wage premiums in the base years. This means that there is only little or not sorting by skill across high-

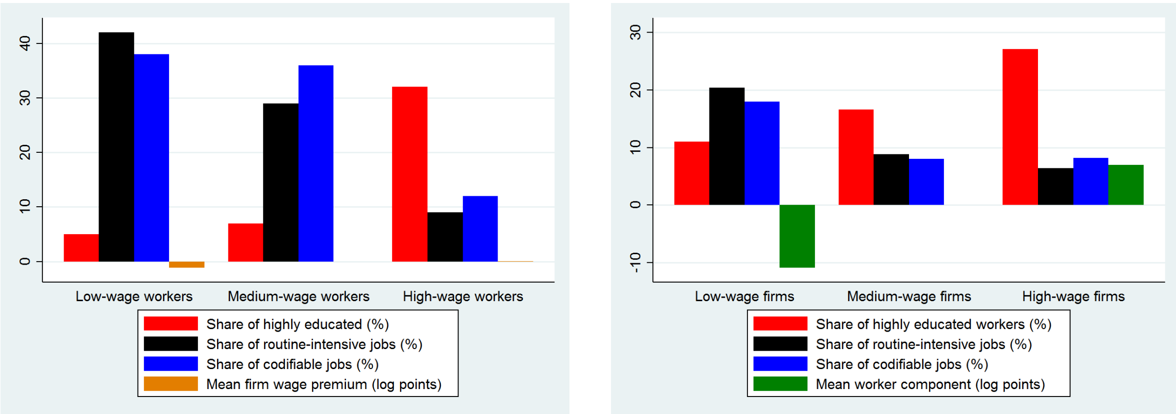
[15] See table D2 for basic summary statistics on the resulting sample.

[16] I use the 1985/86 BIBB/BAuA survey and focus on these two questions: 1) Are the contents of your job minutely described by the employer? (codifiable) 2) Does the job sequence repeat itself regularly? (routine) I compute the share of workers within 3-digit occupations who report 'almost always' for a given question. Finally, I label the top 25% of occupations with the highest share as routine/codifiable.

paying and low-paying manufacturing firms in the base years. More specifically, the figure plots the mean firm wage premium for low-wage and high-wage workers, as a deviation from the mean firm wage premium of medium-wage workers. It turns out that the mean firm wage premium is virtually identical across all skill groups.[17]

Figure 3: Characteristics of workers and firms

(a) Manufacturing workers (b) Non-manufacturing firms



Notes: Workers (firms) are grouped into terciles according to the estimated worker component (firm wage premium) in equation 1. N=3,369,473 manufacturing workers in panel in panel (a). N=1,478,790 non-manufacturing firms (b). The mean firm wage premium in panel (a) is displayed as a deviation from the mean firm wage premium of medium-wage workers. The mean worker component in panel (b) is displayed as a deviation from the mean worker component in medium-wage firms. Values in panel (a) refer to the base years t (1990 and 2000). Values in panel (b) refer to $t + 10$. See section 3.2 for a more detailed explanation of the data preparation and wage decomposition.

Table 1 suggests that low-wage workers who reallocate into the non-manufacturing sector have lower access to high-paying non-manufacturing firms than reallocating high-wage workers. This table provides a look at reallocation into the non-manufacturing sector between the years t and $t + 10$ for the sample of manufacturing workers in t. Overall, 14.6% of the manufacturing workers move into the non-manufacturing sector between years t and $t + 10$. Columns (2)-(4) provide evidence that most of this mobility is absorbed by high-wage non-manufacturing firms, i.e. firms which belong to the top tercile of the distribution of firm wage premiums in the economy in $t + 10$. Table 1 hints at substantial differences between workers of different skill groups in the reallocation into high-paying and low-paying non-manufacturing firms. The vast majority of high-wage workers who reallocate into non-manufacturing move to high-wage firms. In contrast, low-wage workers more often move to low-wage non-manufacturing firms. In fact, for low-wage workers, mobility is relatively balanced across the firm types with equal shares of worker moving to high-wage, medium-wage, and low-wage firms. To the extent that the descriptive findings in table 1 reflect lower access to high-paying non-manufacturing firms

[17] Table D3 in the appendix provides additional summary statistics on the different skill groups. It shows for example that high-wage workers on average are employed in more skill-intensive occupations.

for low-skilled manufacturing workers, a contraction of the non-manufacturing causes an increase in sorting and wage inequality. Table D5 further differentiates between initial firm types in the manufacturing sector. The basic conclusion remains unchanged.

Table 1: Reallocation into non-manufacturing and sorting

Manufacturing in t	**Non-manufacturing in $t+10$ (%)**			
		Firm type:		
	All firms	High-wage	Medium-wage	Low-wage
	(1)	(2)	(3)	(4)
All workers	14.6	6.8	4.6	3.2
High-wage workers	13.0	8.6	3.0	1.4
Medium-wage workers	13.9	6.4	4.7	2.8
Low-wage workers	16.7	5.5	5.8	5.4

Notes: N=3,369,473. Sample includes full-time employed manufacturing workers aged 20-50 in 1990 or 2000 (t). Column (1) shows the share of workers who are full-time employed in the non-manufacturing sector in $t+10$. Columns (2)-(4) split up the share from column (1) into employment by high-wage, medium-wage, and low-wage firms (terciles of the distribution of firm wage premiums in $t+10$). See section 3.2 for a more detailed explanation of the data preparation and wage decomposition.

Panel (b) of figure 3 supports the idea that low-wage manufacturing workers have lower access to high-paying non-manufacturing firms from a different angle. It provides evidence that high-paying non-manufacturing firms produce more skill-intensive than low-paying non-manufacturing firms. High-wage non-manufacturing firms employ a higher share of workers with high formal education than medium-wage and low-wage firms in $t+10$. In addition, the figure suggests that high-wage firms employ a lower share of workers that perform routine-intensive and codifiable tasks than medium-wage and low-wage firms. As a consequence, high-wage non-manufacturing firms also employ workers with a higher estimated worker component on average.

The differences in panel (b) of figure 3 might be driven by inherent differences in the skill requirements between firms and industries. Additionally, they might accrue endogenously, for example in response to technological progress which decreases the number of routine and codifiable jobs at high-paying non-manufacturing firms (Autor et al. 2003). Spitz-Oener (2006) provides evidence that computerization triggered a decrease in routine jobs and educational upgrading in Germany. The pattern in (b) of figure 3 suggests that this process did not take place uniformly across high-paying and low-paying non-manufacturing firms industries. Acemoglu (1999) provides a model in which technological change can trigger an increase in the segregation of skills across heterogeneous firms.

3.4 Conceptual framework

The previous descriptive results indicate a potential link between a contraction of the manufacturing sector and economy-wide labor market sorting. To fix ideas, this subsection provides a conceptual framework which serves to illustrate this link and which guides the subsequent empirical analysis.

3.4.1 Firms

Consider an economy which consists of four firms: one manufacturing firm and three non-manufacturing firms. Suppose that wages in this economy are additive in a worker component and a firm wage premium, as in equation 1. The manufacturing firm pays a wage premium of ψ_{Man}. The non-manufacturing sector consists of one high-wage firm, one medium-wage firms, and one low-wage firm, where $\psi^H_{Non} > \psi^M_{Non} > \psi^L_{Non}$. Further, suppose that the wage premium in the high-wage non-manufacturing firm is equal to the wage premium in the manufacturing firm: $\psi_{Man} = \psi^H_{Non} > \psi^M_{Non} > \psi^L_{Non}$. Under the assumption that each firm employs a mass of workers larger than zero, this set-up captures the descriptive results from figure 2 in a stylized way. First, the employment-weighted average firm wage premium is larger in the manufacturing than in the non-manufacturing sector. Second, the distributions of the two sectors overlap, such that the non-manufacturing sector contains a segment of firms that pay wage premiums comparable to the manufacturing sector.

In the AKM estimation of 1, the estimated firm wage premiums constitute dummy variables which need to be interpreted relative to a reference group. In what follows, I will treat the medium-wage non-manufacturing firm as the reference group, such that $\psi^M_{Non} = 0$ and $\psi^L_{Non} < 0$ by construction.

3.4.2 Workers

The manufacturing sector contains low-skilled and high-skilled workers, each with a mass of one. The worker component of the wage for high-skilled workers exceeds the worker component of the wage for low-skilled workers: $\alpha^H > \alpha^L$. Consistent with the descriptives in panel (a) of figure 3, one can think of the differences in the worker component as the result of differences in formal education and tasks performed on the job. By construction, this stylized economy captures the descriptive result in panel (a) of figure 3 that high-skilled and low-skilled workers in the manufacturing sector are employed in firms that pay very similar wage premiums, i.e. there is very little or no sorting by skill in the manufacturing sector in the base years. For simplicity of the exposition, I abstract from initial employment in the non-manufacturing sector and assume that all workers are employed in the manufacturing sector.[18]

3.4.3 Sorting and wage inequality

In this simple framework, a natural measure for the degree of sorting by skill across high-paying and low-paying firms in the economy is the difference in average firm wage premiums across skill groups. By construction, this difference amounts to zero in this economy. Wage inequality, therefore is captured exclusively by the difference in the worker components across high-skilled and low-skilled workers.

3.4.4 Labor reallocation, sorting, and wage inequality

Now suppose that a share of low-skilled workers (β^L) and a share of high-skilled workers (β^H) is being displaced from the manufacturing firm and reallocates into the non-manufacturing sector. Importantly, I assume that this share is equal across both skill groups: $\beta^L = \beta^H = \beta$. This (skill-unbiased) reallocation into the non-manufacturing sector can be the result of labor-saving technological progress in the manufacturing sector, lower demand for manufacturing goods in the context of non-homothetic preferences and rising incomes, or any negative demand shock on the manufacturing sector, for example from increased import competition.

Conditional on being displaced from the manufacturing sector, high-skilled (low-skilled) workers move to the high-wage non-manufacturing firm with probability κ^H (κ^L) and to the medium-wage non-manufacturing firm with probability λ^H (λ^L). With the remaining probability of 1-κ^H-λ^H (1-κ^L-λ^L), high-skilled (low-skilled) workers move to the low-wage manufacturing firm.

The descriptives on labor reallocation and sorting in table 1 as well as the descriptives on the composition of non-manufacturing firms in panel (b) of figure 3 suggest that κ^H > κ^L. In other words, conditional on reallocating into the non-manufacturing sector, high-skilled workers are more likely to move to the high-paying non-manufacturing firm than low-skilled workers. They also suggest that (1-κ^L-λ^L) > 1-κ^H-λ^H, i.e. conditional on moving into the non-manufacturing sector, low-skilled workers are more likely to move to a low-wage firm. I assume that the worker components of the wage, α^H and α^L, remain unaffected by the labor reallocation. The effects on sorting therefore translate one-to-one into effects on wage inequality.[19]

[18] An alternative would be to assume that workers initially employed in the non-manufacturing sector are unaffected by the subsequent labor reallocation. See section 3.4.4.

[19] This assumption is consistent with the empirical exercise which isolates the effects coming from relative gains and losses of firm wage premiums. There are reasons to expect that changes in worker components work into the same direction, contributing to the rise in wage inequality. See for example Cravino and Sotelo (2019) who argue that a decline of the manufacturing sector raises the skill premium because the non-manufacturing sector is more skill-intensive than the manufacturing sector. In an AKM framework, this would show up as an increase in ($\alpha^H - \alpha^L$).

How does labor reallocation in this context affect sorting? Provided that initial sorting as measured by the difference in firm wage premiums between skill groups is zero by construction, the change in sorting is given by the difference in expected average firm wage premiums across skill groups. For high-skilled workers, the expected average firm wage premium after reallocation reads:

$$E(\psi|H) = \beta[\kappa^H \psi^H_{Non} + (1 - \kappa^H - \lambda^H)\psi^L_{Non}] + (1 - \beta)\psi_{Man} \tag{2}$$

Setting up an analogous equation for low-skilled workers, taking the difference, and simplifying the resulting terms, one obtains the expected increase in sorting and wage inequality:

$$E(\psi|H) - E(\psi|L) = \beta[(\kappa^H - \kappa^L)\psi^H_{Non} - (\kappa^H - \kappa^L + \lambda^H - \lambda^L)\psi^L_{Non}] \tag{3}$$

This equation provides several important insights. For a given dispersion of firm wage premiums, reflected by the absolute size of ψ^H_{Non} and ψ^L_{Non} (<0), the sorting and wage inequality effects of a given labor reallocation ($\beta > 0$) increase with the extent to which high-skilled workers are more likely to move to high-wage firms ($\kappa^H > \kappa^L$) and to medium-wage firms ($\lambda^H > \lambda^L$) than low-skilled workers. If high-skilled and low-skilled workers were equally likely to move to the respective different non-manufacturing firms (($\kappa^H = \kappa^L$) and ($\lambda^H = \lambda^L$)), skill-unbiased labor reallocation would not affect sorting. It is important to note that the effects on sorting and wage inequality between skill groups do not depend on the absolute size of the parameters κ^H, κ^L, λ^H and λ^L.[20] Finally, for a given difference in firm wage premiums within non-manufacturing and a given ($\kappa^H - \kappa^L$) and ($\lambda^H - \lambda^L$), the sorting and wage inequality effects increase with β, the share of workers who reallocate in response to a given shock.

In a last step, I bring β into the brackets and obtain an equation which can be used to perform a back-of-the-envelope calculation of the effects of a given labor reallocation on sorting and wage inequality:

$$E(\psi|H) - E(\psi|L) = [(\beta\kappa^H - \beta\kappa^L)\psi^H_{Non} - (\beta\kappa^H - \beta\kappa^L + \beta\lambda^H - \beta\lambda^L)\psi^L_{Non}] \tag{4}$$

The empirical analysis will yield estimates for β as well as for ($\beta\kappa^H - \beta\kappa^L$) and ($\beta\lambda^H - \beta\lambda^L$). The latter two terms reflect the differences in the probability to reallocate to a high-wage and medium-wage non-manufacturing firm in response to a given shock with

[20] The effects on absolute wages, however, depend on the absolute sizes of κ^H, κ^L, λ^H and λ^L, as they govern the likelihood to experience wage losses through mobility to firms paying lower wage premiums as the manufacturing firm. Additionally, their size affects the effects on wage inequality within the groups of high-skilled and low-skilled workers. In the empirical exercise, I focus on sorting and wage inequality between skill groups as defined by the estimated worker components, formal education, and tasks performed on the job.

a given β. Together with the estimated firm wage premiums, this gives rise to a back-of-the-envelope calculation of the sorting and wage inequality effects of a labor reallocation with a given β. The empirical exercise identifies sorting and wage inequality effects for manufacturing workers. To end up with an estimation for economy-wide sorting and wage inequality, the results can be scaled down by the manufacturing employment share. Implicitly, this is to assume that sorting and wage inequality among the group of incumbent non-manufacturing workers and new entrants is not affected by labor reallocation from manufacturing into non-manufacturing.

The conceptual framework imposes $\beta^L = \beta^H = \beta$ because the empirical exercise identifies a shock whose initial effect of bringing workers into the non-manufacturing sector is similar across skill groups. Table 1, however, suggests that less skilled workers are more likely to move into the non-manufacturing sector, i.e. $= \beta^H < \beta^L$. Given that low-wage manufacturing workers more often perform routine-intensive tasks (see figure 3), this pattern is consistent for example with technological progress adversely affecting workers performing routine-intensive tasks as in Autor et al. (2003). To the extent that a given labor reallocation is biased against low-skilled workers, the estimates for the effects on sorting and wage inequality in this paper are a lower bound for the total effect.

3.5 Identifying the link between labor reallocation and sorting

The differential mobility pattern between skill groups documented in the descriptive table 1 do not necessarily reflect the mechanism outlined in section 3.4. Overall labor reallocation into the non-manufacturing sector is most likely a cause of a variety of different shocks, or more generally speaking, reflects a variety of different causes. The differences in the mobility pattern therefore can be driven for example by high-skilled and low-skilled workers being affected by different types shocks.

The main empirical analysis identifies a shock which has a common initial effect across all skill groups by bringing them into the non-manufacturing sector at higher rates ($\beta \approx \beta^H \approx \beta^L > 0$). Conditioning on a variety of controls at the worker, firm, industry, and regional level, this shock allows to test whether, all else being equal, more skilled workers are more likely to move to high-paying non-manufacturing firms than low-skilled workers in response to this shock ($\beta\ \kappa^H > \beta\ \kappa^L$).

3.5.1 Trade-induced labor reallocation

Analogously to the descriptives on labor reallocation in section 3.3.2, I focus on manufacturing workers aged 20-50 in 1990 or 2000 (the base years t) in full-time employment and follow these workers over a period of ten years. I estimate variants of the following specification:

$$Non_i^{t+10} = \beta \Delta NetImp_k^{t,t+10} + \xi X_{ikt} + \epsilon_{ikt} \tag{5}$$

Non_i^{t+10} is a dummy variable which has the value 1 if worker i initially employed in manufacturing industry k in year t is full-time employed in the non-manufacturing sector in year $t+10$. The main explanatory variable in this regression is the change in net import exposure in industry k in which worker i is initially employed in year t:

$$\Delta NetImp_k^{t,t+10} = \frac{\Delta Imports_k^{t,t+10} - \Delta Exports_k^{t,t+10}}{10,000 \times WageSum_{kt}} \tag{6}$$

$\Delta NetImp_k^{t,t+10}$ captures the extent to which industry k experiences net import exposure from China and Eastern Europe during t and $t+10$ and is defined as the increase in net imports ($\Delta Imports_k^{t,t+10} - \Delta Exports_k^{t,t+10}$) normalized by the initial industry wage bill to control for size differences across industries.[21]

Variation in the growth of net import exposure creates quasi-exogenous variation in trade-induced labor reallocation into the non-manufacturing sector. To the extent that growing net import exposure constitutes a negative demand shock on the industry, it generates increasing rates of displacement at the initial firm for all skill groups. In the light of the ongoing contraction of the manufacturing sector, displaced workers are expected to move into the non-manufacturing sector rather than into other manufacturing sectors. Growing net import exposure therefore is expected to accelerate the ongoing process of structural change. The opposite is true for growing net export exposure. The effects of growing net export exposure can work through different channels. First, the positive demand shock associated with growing export opportunities might (partly) offset any negative demand shock and thereby translate into a positive job stability effect for workers, relative to workers in industries which do not experience an increase in exports. Second, growing exports might decelerate labor reallocation in response to labor-saving technological progress. This is because, in the context of strong unions, it might be harder to justify layoffs in the presence of a substantial positive demand shock stemming from increased exports.[22]

I allow the effects to differ across skill groups by interacting the growth of net import exposure in equation 5 with indicators for the skill level of a worker. If the coefficients on the interaction effects are close to zero and statistically insignificant, the effects of growing net import exposure on reallocation into the non-manufacturing sector are equal across skill groups, i.e. $\beta \approx \beta^H \approx \beta^L > 0$.

[21] From the perspective of the domestic 3-digit industry, $\Delta Imports_k^{t,t+10}$ can reflect either import competition in the final goods market or, if the imports are used in exactly that same industry as intermediates, offshoring. Given that I cannot observe the use of the imports at the level of 3-digit industries, I cannot differentiate between these two types of imports.

[22] Figure D4 graphically illustrates the variation in net import exposure in the sample. Figure D5 illustrates the rapid increase in exports to and imports from China and Eastern Europe, starting in the early 1990s. The extent of this trade shock was not anticipated and trade with China and Eastern Europe grew much stronger as trade with the rest of the world, as illustrated by panel (b) of figure D5. Table D6 further provides a list of top exporting and importing industries.

X_{ikt} contains control variables at the worker, firm, industry, and regional level, held constant at the base year t. It contains dummies for worker types and initial firm types (terciles), dummies for age groups (30-40 and 40-50 years of age in the base year), a dummy for high formal education (college or university degree), binary variables for performing routine-intensive and codifiable tasks and dummies for tenure (2-5 and >5 years). X_{ikt} also includes firm size dummies (number of employees: 10-100, 100-1,000, >1,000) and dummies for broad industry groups (food, consumer goods, capital goods, with production goods being the reference group). Finally, X_{ikt} contains dummies for labor market regions.

3.5.2 Trade-induced labor reallocation and sorting

To study the effects on sorting across high-paying and low-paying firms within the non-manufacturing sector, I modify the dependent variable:

$$PremiumNon_i^{t+10} = \beta \Delta NetImp_k^{t,t+10} + \xi X_{ikt} + \epsilon_{ikt} \tag{7}$$

$PremiumNon_i^{t+10}$ is equal to 1 if the worker is full-time employed by a given firm type (high-wage, medium-wage, or low-wage) in non-manufacturing in $t+10$. The firm type reflects the tercile of the firm in the distribution of firm wage premiums in the economy in $t+10$.

Trough interaction effects of net import exposure with dummies for skill groups, this specification allows to test whether certain skill groups are more or less likely to move to a high-paying non-manufacturing firms than others in response to the shock. For example, it allows to test whether $\beta\ \kappa^H > \beta\ \kappa^L$. I also employ the estimated firm wage premium in $t+10$ as an alternative outcome variable.

Overall, the goal of equations 5 and 7 is to implicitly compare workers who have very similar demographic characteristics, are initially employed in similar firms and industries in the same local labor market, but are differently affected by Germany's trade integration with China and Eastern Europe due to differences in industry affiliation in year t. Through the interaction effects of growing net import exposure, I make this kind of comparison separately for different skill groups and thereby allow the estimated effect to differ across skill groups. In that sense, the estimation resembles a triple-differences regression which compares trade-exposed to non-exposed workers over time, separately by skill group.[23] In the baseline specification, I interact net import exposure with dummies for worker types as reflected by terciles of the estimated firm components in the base year (high-wage, medium-wage, and low-wage workers). At a later stage, I employ interactions with variables for formal education and tasks performed on the job.

[23] See Dauth et al. (2019a) for a similar empirical exercise in the context of trade with China and Eastern Europe. They, however, do not analyze sorting into high-paying and low-paying non-manufacturing firms.

In the baseline estimates, I pool all workers in the manufacturing sector, regardless of the firm wage premium of the initial firm of employment. In an extension, I differentiate between effects on workers initially employed in high-paying and low-paying manufacturing firms. This differentiation allows to provide a closer look at whether workers experience gains and losses of firm wage premiums upon moving into non-manufacturing.

3.5.3 Instrument

Remaining threats to identification are industry-level demand and productivity shocks which might be correlated with trade exposure and at the same time influence the workers' mobility pattern. For example, in the context of domestic demand shocks which drive increased imports, the point estimates of increasing net import exposure will be biased towards zero. I apply the instrumental variable strategy pioneered by Autor et al. (2014) and adapted to the German context by Dauth et al. (2019a) More specifically, I instrument growing net import exposure with growing net import exposure on a group of instrument countries:

$$\Delta NetImp_k^{t,t+10,Ins} = \frac{\Delta Imports_k^{t,t+10,Ins} - \Delta Exports_k^{t,t+10,Ins}}{10,000 \times WageSum_{kt}} \tag{8}$$

where $\Delta Imports_k^{t,t+10,Ins} - \Delta Exports_k^{t,t+10,Ins}$ denotes the increase in net imports from China and Eastern Europe in industry k of a group of instrument countries, namely Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom. Underlying to this strategy is the idea that China and Eastern Europe experienced rapid productivity growth due to their transition to a market economy which went along with capital accumulation, migration to rural areas and improvement of the infrastructure (Naughton 2007; Hsieh and Klenow 2009; Burda and Severgnini 2009). The productivity growth translated into a strong increase in export capabilities in certain industries. For China, this effect was amplified through its entry into the WTO at the beginning of the 2000s. This effect should not only be present for Germany in the form of increasing net imports in these industries, but also in other high-income countries. Then, instrumenting German industry-level net import exposure with industry-level net import exposure of these high-income countries should isolate the exogenous increase in net import exposure that is related to the productivity growth in China and Eastern Europe. For this strategy to be valid, net import exposure of the instrument countries must not have a direct impact on German industries and industry-level supply and demand shocks in these countries should not be strongly correlated with those for German industries. The instrument group therefore does not contain any direct neighbors to Germany, no members of the European Monetary Union, and excludes the USA. See also Autor et al. (2014) and Dauth et al. (2014) for a discussion. To instrument for the interaction effects in the regression, I employ interactions of the instrument with dummies for skill groups.

3.6 Results

3.6.1 Baseline estimates

Table 2 provides the main estimates. Panel (a) starts with a simple specification without interaction effects and therefore captures the average effect across all skill groups. Panels (b) and (c) allow the estimates the differ across skill groups.

Column (1) of panel (a) provides evidence that net import exposure does generate structural change in the form of labor reallocation from manufacturing into non-manufacturing. The estimate suggests that manufacturing workers who experience a stronger increase in net import exposure between t and $t+10$ are more likely to be employed in the non-manufacturing sector in $t+10$. To gauge the magnitude of the effect, compare a worker at the 75th percentile of increasing net import exposure (0.02) to a worker at the 25th percentile (-0.10). The point estimate implies a 1.3 percentage points higher probability for the former group to be employed in non-manufacturing in $t+10$ ($0.11 * 0.12 \approx 0.013$). This effect amounts to almost ten percent of the raw probability of moving into non-manufacturing (or mean dependent variable) of 14.6% displayed in table 1. Variation in net import exposure therefore generates non-negligible variation in labor reallocation. Columns (2)-(4) decompose the point estimate of 0.11 into the effects of being employed by a high-wage, medium-wage, and low-wage non-manufacturing firm in $t+10$. It turns out that most of the mobility into the non-manufacturing sector is absorbed by high-wage firms. Finally, column (5) employs the estimated firm wage premium in $t+10$ as a dependent variable. Consistent with the finding that the level of firm wage premiums is lower in non-manufacturing (see figure 2), net import exposure goes along with lower firm wage premiums on average in $t+10$.

Turning to the estimates in panel (b), column (1) shows that the initial effect of bringing workers into the non-manufacturing sector is very similar across skill groups. The estimated interaction effects are positive, but small and statistically insignificant. This result is consistent with the idea the increased import exposure constitutes a negative demand shock on the industry which increases the likelihood of displacement for all skill groups. Referring to the conceptual framework in section 3.4, this result corresponds to $\beta^L \approx \beta^H$. Table D7 in the appendix confirms this result from a different angle. It shows that the negative effect of import exposure on employment in the initial firm and in the manufacturing sector is virtually identical across skill groups. The slightly positive (but statistically insignificant) interaction effects in column (1) of table 2 are mirrored by a slightly higher probability of less skilled workers to be out of the sample in $t+10$.

While the initial effect of bringing workers into the non-manufacturing sector is identical across skill groups, the resulting allocation within the non-manufacturing sector is not. Columns (2)-(4) provide evidence that high-skilled and low-skilled workers sort into different tails of the distribution of firm wage premiums in the non-manufacturing sector.

Column (2) shows that high-wage workers are substantially more likely to reallocate to a high-wage non-manufacturing firm than low-wage workers. The point estimate for high-wage workers (0.04+0.06=0.1) is 2.5 times bigger than the point estimate for low-wage workers (0.4) and is statistically significant. Column (4) shows that low-wage workers, in contrast, are more likely to move to low-wage non-manufacturing firms than high-wage workers.

Finally, column (5) of panel (b) displays the differential effects on the firm wage premium in $t+10$. In response to increased import exposure, low-wage workers experience a decrease in the firm wage premium in $t+10$. High-skilled workers, in contrast, are better able to move to high-wage non-manufacturing firms and therefore manage to reallocate into the non-manufacturing sector without major losses in firm wage premiums. As a consequence, this result suggests that labor reallocation generates an increase in sorting and wage inequality as high-skilled workers are relatively more likely to transition into well-paying non-manufacturing firms. Panel (c) shows that the OLS/LPM estimates are qualitatively very similar. Consistent with the idea that part of the observed increase in imports are in fact driven by a rise in domestic demand, the point estimates are slightly lower.[24]

A natural question to ask is whether sorting would also have increased to the same extent if workers remained within the manufacturing sector. First, note that the scope for an increase in sorting within the manufacturing sector is constrained by the lack of low-paying firms in the manufacturing sector, as illustrated by figure 2. The figure shows that most of the low-wage firms in the economy are non-manufacturing firms. However, it is still possible that, in absence of the shock causing labor reallocation into non-manufacturing, low-wage workers disproportionately move to low-paying manufacturing firms, with an increase in sorting as the result. Column (1) of table D7 in the appendix provides evidence that this is not the case. The result suggests that, in absence of the shock, workers of all skill groups remain in their initial manufacturing firm. Finally, not that the results in table 2 pool all manufacturing workers and thereby abstracts from the dispersion of firm wage premiums within the manufacturing sector. Table D8 in the appendix provides separate results for workers initially employed in high-wage, medium-wage, and low-wage manufacturing firms. The basic results remain unchanged. See section 3.7 for an explanation.

3.6.2 Back-of-the-envelope calculation

What do the estimates in table 2 imply for the effects of labor reallocation on sorting and wage inequality? Note that the trade shock on net does not explain any of the labor reallocation and sorting, because the increase in in import exposure on average is negative

[24]The first stages are strong with F statistics of more than 200. Figure D7 in the appendix shows a visual representation of the first stage relationship for export and import exposure.

Table 2: Baseline estimates

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Dummy: Non-manufacturing in $t+10$				Premium
	All firms	High-wage	Medium-wage	Low-wage	in $t+10$
[**2SLS**]	**(a) Average effects across all skill groups**				
Δ NetImp	0.11***	0.07***	0.03***	0.01**	-0.03**
	(0.03)	(0.02)	(0.00)	(0.00)	(0.01)
R^2	0.05	0.03	0.02	0.02	0.47
[**2SLS**]	**(b) Sorting by skill group (2SLS)**				
Δ NetImp	0.10***	0.04***	0.03***	0.03***	-0.06***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
ΔNetImp*Medium-wage worker	0.02	0.03**	0.00	-0.01***	0.02***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
ΔNetImp*High-wage worker	0.02	0.06**	-0.01***	-0.02***	0.05***
	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)
R^2	0.05	0.03	0.02	0.02	0.47
[**OLS**]	**(c) Sorting by skill group (OLS)**				
Δ NetImp	0.07***	0.03***	0.02***	0.02***	-0.02***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
ΔNetImp*Medium-wage worker	0.01	0.01	-0.00	-0.00	0.01**
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
ΔNetImp*High-wage worker	0.01	0.03**	-0.01***	-0.01**	0.03**
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
R^2	0.05	0.03	0.02	0.02	0.47

Notes: N=3,369,473. See equations 5 and 7. Sample includes full-time employed manufacturing workers aged 20-50 in 1990 or 2000 (t). In column (1), the dependent variable is 1 if the worker is full-time employed in non-manufacturing in $t+10$. In column (2), the dependent variable is 1 if the worker is employed in a high-wage non-manufacturing firm in $t+10$ (top tercile of the distribution of firm wage premiums in $t+10$). Analogously for columns (3) and (4). Column (5) shows the results with the estimated firm wage premium in $t+10$ as a dependent variable. Additional controls (held constant at year t): dummies for worker types and initial firm types (terciles), the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 3.2 and 3.5 for a more detailed explanation. Levels of statistical significance: *10%, **5%, ***1%.

and close to zero (see table D2). This result is consistent with Dauth et al. (2014) and Dauth et al. (2019a) who argue that increased trade with China and Eastern Europe on net has retained German manufacturing jobs.

However, variation in trade exposure across industries generates variation in labor reallocation which allows to draw conclusions about the effects of labor reallocation on sorting. A potential exercise is to compute the change in sorting that would have occurred if all the labor reallocation observed in the data were driven by the shock with the properties displayed in table 2.

Based on equation 4 derived in section 3.4, one can use the interaction effects in columns (2) and (3) of panel (b), which yield estimates for $(\beta\kappa^H - \beta\kappa^L)$ and $(\beta\lambda^H - \beta\lambda^L)$, as well as the average difference in firm wage premiums between firm types at $t+10$ ($\psi^H_{Non} = 21.5$, $\psi^L_{Non} = -35.2$), to obtain a back-of-the-envelope calculation on the sorting and wage inequality effects.[25] Two adjustments need to be made. First, the interaction effects in table 2 refer to a shock which brings roughly 10% of workers into the non-manufacturing sector (see column (1)). I scale up the effect by the factor of 1.46 to match the observed probability of moving into the non-manufacturing sector of 14.6% (table 1). Second, the estimates only refer to manufacturing workers and not to non-manufacturing workers. I therefore multiply the effect by the average manufacturing employment share in the sample (41%).[26]

The estimates imply that the firm wage premium gap between low-wage and high-wage workers grew by 1.83 log points in response to labor reallocation between t and $t+10$.[27] This corresponds to 31.0% of the rise in sorting as measured by the rise in the difference in average firm wage premiums between high-wage and low-wage workers between t and $t+10$. Analogously, it corresponds to 11.3% of the rise in wage inequality as measured by the rise in the wage gap between high-wage and low-wage workers between t and $t+10$.[28]

An alternative back-of-the-envelope calculation relies on the effects on the continuous firm wage premium in column (5). The estimates in panel (b) of table 2 imply that a shock which brings 10% of the workers into the non-manufacturing sector (column 1) leads to a loss of firm wage premiums of 5 log points for low-wage workers relative to high-wage workers (column 5). Scaling up to the observed probability of reallocation and adjusting for the manufacturing employment share as above, the effect implies a loss of firm wage premiums of 3.0 log points for low-wage workers relative to high-wage workers

[25] See table D2 for an overview of the values that are necessary to conduct the back-of-the-envelope calculation.

[26] This share is relatively high as the BeH do not include most of the workers in the public sector, for example civil servants. These workers are also not covered in Card et al. (2013). The aggregate statistics displayed in figure 1 include the public sector and therefore show a smaller manufacturing employment share.

[27] $[0.06 * 21.5 + (0.06 - 0.01) * 35.2] * 1.46 * 0.41 \approx 1.83$. See equation 4.

[28] $1.83/5.9 \approx 31.0\%$ and $1.83/16.2 \approx 11.3\%$.

between t and $t + 10$.[29] This corresponds to 50.8% of the rise in sorting and 18.5% of the rise in wage inequality between t and $t + 10$.[30]

In both alternatives, labor reallocation explains a substantial share of the rise in sorting and wage inequality. Note that in this back-of-the envelope calculation, I assume that worker components remain unchanged. Further, I assume that the allocation of workers initially employed in non-manufacturing across firms is not affected by the reallocation of manufacturing workers.

3.6.3 Sorting between versus within sectors

Firm wage premiums differ both between and within non-manufacturing industries. It is therefore natural to ask whether the estimates documented so far reflect sorting of high-skilled and low-skilled workers into high-paying and low-paying non-manufacturing industries versus sorting into high-paying and low-paying firms within non-manufacturing industries. It turns out that both is the case.

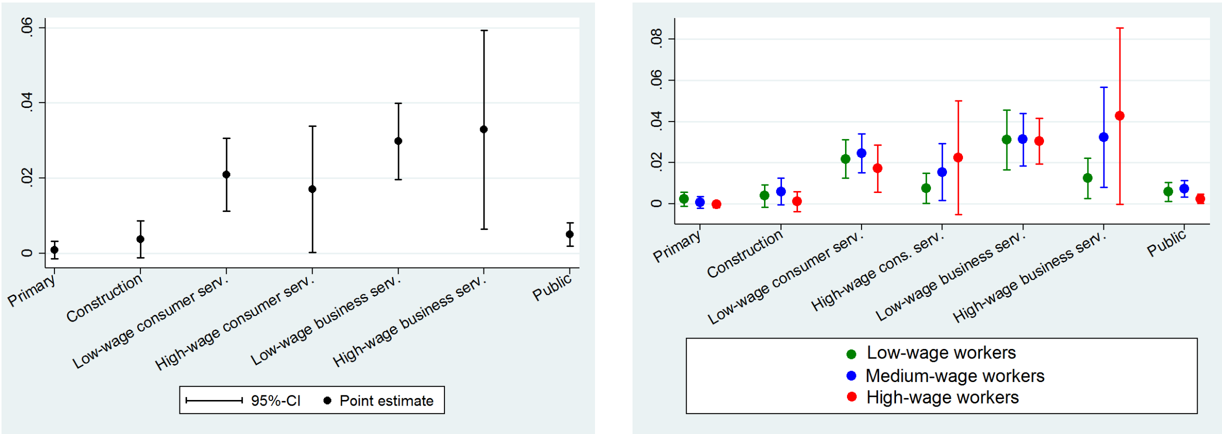
Sorting between industries. Figure 4 provides a look at sorting into different sub-sectors of the non-manufacturing sector. I divide the non-manufacturing sector into the following sub-sectors: the primary sector, the construction sector, low-wage business services (e.g. industrial cleaning), high-wage business services (e.g. financial intermediation), low-wage personal services (e.g. hotels), high-wage personal services (e.g. radio and television), and the public sector. I divide business and personal service industries into high-wage and low-wage based on the median firm wage premium within the respective group. Figure 4 provides the point estimates of the impact of increasing net import exposure on employment in one of these sub-sectors. Panel (a) first depicts the average effect across all skill groups. Not surprisingly, most of the workers reallocating into non-manufacturing move into business and personal service firms, with mobility into business services having a slightly higher probability. Panel (b) displays the point estimates of separate regressions by skill group. Even though, partly driven by the sample split, the confidence intervals are large, a clear pattern emerges. High-wage workers are substantially more likely to move into high-wage business service firms than less skilled workers. Less skilled workers, in contrast, are more likely to move into low-wage personal services, the construction sector, and the public sector. Therefore, a lower access for the least skilled workers to high-wage business service firms seems to be part of the explanation for the sorting effects of labor reallocation.

[29] $1.46 * 5 * 0.41 \approx 3.0$.
[30] $3.0/5.9 \approx 50.8\%$ and $3.0/16.2 \approx 18.5\%$.

Figure 4: Sorting between non-manufacturing industries

(a) Average effect

(b) Effects by skill group



Notes: Panel (a) depicts the effect of the increase in net import exposure on full-time employment in one of the sub-sectors of non-manufacturing. Panel (b) provide separate estimates by worker type. High-wage (low-wage) consumer service industries are industries with a mean firm wage premium above (below) the median firm wage premium across all consumer service industries. Analogously for business service industries. Across all outcome variables, the point estimates sum up to the respective point estimate in table 2.

Table 3: Sorting within non-manufacturing industries

	(1)	(2)	(3)	(4)
Dependent variable:	Dummy: Non-manufacturing in $t+10$			
(ranking within industry)	All	High-wage	Medium-wage	Low-wage
Δ NetImp	0.10***	0.06***	0.02**	0.02*
	(0.02)	(0.02)	(0.01)	(0.01)
ΔNetImp*Medium-wage worker	0.02	0.03**	0.00	-0.01***
	(0.01)	(0.01)	(0.00)	(0.00)
ΔNetImp*High-wage worker	0.02	0.04**	-0.01*	-0.01**
	(0.03)	(0.01)	(0.01)	(0.01)
R^2	0.05	0.03	0.02	0.02

Notes: N=3,369,473. In column (1), the dependent variable is 1 if the worker is full-time employed in non-manufacturing in $t+10$. In column (2), the dependent variable is 1 if the worker is employed in a firm with an estimated firm wage premium in the top tercile **within** the industry. Analogously for columns (3) and (4). Additional controls (held constant at year t): dummies for worker types and initial firm types (terciles), the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 3.2 and 3.5 for a more detailed explanation. Levels of statistical significance: *10%, **5%, ***1%.

Sorting within industries. Table 3 provides evidence on the effects on sorting within non-manufacturing industries. In the underlying regressions, I construct the outcome variables in columns (2)-(4) by ranking firms by their estimated firm wage premium **within** industries. Table 3 provides two main insights. First, the relatively large point estimates for all skill groups in column (2) suggest that most of the mobility into the manufacturing sector is absorbed by the highest-paying firms in the respective target industry. Second, and more importantly for the question in this paper, high-skilled workers are relatively more likely to move into the highest paying firms within the respective industry than less skilled workers. To sum up, the results in figure 4 and table 3 provide evidence that the overall effects on sorting are the result of differential sorting between and within industries.

3.6.4 Effects on the skill premium and residual wage inequality

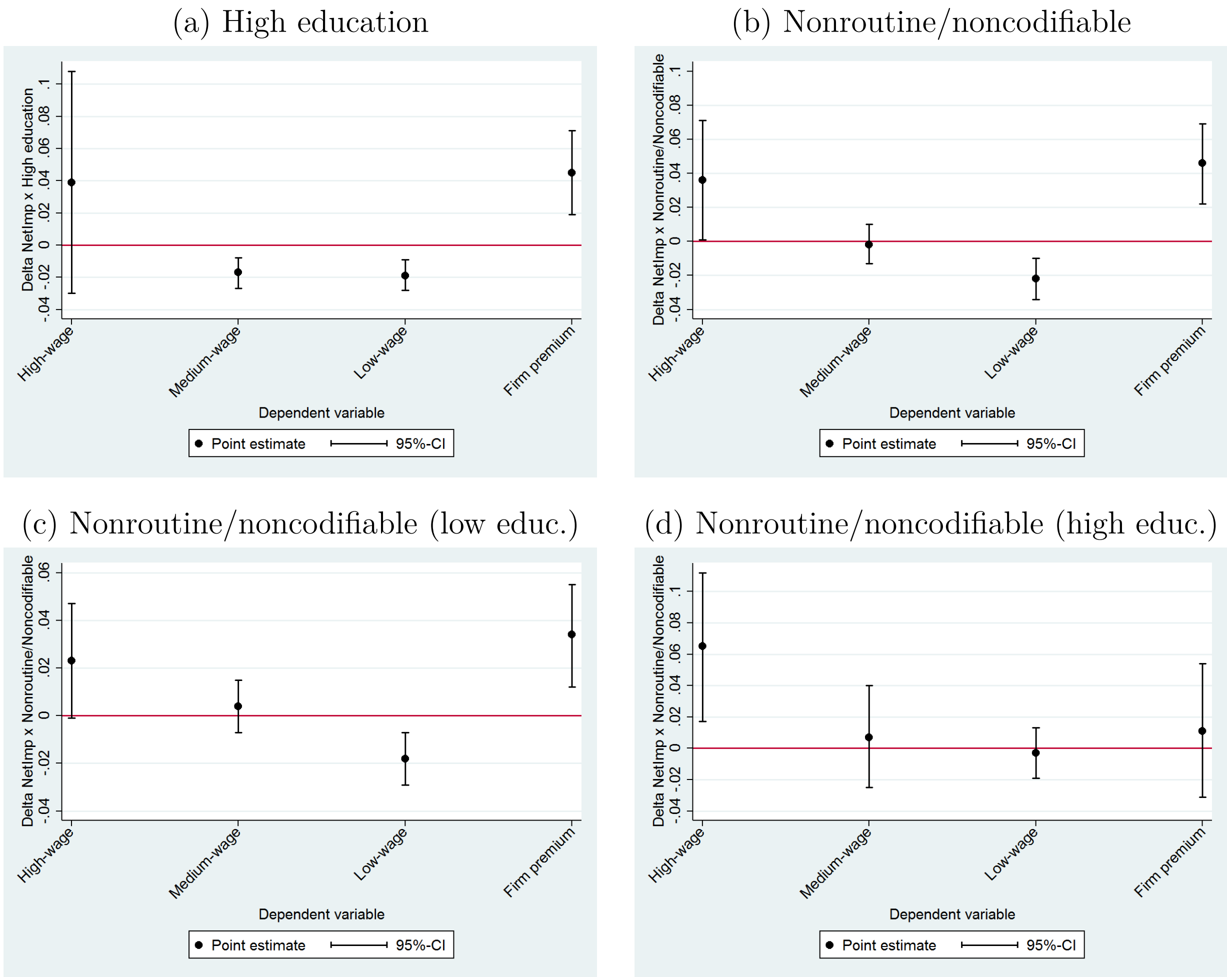
The descriptives in figure 3 show that high-wage workers on average have a higher level of formal education and perform more complex tasks than medium-wage and low-wage workers. In this section, I therefore analyze to what extent the differential effects across high-wage, medium-wage, and low-wage workers documented so far are driven by formal education and tasks performed on the job. This exercise is interesting in itself, but also provides evidence on the nature of wage inequality which is affected by labor reallocation. An increase in sorting upon formal education triggers a rise in the skill premium, whereas an increase in sorting upon tasks or occupations, conditional on formal education, triggers a rise in residual wage inequality.

Panel (a) of figure 5 provides evidence that labor reallocation triggers a rise in sorting by formal education and thereby raises the skill premium. The figure plots the point estimates on the interaction effect of net import exposure with a dummy for formal education, for four different outcome variables: full-time employment by high-wage, medium-wage, and low-wage firms in the non-manufacturing sector as well as the estimated firm wage premium in $t + 10$. The estimates suggest that, in response to increasing net import exposure, workers with high formal education are relatively more likely to move to a high-paying and relatively less likely to move into a low-paying non-manufacturing firm. This translates into a relatively higher firm wage premium in $t + 10$ for workers with high formal education.

Panel (b) of figure 5 shows evidence in favor of increased sorting by tasks performed on the job in response to labor reallocation. Analogously to panel (a), the figure shows interactions of net import exposure with a dummy for performing non-routine and non-codifiable tasks at the manufacturing workplace. The figure suggests that workers who initially perform more complex tasks find it substantially easier to reallocate to a high-paying non-manufacturing firm than workers initially performing routine and codifiable tasks.

Panels (c) and (d) of figure 5 show that this effect is also present conditional on formal education. The effect of tasks is especially strong within the group of workers with low formal education. It follows from panels (b)-(d) that labor reallocation also increases residual wage inequality as it favor workers who initially perform more complex tasks in the manufacturing sector.

Figure 5: The role of education and tasks



Notes: Panel (a) depicts the point estimate of the coefficient on the change in net import exposure interacted with a dummy for high formal education, for four different outcome variables: full-time employment by a high-wage, medium-wage, and low-wage non-manufacturing firm in $t+10$ as well as the estimated firm wage premium in $t+10$. Analogously, panel (b) provides estimates for interactions with a dummy for performing nonroutine and noncodifiable tasks. Panels (c) and (d) restrict the sample on workers with low and high formal education, respectively. See equations 5 and 7.

3.7 Robustness and Extensions

3.7.1 Upward versus downward mobility

Table D8 in the appendix provides separate estimates for worker initially employed in high-wage, medium-wage, and low-wage manufacturing firms in t. It thereby allows to differentiate between downward mobility from high-wage manufacturing towards low-wage non-manufacturing firms and upward mobility from low-wage and medium-wage manufacturing towards high-wage non-manufacturing firms. Due to the higher level of firm wage premiums in manufacturing as compared to non-manufacturing, and because high-wage firms on average are larger than low-wage firms, about 73% of manufacturing workers are employed by high-wage firms and only about 5% are employed by low-wage firms.

It turns out that the effects on labor reallocation, depicted in column (1), are strongest for workers initially employed by high-wage manufacturing firms. This result is consistent with Dauth et al. (2019a) who show that the negative effect of growing imports on cumulative earnings are largest for the group of workers employed by high-wage manufacturing firms. To the extent that the firm wage premiums reflect rent sharing through collective bargaining, a plausible explanation for this finding is that the effects of rising import competition are strongest for industries which are less competitive due to a higher level of wages. Importantly for the purpose of this paper, the main finding that high-wage workers are more likely to move to high-wage non-manufacturing firms in response to rising net import exposure (column (2)) is robust across all sub-samples. Column (5) shows that the losses in firm wages premiums are largest for low-wage workers starting in high-wage manufacturing firms. This is a natural consequence of the difference in wage premiums between high-wage, medium-wage, and low-wage firms. Overall, table D8 suggests that trade-induced structural change triggers an increase in sorting and wage inequality, mostly driven by higher downward mobility among low-wage workers who are initially employed by high-wage manufacturing firms.

3.7.2 Domestic outsourcing

Goldschmidt and Schmieder (2017) provide convincing evidence that German firms paying high wage premiums have increasingly engaged in domestic outsourcing of low-skilled workers in food, cleaning, security, logistics, and catering occupations, arguably to exclude them from firm-specific rents. Domestic outsourcing triggered mobility of these workers from high-wage towards low-wage firms and thereby contributed to the increase in sorting and wage inequality. To mitigate concerns that the effects documented in this paper in fact reflect mobility in response to domestic outsourcing and not in response to increasing net import exposure, I drop workers in food, cleaning, security, logistics and catering occupations in a robustness check, which reduces the sample size by about 7%. A closer inspection shows that these workers tend to be concentrated in the group of low-wage workers (as expected). They, however, do not seem to be over- or underrepresented in industries experiencing large increases in net import exposure. It is therefore not surprising that table D9 shows very similar results as table 2.

3.7.3 Non-monotonicities

A potential concern is related to the strong monotonicity assumption implied by the functional form of the fixed effects specification in equation 1, which implies that switching to a firm of lower type (e.g. from a high-wage to a low-wage firm) always goes along with the same log wage loss, regardless of the worker type. Models that incorporate search frictions and wage bargaining into a world with complementarity between workers and firms predict deviations from monotonicity, with wages decreasing to the left and to the right of the 'ideal' match that corresponds to perfect assortative matching (see e.g. Gautier and Teulings 2006; Eeckhout and Kircher 2011; Hagedorn et al. 2017; Lopes De Melo 2018).[31] This non-monotonicity is at odds with the log additive structure in equation 1. A closely related point of critique is the potential existence of match-specific effects. There is a class of trade models which emphasizes the existence of match-specific productivity draws (Helpman et al. 2010; Helpman 2017). Systematic match-specific effects constitute a violation of the AKM assumption and, similar to non-monotonicity, a threat to the following empirical analysis.

First, note that strong non-monotonicities and match-specific effects imply high residuals in the AKM estimation. The residual are generally very small, which is also reflected in the high R squared of around 90%. In addition, replacing the separate worker and establishment fixed effect by job fixed effects does only yield a minor improvement of the model fit of around two percentage points (Card et al. 2013). However, the residuals are large for some observations and this could reflect systematic violations of the AKM assumptions.

The robustness check I conduct is based on the finding by Lochner and Schulz (2016). Reconciling the AKM specification with models with search frictions and wage bargaining, they emphasize that log additivity provides a valid approximation of the wage structure for a large part of the data. They, however, find deviations from monotonicity (implying high residuals) for the very least skilled workers, who seem to select into low-type firms where they maximize their earnings. Observing a switch from a high-wage to a low-wage firm for these types of workers, I would wrongly conclude that this goes along with a wage loss. To mitigate this concern, I drop the bottom 10% of workers with the lowest fixed effects in one robustness check. The results, shown in table D10 remain robust to this manipulation.

[31] In a world without frictions, the existence of complementarities between worker and firm types would imply perfect positive assortative matching as in Becker (1973). In a world with search frictions, firms and workers must accept deviations from the ideal match. Wages are maximized at the ideal match and apart from the ideal match, wages are smaller because workers need to compensate firm for the foregone option value of continuing to search. The log additive structure of the AKM model allows for some degree of complementarity. To see this, note that in absolute terms, the wage increase of switching to a higher-type firm is larger for high-wage workers than for low-wage workers.

3.7.4 Separate effects of import and export exposure

As a final robustness check, I employ import and export exposure separately as explanatory variables in the regression. These measures are computed analogously to the measure in the main specification and the respective instruments are also constructed analogously. Table D11 shows the results.

The results for import exposure are very similar to the results for net import exposure in the baseline specification. As expected, growing import exposure increases the likelihood for all skill groups to move into the non-manufacturing sector. Conditional on moving into the non-manufacturing sector, high-wage workers more often move to high-paying firms than low-wage workers.

Table D11 also shows that growing export exposure generates lower mobility into the non-manufacturing sector for all skill groups. However, this effect is smaller for high-wage workers than for medium-wage and low-wage workers. This result can be explained by the different channels through which growing exports might affect job stability within manufacturing. First, growing exports potentially (partly) offset any negative demand shock on the respective industry or firm which would have triggered displacement of workers. This effect should play out similarly for all skill groups, just as the effects of growing import exposure are similar across all skill groups. On top of that, however, growing exports might shield workers who are at risk of displacement from technological progress. Labor unions and works councils traditionally play a strong role in Germany and their presence increases job stability for workers, especially for low-skilled workers who increasingly face the risk of displacement due to technological progress or outsourcing. In such an environment, it is particularly difficult for firms to justify layoffs in the presence of a positive demand shock stemming from increased exports to Eastern Europe and China. As low-wage and medium-wage workers tend to specialize in routine-intensive and codifiable tasks (see figure 3), they are at risk of being adversely affected by routine-biased technological progress, and therefore they benefit most from this effect.

3.8 Conclusion

Using a large administrative dataset, this paper provides robust evidence on the link between labor reallocation from the manufacturing into the non-manufacturing sector, sorting, and wage inequality. Exploiting the large and sudden increase in Germany's exports to and imports from China and Eastern Europe, I provide evidence that labor reallocation resulting from a contraction of a manufacturing industry results in an increase in sorting by skill across high-paying and low-paying firms. The results emphasize the crucial role that worker characteristics such as education and tasks performed on the job play for the mobility pattern which is underlying to the change in sorting.

The results in this paper carry over to any shock or policy which triggers a contraction of the manufacturing sector and thereby causes labor reallocation into the non-manufacturing sector. In the light of the rapid pace of technological progress experienced in the last years, the manufacturing employment share can be expected to further decrease in the upcoming years. The results in this paper suggest that the welfare gains from these technological advances might be unequally distributed within the economy. By pushing low-wage workers out of high-wage firms at higher rates, a contraction of the manufacturing sector creates persistent distributional effects. First, there is an immediate distributional effect which stems from an increasing wage gap, driven by the (relative) loss of firm wage premiums for low-wage workers. Second, there are reasons to believe that the increased sorting goes along with distributional effects in the longer-run as well. Abowd et al. (2018) for example show that employment at a high-wage firm facilitates upward-mobility in the earnings distribution in the following years. From the perspective of a policymaker who aims to curb the distributional effects of technological progress, international trade, or any other factor which triggers a contraction of manufacturing employment, is therefore crucial to focus on the skills and the human capital which enable workers to move into high-paying firms in the service sector.

This paper also provides new insights on the discussion about the distributional effects of trade with low-wage countries. Previous studies focus on the effects of growing import competition on cumulative earnings and typically find that the negative effects are largest for low-wage workers (e.g. Autor et al. 2014; Dauth et al. 2019a; Utar 2018). It is still an open discussion to what extent these results reflects transitional effects, coming for example from temporary unemployment or temporarily depressed wages, or more long-term effects which persist even after the economy has adjusted to the new equilibrium. The results in this paper isolate a specific component of inequality which is long-term in nature. It therefore suggests that growing imports do indeed generate persistent effects on wage inequality. Relatedly, the results in this paper suggest that bringing trade-displaced workers into full-time employment in the service sector is not sufficient to fully curb these adjustment costs and the resulting distributional effects.

3.9 Appendix C: AKM estimation

This section provides further details on the estimation of the following empirical specification, which dates back to Abowd et al. (1999):

$$y_{i\tau} = \alpha_i + \psi_{J(i\tau)} + x'_{i\tau}\beta + r_{i\tau} \tag{C1}$$

Section 3.2 explains the interpretation of the components $y_{i\tau}$, α_i, $\psi_{J(i\tau)}$ and $x'_{i\tau}$. It is worthwhile to have a closer look at the error term which consists of three components for which I assume mean zero and orthogonality to worker and firm effects conditional on the control variables:

$$r_{i\tau} = \eta_{iJ(i\tau)} + \xi_{i\tau} + \epsilon_{i\tau} \tag{C2}$$

The error term $r_{i\tau}$ consists of a worker-firm match component $\eta_{iJ(i\tau)}$, a unit-root component $\xi_{i\tau}$, which captures a potential drift in workers' wages, and a transitory error, $\epsilon_{i\tau}$.

Match effects. Especially the match effect $\eta_{iJ(i\tau)}$ deserves close attention. The estimation of the firm effects ψ_j relies on mobility of workers between firms. The difference in the firm wage premium between two firms captures systematic wage changes for workers that move between those firms. When workers moving into a given firm experience high wage gains, conditional on α_i and $x'_{i\tau}$, the estimated firm wage premium of this firm will be high. However, the wage change that workers experience by moving between two firms can be due to differences in the firm wage premium or due to differences in the average worker-firm match component between those firms. Systematic mobility of certain workers into firms based on a worker-firm match component therefore will be picked up by ψ_j, but precludes its interpretation as a ceteris paribus wage premium that every worker employed by this firm receives. Therefore, I need to assume that $\eta_{iJ(i\tau)}$ has mean zero and is orthogonal to worker and firm effects.

Card et al. (2013) check the plausibility of this assumption for the German case in different ways. First, in an event-study, they observe wage changes of workers moving from one firm to another to the wage change of movers into the opposite direction. They find that wage gains for workers moving from low coworker-wage firms to high coworker-wage firms are about as large as the losses of workers moving into the opposite direction. In the presence of strong match-specific effects, the wage changes should not be symmetric. In extreme cases with very strong match effects, wage changes should be positive for movers in both directions. Second, they compare the fit of equation C1 to the fit of a model with fixed effects for every worker-firm match. The R-squared of the baseline model is very high with values around 90% and stable over time. Match-effects, which are part of the residual, therefore are relatively small on average. Inclusion of match-specific fixed effects instead of worker and firm effects improves the R-squared by only 2 percentage points on average. The additive specification in equation C1, which abstracts from match-specific effects therefore seems to provide a very good fit to the data. Lochner and Schulz (2016) argue that this assumption might be violated for the least skilled workers in Germany. As a robustness check, therefore, I drop workers in the bottom 10% of the distribution of worker effects.

Worker mobility. In contrast, equation C1 is consistent with non-random mobility of workers with different worker components across firms. This is because the estimator conditions on the actual sequence of firms by which a given worker is employed. The main empirical analysis in this paper, which investigates whether trade induces non-random mobility of workers with different worker effects across firms that pay different wage premiums, therefore is consistent with equation Equation C1.

Worker and firm effects in equation C1 can only be separately identified within a connected set of firms which are linked by worker mobility. Following Card et al. (2013), I focus on the largest connected set in each interval. The largest connected set comprises about 95% of the workers in the raw data. In the main analysis wich focuses on the effects of trade, I drop workers who belong the the largest connected set in t but not in $t+10$. In an alternative estimation, keep them in the analysis and code them as 'out'. The results remain unchanged and are available upon request.

Variance decomposition. Having estimated equation C1, one can perform a decomposition of the variance of log wages into the respective worker- and firm-related components as done in Card et al. (2013):

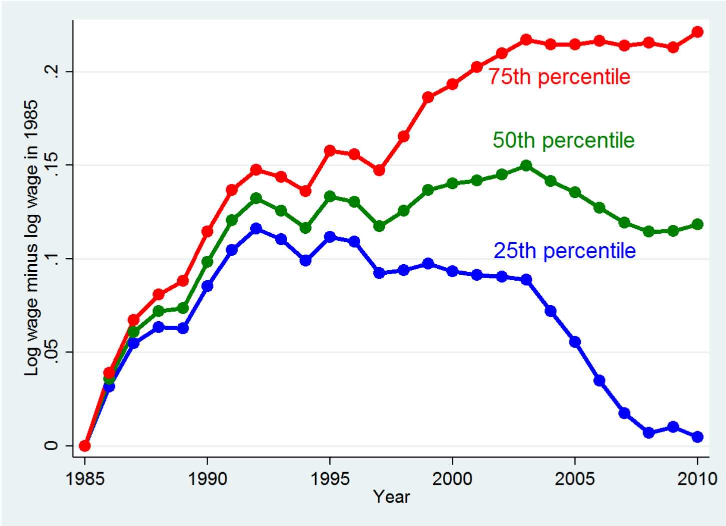
$$\begin{aligned}\mathrm{var}(\mathrm{y}_{i\tau}) &= var(\alpha_i) + var(\phi_{J(i\tau)}) + var(\beta x'_{i\tau}) \\ &+ 2\mathrm{cov}(\alpha_i, \phi_{J(i\tau)}) + 2cov(\alpha_i, \beta x'_{i\tau}) + 2cov(\phi_{J(i\tau)}) \\ &+ \mathrm{var}(\mathrm{r}_{i\tau}) \text{ (C3)}\end{aligned}$$

Using equation C3, Card et al. (2013) decompose cross-sectional wage inequality as well as the rise in wage inequality. It turns out that the rise in wage inequaliy is driven by three main factors: a rise in the dispersion of the worker components $var(\alpha_i)$, a rise in the dispersion of firm wage premiums $var(\phi_{J(i\tau)})$, and a rise in worker-firm sorting as reflected by the covariance between worker components and firm wage premiums $2cov(\alpha_i, \phi_{J(i\tau)})$.

For the purpose of this paper, I use slightly different time intervals as Card et al. (2013). For example, my first interval comprises the years 1985-1990, whereas the first interval in Card et al. (2013) contains the years 1985-1991. The results of the variance decomposition however are very similar. Figure D6 plots the variance of wages as well as the three main components for the intervals I use in the empirical analysis (1985-1990, 1995-2000, 2005-2010), and for the sake of completeness, the intervals 1990-1995 and 200-2005. In the cross-section, the variance of worker components is clearly the dominant component of wage inequality. However, looking at the change in wage inequality over time, the increase in sorting is almost as important as the increase in the variance of worker components. The increase in sorting from the first to the last interval explains roughly 30% of the increase in the variance of wages between these intervals.

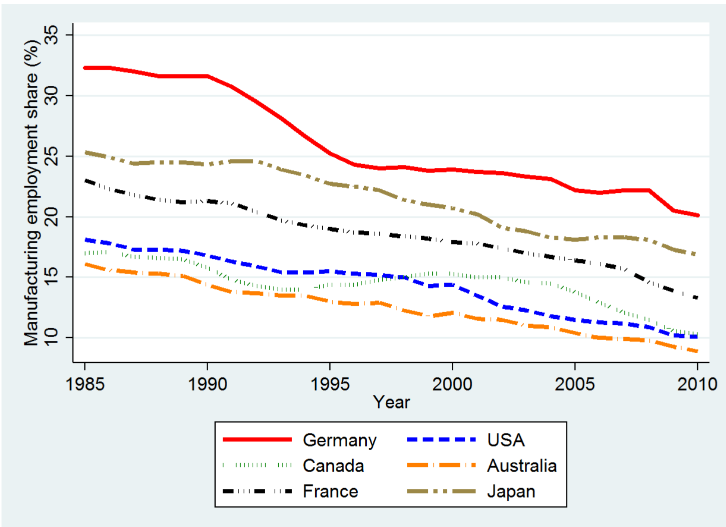
3.10 Appendix D: Figures and tables

Figure D1: Wage inequality: percentiles



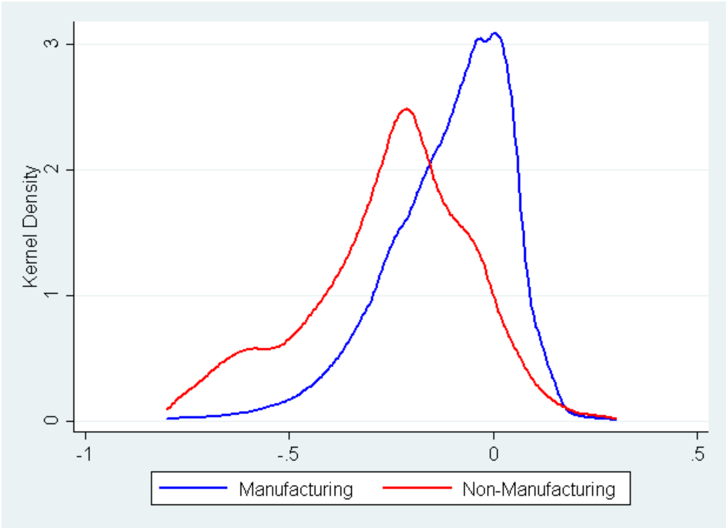
Notes: The table denotes the log daily wage in the 75th, 50th and 25th percentile in the overall wage distribution (manufacturing plus non-manufacturing) minus the respective log wage in the percentile in 1990. The table includes 50% of all male full-time employed employees subject to social security contributions in West Germany. See section 3.2 for more information on the data.

Figure D2: The decline in the manufacturing employment share in selected countries



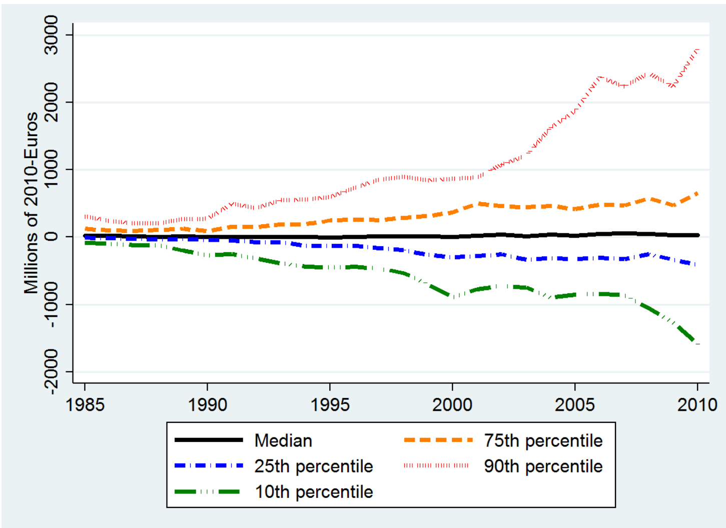
Notes: The figure plots the manufacturing employment share over time for selected countries. Data source: U.S. Bureau of Labour Statistics.

Figure D3: Dispersion of firm wage premiums, by sector, 2010



Notes: The figure depicts the employment-weighted distribution of estimated firm wage premiums in 2010, separately for the manufacturing and the non-manufacturing sector. See section 3.2 for a more detailed explanation of the data preparation and wage decomposition.

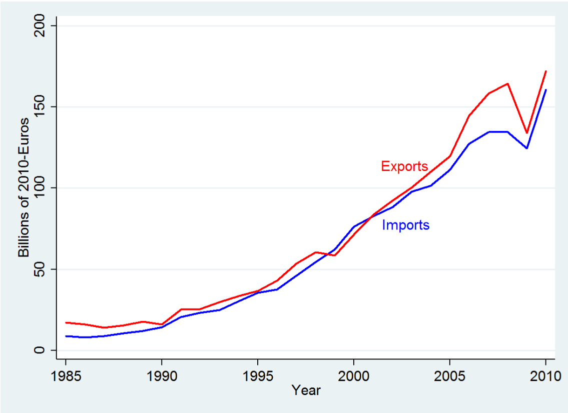
Figure D4: Variation in net imports across industries



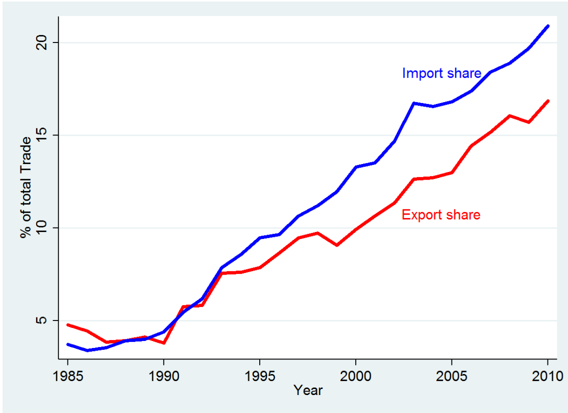
Notes: The figure depicts annual net German imports from China and Eastern Europe of industries at various percentiles. Eastern Europe includes: Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, the former USSR, and its successor states the Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan. See sections 3.2 for a more detailed explanation of the data.

Figure D5: Trade with China and Eastern Europe

(a) Absolute trade



(b) Share in total trade



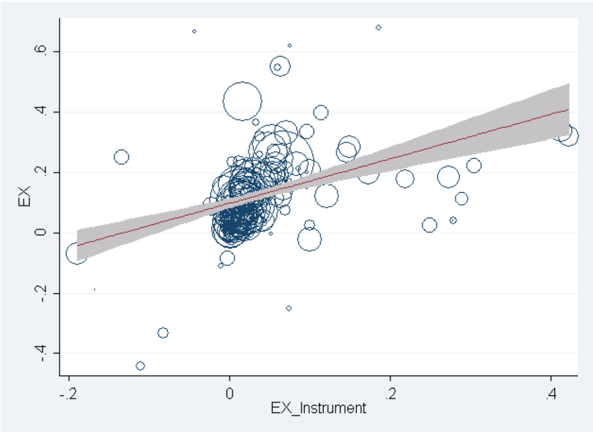
Notes: Panel (a) depicts the value of German exports to and imports from China and Eastern Europe in each year. Panel (b) depicts the share of German exports to and imports from Eastern Europe and China in total German export and imports. Eastern Europe comprises the following countries: Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, the former USSR, and its successor states the Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan. See sections 3.2 for a more detailed explanation of the data.

Figure D6: AKM decomposition: main components

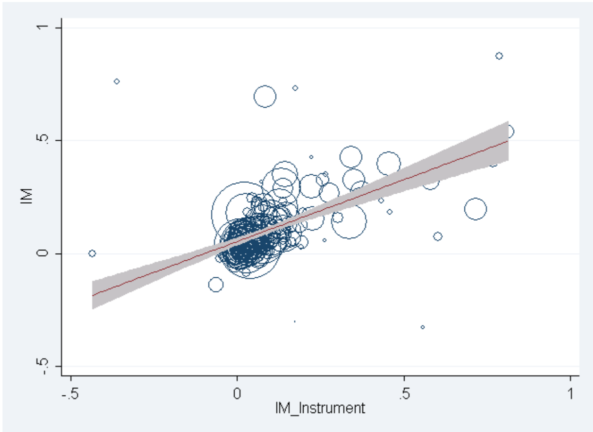
Notes: The figure plots the main components of the variance decomposition explained in appendix 3.9. 'Wage inequality' denotes the variance of log daily wages. 'Worker component' denotes the variance of estimated worker components. 'Firm wage premium' denotes the variance of estimated firm wage premiums. 'Worker-firm sorting' denotes twice the covariance of estimated worker components and firm wage premiums. The decomposition is based on 50% of all male full-time employed employees subject to social security contributions in West Germany. See section 3.2 for a more detailed explanation of the data preparation and wage decomposition.

Figure D7: First Stage

(a) Export Exposure



(b) Import Exposure



Notes: The graphs represent the first stage for export and import exposure at the industry-year level. The size of the circle reflects the number of workers employed in the industry as of the base year t. The shaded area reflects a 95% confidence interval.

Table D1: Estimated firm wage premiums in selected industries

3-digit industry	Mean	Standard Deviation	Number of firms
(a) Manufacturing			
Refined petroleum	0.12	0.15	136
Basic chemicals	0.06	0.16	822
Other general purpose machinery	0.02	0.17	3624
Furniture	-0.09	0.24	6558
Other wearing apparel	-0.12	0.27	1258
(b) Non-manufacturing			
Monetary intermediation	0.10	0.20	9809
Insurance and pension	0.04	0.17	2009
Advertising	-0.07	0.33	2721
Industrial cleaning	-0.11	0.30	3495
Hotels	-0.28	0.29	5565

Notes: The table displays summary statistics about estimated firm wages premiums in selected industries in 1990 and 2000. See sections 3.2 and 3.5 for the data preparation and wage decomposition.

Table D2: Sample descriptives

	Mean	Median	p75	p25	N
	(a) General descriptives				
Log daily wage (imputed)	4.48	4.44	4.68	4.25	3,369,473
High education	0.14	0	0	0	3,369,473
Age	35.75	36	29	42	3,369,473
Occupational groups:					
Manager/engineer/professional	0.09	0	0	0	3,369,473
Technician, qual. services, admin.	0.21	0	0	0	3,369,473
Manual/simple services	0.70	1	1	0	3,369,473
Tasks:					
Routine job	0.28	0	1	0	3,369,473
Codifiable job	0.33	0	1	0	3,369,473
AKM effects:					
Estimated worker effect ($\hat{\alpha}_i$)	4.38	4.34	4.51	4.21	3,369,473
Estimated firm wage premium ($\hat{\psi}_{J(it)}$)	0.08	0.09	0.16	0.01	3,369,473
	(b) Descriptives on trade exposure				
Change in net import exposure:					
Δ NetImp (All workers)	-0.01	-0.03	0.02	-0.10	3,369,473
Δ NetImp (Low-wage workers)	-0.01	-0.03	0.02	-0.10	1,131,725
Δ NetImp (Medium-wage workers)	-0.02	-0.04	0.02	-0.11	1,218,432
Δ NetImp (High-wage workers)	-0.01	-0.03	0.02	-0.10	1,019,316
Change in export exposure:					
Δ EX (All workers)	0.13	0.10	0.18	0.06	3,369,473
Δ EX (Low-wage workers)	0.12	0.10	0.17	0.05	1,131,725
Δ EX (Medium-wage workers)	0.13	0.10	0.18	0.05	1,218,432
Δ EX (High-wage workers)	0.13	0.10	0.19	0.06	1,019,316
Change in import exposure:					
Δ IM (All workers)	0.12	0.07	0.15	0.03	3,369,473
Δ IM (Low-wage workers)	0.11	0.07	0.04	0.03	1,131,725
Δ IM (Medium-wage workers)	0.11	0.07	0.05	0.03	1,218,432
Δ IM (High-wage workers)	0.12	0.07	0.16	0.03	1,019,316
	(c) Descriptives for back-of-the-envelope calculation				
Change in wage gap t, $t+10$					
High-wage worker/low-wage worker	16.2 log points				
High-wage worker/medium-wage worker	8.1 log points				
Medium-wage worker/low-wage worker	8.1 log points				
Change in firm wage premium gap t, $t+10$					
High-wage worker/low-wage worker	5.9 log points				
High-wage worker/medium-wage worker	2.0 log points				
Medium-wage worker/low-wage worker	3.9 log points				
Average firm wage premium in $t+10$					
High-wage firms	21.5 log points (dev. from medium-wage firms)				
Low-wage firms	-35.2 log points (dev. from medium-wage firms)				

Notes: Panels (a) and (b) provide summary statistics for the main estimation sample in the base years 1990 and 2000. Panel (c) provides the basic variables needed for the back-of-the-envelope calculation of labor reallocation on sorting and wage inequality. The numbers in panel (c) refer to the whole economy (manufacturing plus non-manufacturing). See section 3.2 and 3.3 for a detailed explanation of the data preparation and wage decomposition.

Table D3: Descriptives on worker groups

[**Sample means**]	**Worker type (tercile of $\hat{\alpha}_i$):**		
	High-wage	Medium-wage	Low-wage
(a) General			
Estimated worker component ($\hat{\alpha}_i$)	4.69	4.36	4.13
Log daily wage (imputed)	4.84	4.43	4.22
High education	0.32	0.07	0.05
(b) Occupational groups:			
Manager/Engineer/Professional	0.25	0.03	0.01
Technician/Qual. services/Admin.	0.42	0.16	0.08
Manual/Simple services	0.33	0.80	0.91
(c) Job tasks:			
Routine job	0.09	0.29	0.42
Codifiable job	0.12	0.36	0.48
(d) Firm type:			
High-wage firm	0.77	0.74	0.70
Medium-wage firm	0.18	0.22	0.25
Low-wage firm	0.05	0.04	0.05
N	1,019,316	1,218,432	1,131,725

Notes: Descriptives on the main estimation sample (N=3,369,473) for the base years t (1990 and 2000). Each value denotes the sample mean of the respective variable. Workers are grouped into terciles according to the estimated fixed effects in equation 1. See section 3.2 for a detailed explanation of the data preparation and wage decomposition.

Table D4: Explaining the variation of estimated worker effects

Dep. var.: Estim. Worker effect	(1)	(2)	(3)	(4)	(5)
High education	0.2930***	0.2463***	0.2239***	0.0412***	0.0407***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Routine job		-0.0747***	-0.0752***	-0.0254***	-0.0250***
		(0.0003)	(0.0004)	(0.0005)	(0.0005)
Codifiable job		-0.0814***	-0.0865***	-0.0054***	-0.0055***
		(0.0003)	(0.0003)	(0.0006)	(0.0006)
R^2	0.19	0.25	0.27	0.40	0.40
Tasks		√	√	√	√
3-digit industry FE			√	√	√
2-digit occupation FE				√	√
Labor market region FE					√

Notes: The table shows the results of a regression of the estimated worker component on various explanatory variables, all the the base year level. All specifications include a cubic term in age and a dummy to differentiate between the cross-sections 1990 and 2000. See section 3.2 for an explanation of the data preparation and wage decomposition. Levels of significance: *10%, **5%, ***1%.

Table D5: Reallocation into non-manufacturing and sorting - by initial firm type

Manufacturing in t	**Non-manufacturing in $t+10$ (%)**			
	Firm type:			
	All firms	High-wage	Medium-wage	Low-wage
	(1)	(2)	(3)	(4)
(a) High-wage firms				
High-wage workers (N=784,836)	12.7	9.4	2.4	0.9
Medium-wage workers (N=905,964)	12.6	6.5	3.8	2.3
Low-wage workers (N=797,306)	15.1	5.6	5.1	4.4
(b) Medium-wage firms				
High-wage workers (N=184,136)	13.0	6.4	4.5	2.1
Medium-wage workers (N=263,843)	16.9	6.2	6.8	3.9
Low-wage workers (N=282,667)	19.7	5.3	7.3	7.1
(c) Low-wage firms				
High-wage workers (N=50,344)	16.9	5.8	6.9	4.2
Medium-wage workers (N=48,625)	23.4	6.7	9.5	7.2
Low-wage workers (N=51,752)	24.8	5.4	8.8	10.6

Notes: Column (1) shows the share of workers who are employed in the non-manufacturing sector in $t+10$. Columns (2)-(4) split up the share from column (1) into employment by high-wage, medium-wage, and low-wage firms. See section 3.2 for a more detailed explanation of the data preparation and wage decomposition.

Table D6: Top net importing and exporting industries

3-digit industry	Change 1990-2010
(a) Increase in net imports	
Office machinery	10.81
Ships	5.27
Electronic components	5.27
Sound and video recording apparatus	4.74
Furniture	3.66
(b) Increase in net exports	
Motor vehicles	9.23
Other special purpose machinery	6.09
Parts and accesoires for motor vehicles	4.25
Machinery for production of mechanical power	4.09
Pharmaceuticals	3.11

Notes: Table displays the industries with the largest increase in net imports and exports from 1990 through 2010, respectively. All values in billions of 2010-euros. Data source: Comtrade.

Table D7: Alternative outcome variables

	(1)	(2)	(3)
Dependent variable (dummy):	Same firm in $t+10$	Manuf. in $t+10$	Out of sample in $t+10$
Δ NetImp	-0.17***	-0.16***	0.06***
	(0.03)	(0.03)	(0.02)
ΔNetImp*Medium-wage worker	0.00	0.00	-0.02***
	(0.00)	(0.00)	(0.01)
ΔNetImp*High-wage worker	0.00	-0.01	-0.01*
	(0.01)	(0.02)	(0.01)
R^2	0.05	0.04	0.03

Notes: N=3,369,473. In column (1), the dependent variable is 1 if the worker is full-time employed in the same manufacturing firm in $t+10$ as in t. In column (2), the dependent variable is 1 if the worker is full-time employed in manufacturing in $t+10$. In column (3), the dependent variable is 1 if the worker is out of the sample in $t+10$. Workers are out of the sample if they are unemployed, self-employed, part-time employed, are in early retirement employed in the public sector as civil servants in $t+10$ or have passed away between t and $t+10$. Additional controls (held constant at year t): dummies for worker types and initial firm types (terciles), the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 3.2 and 3.5 for more details. Levels of statistical significance: *10%, **5%, ***1%.

Table D8: Upward and downward mobility

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Dummy: Non-manufacturing in $t+10$				Premium
	All	High-wage	Medium-wage	Low-wage	in $t+10$
[**2SLS**]	**(a) Workers employed by high-wage firms in** t				
			N=2,488,106		
Δ NetImp	0.11***	0.05***	0.03***	0.03***	-0.07***
	(0.03)	(0.02)	(0.01)	(0.01)	(0.02)
ΔNetImp*Medium-wage worker	0.01	0.03*	-0.00	-0.02***	0.04***
	(0.02)	(0.02)	(0.00)	(0.00)	(0.01)
ΔNetImp*High-wage worker	0.01	0.06	-0.02***	-0.03***	0.06***
	(0.03)	(0.04)	(0.01)	(0.01)	(0.02)
R^2	0.05	0.03	0.02	0.02	0.43
[**2SLS**]	**(b) Workers employed by medium-wage firms in** t				
			N=730,646		
Δ NetImp	0.06***	0.02***	0.03***	0.01***	-0.02**
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
ΔNetImp*Medium-wage worker	0.03***	0.02	0.01*	0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ΔNetImp*High-wage worker	0.03*	0.04**	-0.00	-0.01	0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
R^2	0.04	0.02	0.02	0.02	0.40
[**2SLS**]	**(c) Workers employed by low-wage firms in** t				
			N=150,721		
Δ NetImp	0.02	0.01	0.01	0.01	-0.02
	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)
ΔNetImp*Medium-wage worker	0.02	-0.00	0.01	0.00	0.00
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
ΔNetImp*High-wage worker	0.04	0.04**	0.01	-0.00	0.02
	(0.03)	(0.02)	(0.01)	(0.01)	(0.02)
R^2	0.04	0.02	0.01	0.02	0.32

Notes: See equation 5. Panel (a) restricts the sample on workers employed in high-wage manufacturing firms in base year t. Analogously, panels (b) and (c) restrict the sample on worker employed in medium-wage and low-wage manufacturing firms in t. Additional controls (held constant at year t): dummies for worker types and initial firm types (terciles), the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 3.2 and 3.5 for more details. Levels of statistical significance: *10%, **5%, ***1%.

Table D9: Drop workers affected by domestic outsourcing

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Dummy: Non-manufacturing in $t+10$				Premium
	All	High-wage	Medium-wage	Low-wage	in $t+10$
Δ NetImp	0.10***	0.04***	0.03***	0.02***	-0.06***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
ΔNetImp*Medium-wage worker	0.02	0.03**	0.00	-0.01***	0.02***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
ΔNetImp*High-wage worker	0.02	0.05**	-0.01**	-0.02***	0.05***
	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)
R^2	0.05	0.03	0.02	0.02	0.47

Notes: N=3,147,481. See equation 5. Workers in food, cleaning, security and catering occupations are dropped. In column (1), the dependent variable is 1 if the worker is full-time employed in non-manufacturing in $t+10$. In column (2), the dependent variable is 1 if the worker is full-time employed in a high-wage non-manufacturing firm in $t+10$. Analogously for columns (3) and (4). Column (5) shows the results with the estimated firm wage premium in $t+10$ as a dependent variable. Additional controls (held constant at year t): dummies for worker types and initial firm types (terciles), the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 3.2 and 3.5 for more details. Levels of statistical significance: *10%, **5%, ***1%.

Table D10: Drop 10% of least skilled workers

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Dummy: Non-manufacturing in $t+10$				Premium
	All	High-wage	Medium-wage	Low-wage	in $t+10$
Δ NetImp	0.11***	0.05***	0.04***	0.03***	-0.06***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
ΔNetImp*Medium-wage worker	0.01	0.02*	-0.00	-0.01***	0.02***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
ΔNetImp*High-wage worker	0.01	0.05*	-0.02***	-0.02***	0.05***
	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)
R^2	0.05	0.03	0.02	0.02	0.47

Notes: N=2,526,031. See equation 5. Workers in bottom decile of estimated worker components are dropped. In column (1), the dependent variable is 1 if the worker is full-time employed in non-manufacturing in $t+10$. In column (2), the dependent variable is 1 if the worker is full-time employed in a high-wage non-manufacturing firm in $t+10$. Analogously for columns (3) and (4). Column (5) shows the results with the estimated firm wage premium in $t+10$ as a dependent variable. Additional controls (held constant at year t): dummies for worker types and initial firm types, the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 3.2 and 3.5 for more details. Levels of statistical significance: *10%, **5%, ***1%.

Table D11: Export and import exposure separately

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Dummy: Non-manufacturing in $t+10$				Premium
	All	High-wage	Medium-wage	Low-wage	in $t+10$
Δ Imp	0.10***	0.04***	0.03***	0.03***	-0.06***
	(0.02)	(0.01)	(0.06)	(0.01)	(0.02)
ΔImp*Medium-wage worker	0.01	0.03**	0.00	-0.01***	0.02***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
ΔImp*High-wage worker	0.02	0.06**	-0.01***	-0.02***	0.05***
	(0.03)	(0.03)	(0.00)	(0.01)	(0.01)
Δ Exp	-0.21***	-0.10**	-0.06**	-0.05**	0.12**
	(0.07)	(0.04)	(0.03)	(0.02)	(0.05)
ΔExp*Medium-wage worker	0.02	0.00	0.01	0.01	-0.02
	(0.06)	(0.06)	(0.01)	(0.02)	(0.03)
ΔExp*High-wage worker	0.14	0.00	0.08**	0.05**	-0.12***
	(0.10)	(0.09)	(0.03)	(0.02)	(0.04)
R^2	0.05	0.03	0.02	0.02	0.47

Notes: N=3,369,473. See equation 5. In column (1), the dependent variable is 1 if the worker is full-time employed in non-manufacturing in $t+10$. In column (2), the dependent variable is 1 if the worker is full-time employed in a high-wage non-manufacturing firm in $t+10$. Analogously for columns (3) and (4). Column (5) shows the results with the estimated firm wage premium in $t+10$ as a dependent variable. Additional controls (held constant at year t): dummies for worker types and initial firm types (terciles), the base year, dummies for high formal education, routine tasks, codifiable tasks, tenure, age groups, firm size, industry groups, and local labor markets. Standard errors are clustered at the 3-digit industry-base year level. See sections 3.2 and 3.5 for more details. Levels of statistical significance: *10%, **5%, ***1%.

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4 International trade and its heterogeneous effect on the college wage premium across regions

International trade and its heterogeneous effect on the college wage premium across regions

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The magnitude of the increase in the college wage premium varies substantially across U.S. commuting zones. Motivated by this phenomenon, I emphasize the heterogeneous effects of trade integration on the college wage premium across regions. I focus on the rise of China as a major exporting country and its impact on the college wage premium in the USA. The main result of the paper is that the impact on the college wage premium in a commuting zone varies, depending on the initial allocation of college and non-college workers across sectors. The college wage premium rises more strongly in commuting zones in which non-college workers select more strongly into the manufacturing sector than college workers. To rationalize differences in the allocation of college and non-college workers across regions and the resulting effects on the regional college wage premium in response to a change in the trade environment, I emphasize a model in which heterogeneous workers self-select into sectors according to their observed and unobserved productivity. I then provide estimates on the heterogeneous effects of the rise of China on the college wage premium across regions, based on the model structure. The results suggest that studies which focus on a single elasticity between the college wage premium and some measure of trade liberalization mask substantial differences between regions.

JEL-Classification: F14, J31
Keywords: Trade, college wage premium, commuting zones, China, labor reallocation

4.1 Introduction

Wage inequality has increased sharply in the USA during the last decades (e.g. Katz and Murphy 1992; Goldin and Katz 2009; Acemoglu and Autor 2011). Motivated by this phenomenon, a growing literature analyzes how globalization, technological progress and institutional changes affect the aggregate wage structure. A feature of the rise in wage inequality which has received less attention is its heterogeneity across regions. Moretti (2013, p.94) for example estimates the college wage premium (CWP) separately by U.S. metropolitan area and year and finds that some areas experienced a rise in the CWP of more than 30 log points between 1980 and 2000, whereas other areas experienced no significant increase or even a decrease in the CWP.[1] This finding implies that a relatively small number of regions produce a large part of the aggregate rise in wage inequality. A full understanding of the causes of the rise in aggregate wage inequality therefore requires an understanding of its regional heterogeneity.

International trade is among the potential drivers of wage inequality. One of the major changes in the trade environment for industrialized countries during the last decades has been the integration of China into the world economy. The rise of China as a major exporting country had profound effects on local labor markets in several countries including the USA (e.g. Autor et al. 2013; Dauth et al. 2014; Balsvik et al. 2015; Acemoglu et al. 2016; Caliendo et al. 2019). The previous literature largely focuses on the differential effects of this trade shock on outcomes such as manufacturing employment, average wages, or welfare within regions. In contrast, the effects of trade with China on wage inequality within regions, and in particular the potential regional heterogeneity in the effects on wage inequality, have received much less attention.[2]

In this paper, I analyze the effect of China's rise as a major exporter of manufacturing goods on the CWP within 722 U.S. commuting zones. In particular, I emphasize the regional heterogeneity of the effect on the CWP. The main result of the paper is that the sign and the magnitude of the change in the CWP in response to the trade shock can differ across regions. While the CWP might rise sharply in some commuting zones, other commuting zones might even see a decline in their CWP in response to a change in the trade environment. The paper therefore suggests that growing international trade has the potential to explain part of the regional heterogeneity in the evolution of the CWP.

In a first step, I provide descriptive evidence that the evolution of the CWP indeed differs strongly between areas. I estimate the CWP separately by commuting zone and year as the gap in log hourly wages between individuals with a bachelor's degree and individuals with a high school degree, controlling for experience, sex, race, and immigra-

[1] See also Black et al. (2008) for similar results.

[2] Studies on trade and inequality typically focus on outcomes at the individual, household, firm, or industry level. See Harrison et al. (2011), Helpman (2017), or Muendler (2017) for extensive surveys of the literature.

tion status. The estimated CWP increased by 9.69 log points in the median commuting zone between 1990 and 2007. The median, however, masks a substantial heterogeneity across commuting zones. In a commuting zone at the 90th percentile, the rise in the estimated CWP amounts to 15.33 log points. A commuting zone at the 10th percentile, in contrast, experiences an increase in the estimated CWP of only 1.95 log points. The estimated CWP declines in 149 out of 722 commuting zones. Several studies suggest that the regional heterogeneity reflects a rural-urban divide, with larger increases of wage inequality in larger or more densely populated areas (e.g. Baum-Snow and Pavan 2013; Baum-Snow et al. 2018). I confirm a positive relationship between initial commuting zone size and the subsequent change in the CWP. The change in the CWP, however, also varies substantially conditional on initial size. To explain the full heterogeneity in inequality trends across regions, one therefore needs to go beyond city size or population density as potential causes.

The main part of the analysis is guided by a theory in which a change in the trade environment affects the regional CWP differently, depending on the regional workforce composition and its allocation across sectors. I lay out a Ricardo-Roy model in the spirit of Costinot and Vogel (2010) and Costinot and Vogel (2015). In this model, college and non-college workers draw a productivity for the manufacturing and the non-manufacturing sector from an underlying distribution and self-select into the sector which maximizes their wage. Importantly, regions differ in their workforce composition within the groups of college and non-college workers. Some regions host college workers who are relatively more productive in the non-manufacturing sector than non-college workers, whereas other regions host college workers who are relatively more productive in the manufacturing sector. Regions are small open economies and workers are mobile across sectors within a region and immobile across regions.

The model yields one important cross-sectional and one important comparative-static prediction. In the cross section, it rationalizes regional differences in the allocation of college and non-college workers across sectors. In the model, workers sort into sectors according to their comparative advantage. This means that relative productivity differences between skill groups across sectors translate into differences in their relative allocation across sectors. Take a region in which college workers are relatively more productive in the non-manufacturing sector than non-college workers. The model predicts that in this region, college workers earn a relatively higher share of their labor income in the non-manufacturing sector than non-college workers. In contrast, in a region in which college workers are relatively less productive in the non-manufacturing sector than non-college workers, they earn a relatively lower share of their labor income in the non-manufacturing sector than non-college workers.[3] A look at the data shows that the allocation of college

[3]Suppose for example that college workers consist of lawyers and engineers. The vast majority of lawyers are employed in non-manufacturing industries providing legal services. For engineers, the

and non-college workers to the manufacturing and non-manufacturing sector indeed differs strongly across U.S. commuting zones. As of 1990, in the median commuting zone, college workers earn 5 percentage points more of their labor income in the non-manufacturing sector than non-college workers do. In the commuting zone at the 90th percentile, this difference amounts to 16 percentage points. In contrast, in the commuting zone at the 10th percentile, the difference is at -1 percentage point, i.e. college workers earn a slightly lower share of their labor income in the non-manufacturing sector than non-college workers.

The main comparative-static prediction concerns the role that these regional differences play for the way in which changes in the trade environment affect the regional CWP. I assume that the integration of China as a large manufacturing exporter into the world economy causes a decrease in the relative price of manufacturing goods. The main prediction of the model is that a given decrease of the relative price of manufacturing goods triggers a higher increase in the CWP in regions in which non-college workers initially earn a higher share of their labor income in the manufacturing sector than college workers. The intuition behind this mechanism is in the spirit of the specific-factors model. Workers' productivities differ across sectors and they endogenously select into a sector for which they have a relatively high productivity draw. Workers therefore are partly specific to the sector in which they are employed and this is why they are disproportionately negatively affected by a decrease in the relative price of goods in that sector.

In a next step, I make use of the model structure to end up with an estimate of the impact of the China shock on the CWP within commuting zones. In the model, the change in the CWP in a commuting zone depends on the change of the relative manufacturing price, the initial allocation of college and non-college workers as reflected by the respective labor income shares, and the dispersion of productivity draws within the groups of college and non-college workers. While the initial allocation is readily observable in the data, the relative price change and the dispersion of productivity draws are not and therefore need to be estimated.

To obtain a result for the change in the relative manufacturing price, I first compute the predicted reallocation of workers from the manufacturing into into the non-manufacturing sector in a region in response to the trade shock. To this end, I regress the change in the share of the their labor income that non-college workers earn in the manufacturing sector in a region on a Bartik-style measure of increased Chinese manufacturing import exposure in the spirit of Autor et al. (2013). The resulting predicted reallocation into the

picture is more mixed. While many engineers work in manufacturing industries, a substantial share of engineers is employed in non-manufacturing industries such as construction or service industries such as computer and data processing. Through the lens of the model, these differences in allocation reflect the idea that lawyers, because of their specific training and skills, are relatively more productive in the non-manufacturing sector (especially in firms specializing on legal services) than engineers. Holding constant the composition of non-college workers across regions, regional differences in the share of lawyers and engineers within the group of college workers translate into regional differences in the allocation of college and non-college workers across sectors. See section 4.3 for more details.

non-manufacturing sector, together with a maximum likelihood estimate of the dispersion of productivity draws, allows to back out the implied decrease in the relative price of manufacturing goods in response to the trade shock. Together with data on the initial allocation of college and non-college workers across sectors, I then compute the predicted impact on the CWP in the respective commuting zone.

The results show a large regional heterogeneity, with estimated changes in the CWP ranging from an increase by 4.96 log points to a decrease by 1.27 log points over a period of ten years. These differences are sizable in the light of the mean observed increase in the CWP over ten years which amounts to 5.39 log points. In a subsequent counterfactual exercise, I gauge the relative importance of initial allocations, relative price changes, and productivity dispersions for this effect by selectively switching off one or two of them. It turns out that the regional heterogeneity is driven mostly by regional differences in the allocation of workers across sectors. I also extend the analysis to a setting with eight education groups. It turns out that the regional differences in the effect are even higher for the wage gap between individuals with a master's, a professional, or a doctoral degree, and individuals with a high school degree.[4]

This paper contributes to the understanding of the regional effects of the rise of China as a major exporter of manufacturing goods. The previous literature on the regional effects of this trade shock mostly focused on local outcomes like manufacturing employment, average wages, or welfare (e.g. Autor et al. 2013; Dauth et al. 2014; Balsvik et al. 2015; Acemoglu et al. 2016; Caliendo et al. 2019).[5] This paper, in contrast, focuses on the differential effect on the CWP across regions and thereby provides evidence that growing international trade is among the contributors to the large regional heterogeneity in the evolution of the observed CWP. Imposing a single elasticity between their measure of local import exposure in U.S. commuting zones and the respective outcome variable, Autor et al. (2013) do not find evidence that growing Chinese import exposure affects local average wages of college and non-college workers differently. The analysis in this paper suggests that studies like the one by Autor et al. (2013) which impose a single elasticity might mask a substantial heterogeneity in the effect across regions. In fact, the results suggest that while some regions experience a sharp rise in the CWP, other regions might even experience a decline in the CWP in response to the trade shock. In studies that use a Bartik-style measure of trade exposure as Autor et al. (2013), variation in the effects on the regional outcome stems from regional variation in the industry structure. While the regional industry structure is certainly an important determinant for regional heterogeneity in labor market outcomes, this paper emphasizes that the inequality effects can also differ across regions with the same industry structure, depending on the initial

[4]For example, the effects on the wage gap between individuals with a master's and a high school degree range from 10.02 log points to minus 1.70 log points.

[5]See also Kovak (2013) and Dix-Carneiro and Kovak (2017b) on the regional effects of trade liberalization in Brazil.

selection of college and non-college workers across sectors.[6]

Only few studies provide evidence that the impact of international trade on wage inequality differs across regions. Michaels (2008) finds that the creation of the interstate highway system and the corresponding decrease in trade barriers differently affected the demand for skilled workers in different U.S. regions. Guided by a specific-factors model with high-skilled and low-skilled workers, a short paper by Dix-Carneiro and Kovak (2015) provides evidence that trade liberalization affected the CWP differently across Brazilian regions. Relative to these studies, I focus on trade with China and choose a structural approach instead of a reduced-form analysis. The approach in this paper lends itself to a counterfactual exercise that allows to illustrate that the effects on the CWP can differ across regions even if all regions have the same industry structure and experience the same change in relative goods prices. Finally, relative to Michaels (2008) and Dix-Carneiro and Kovak (2015), I extend the analysis to more than two education groups and show that the dispersion in the effects differs, depending on the education groups that are being compared.

With its modeling approach of combining a Roy-type assignment model along the lines of Costinot and Vogel (2010) and Costinot and Vogel (2015) with a stochastic productivity distribution for factors of production, this paper is related to Lakagos and Waugh (2013), Costinot et al. (2016), Galle et al. (2017), Fajgelbaum and Redding (2018), Hsieh et al. (2019), and Burstein et al. (2019). Among these studies, the paper is most closely related to Galle et al. (2017) and Burstein et al. (2019). Galle et al. (2017) analyze the effects of the rise of China on the CWP in the USA and the corresponding welfare effects in the presence of inequality aversion. Burstein et al. (2019) analyze the nexus between computerization, international trade, and the skill premium in the USA. Relative to those studies, this paper is explicitly focuses on the extent to which the rise of China affects the CWP differently across regions and the role that the allocation of skill groups across sectors play for these differences.[7] The paper is also related to quantitative trade models which study the local labor market effects of large aggregate or disaggregated shocks in the presence of regional mobility of workers (Monte et al. 2018; Krebs and Pflueger 2019). Relative to this literature, I abstract from the role of labor mobility across regions and allow for substantial worker heterogeneity.

Finally, the paper is related to different strands of the literature which analyze regional differences in wages and wage inequality. A number of studies emphasize that wages are higher in urban areas ("urban wage premium") and analyze the underlying causes (e.g. Combes et al. 2008; Baum-Snow and Pavan 2012; De La Roca and Puga 2017; Autor

[6]Studies which focus on the effects of trade with China on wage and earnings inequality typically take a worker or household-level perspective (e.g. Autor et al. 2014; Utar 2018; Huber and Winkler 2019; Keller and Utar 2019; Dauth et al. 2019a).

[7]See also Buera and Kaboski (2012) and Cravino and Sotelo (2019) for an analysis of the link between structural change and the skill premium in the USA which abstracts from regional heterogeneity.

2019; Dauth et al. 2019b). Baum-Snow and Pavan (2013) find that the rise in wage inequality is stronger in larger and more densely populated areas and Baum-Snow et al. (2018) emphasize an increase in the skill bias of agglomeration economies as a driver of this phenomenon. Black et al. (2008) argue that, in the presence of non-homothetic preferences, the CWP is smaller in cities with higher housing costs and a higher level of amenities. A recent strand of the literature focuses on welfare differences between different skill groups in the presence of local skill-biased demand shocks, regional mobility, as well as local differences in prices and amenities (Moretti 2013; Diamond 2016).

4.2 The increase in the CWP - a regional perspective

4.2.1 Data and measurement

The micro data used in this paper stem from the decennial Census for the years 1990 and 2000 and from the American Community Survey (ACS) for the years 2006 and 2007 (Ruggles et al. 2010). The data can be accessed via https://usa.ipums.org/usa/. The Census data for the years 1990 and 2000 consist of a 5%-sample of the U.S. population in the respective year and provide detailed information such as annual labor income, weeks worked, usual working hours, occupation, industry affiliation, and the location of individuals. The ACS data for the years 2006 and 2007 are a corresponding 1%-sample of the US population in the respective year and provide the same type of information as the Census data. I pool the years 2006 and 2007 and treat the data as referring to one single year, 2007.[8] In all the computations and estimations, I make use of sample weights to ensure the representativeness of the results.

To provide a regional perspective on the change in the CWP, I draw on the concept of a commuting zone which was developed by Tolbert and Killian (1987) and Tolbert and Sizer (1996). Commuting zones can be understood as clusters of counties which are characterized by strong commuting ties. Relative to the use of Metropolitan Statistical Areas (MSAs) as the concept of a local labor market (e.g. Moretti 2010; Baum-Snow and Pavan 2012; Moretti 2013), the advantage of using commuting zones is that this concept includes rural areas in addition to urban areas.[9] Tolbert and Sizer (1996) define a total of 741 commuting zones for the year 1990, covering both metropolitan and rural areas in the USA. I follow Autor and Dorn (2013) and Autor et al. (2013) and use the 722 commuting zones which cover the mainland of the United States. I create time-consistent commuting zones in all years in the Census and ACS data using the crosswalk from Public Use Micro

[8]This step serves to increase the sample size and measurement precision for the later years which are based on the smaller ACS sample. See for example Baum-Snow and Pavan (2013) or Autor et al. (2013).

[9]MSAs mostly include major urban areas. To still include rural areas into the analysis, some studies group observations which are not assigned to an MSA into one single group (e.g. Baum-Snow and Pavan 2012).

Areas (PUMAs) to commuting zones developed by Dorn (2009). Appendix E provides more details on this procedure.

I restrict the sample to individuals with either a high school or a bachelor's degree with an age between 16 and 64 and exclude workers in the military. I compute hourly wages as annual labor income divided by the number of weeks worked times usual hours worked per week. Following Baum-Snow and Pavan (2012), I drop observations with an hourly wage lower than 75% of the federal minimum wage in a given year. I deflate wages using the consumer price index to obtain constant 2007-USD. With these restrictions, I end up with 3,607,572 observations for the year 1990, 3,968,548 observations in 2000, and 1,730,749 observations in 2006-2007. Table G1 in the appendix provides basic summary statistics on the resulting sample. As a robustness check, I also employ a more restricted sample which focuses on individuals with an age between 25 and 55 who have worked at least 40 weeks and 35 hours per week. The results remain robust to using this alternative sample. Throughout the main part of the analysis, I focus on wage differences between individuals with a bachelor's degree (college) and individuals with a high school degree (non-college). At a later stage, I expand the analysis to a total of eight education groups.

4.2.2 Results

Figure 1 and table 1 show that the CWP in the year 1990 and its change from 1990 through 2007 differ strongly across U.S. commuting zones. I define the raw CWP in a commuting zone in a given year as the difference in mean log hourly wages between college and non-college workers. The adjusted CWP stems from a Mincer regression of log hourly wages on an indicator for college degree, controlling for 60 groups defined by sex (male and female), race (white, black, and other), potential experience (<10, 10-20, 20-30, 30-40, >40), and immigration status (foreign-born or not), separately by commuting zone and year. Potential experience is computed as age minus years of schooling minus 6.

As of 1990, the adjusted CWP amounts to 41.93 log points in the median commuting zone. This corresponds to a wage difference between college and non-college workers of 52% (exp(0.4193)-1 $\approx$ 0.52). This value is also very close to the estimated aggregate national college wage premium of 41.66 log points.[10] However, the estimated CWP differs markedly across regions. It amounts to 46.85 log points in a commuting zone at the 90th percentile and to 36.30 log points in a commuting zone at the 10th percentile.

The heterogeneity across regions is even more pronounced in terms of the change in the CWP between the years 1990 and 2007. The median commuting zone experienced a rise in the adjusted CWP of 9.69 log points. Again, this value is close to the aggregate national rise in the adjusted CWP of 9.63 log points. This result is in line with a large literature documenting that the CWP has been increasing in the USA during the last

[10]To obtain this value, I pool all commuting zones in 1990 and estimate the same type of regression, additionally including commuting zone dummies as suggested by Black et al. (2008).

decades (e.g. Goldin and Katz 2009; Acemoglu and Autor 2011). The aggregate national trend, however, masks a considerable heterogeneity across regions. According to table 1, the commuting zone at the 90th percentile experienced a rise in the adjusted CWP of 15.33 log points, whereas the commuting zone at the 10th percentile saw its adjusted CWP increase by only 1.95 log points. The change in the CWP ranges from an increase by 32.99 log points to a decrease by 15.01 log points. A total of 149 out of 722 commuting zones experienced a decline in the CWP between 1990 and 2007. This finding suggests that not all commuting zones contribute equally to the aggregate rise in the CWP. In fact, a limited number of commuting zones produce a large part of the increase in the national CWP documented in previous studies. Table G3 and figure G1 in the appendix show that this pattern holds also for a sample that restricts the attention to individuals aged 25-55 who have worked at least 40 weeks and 35 hours per week.

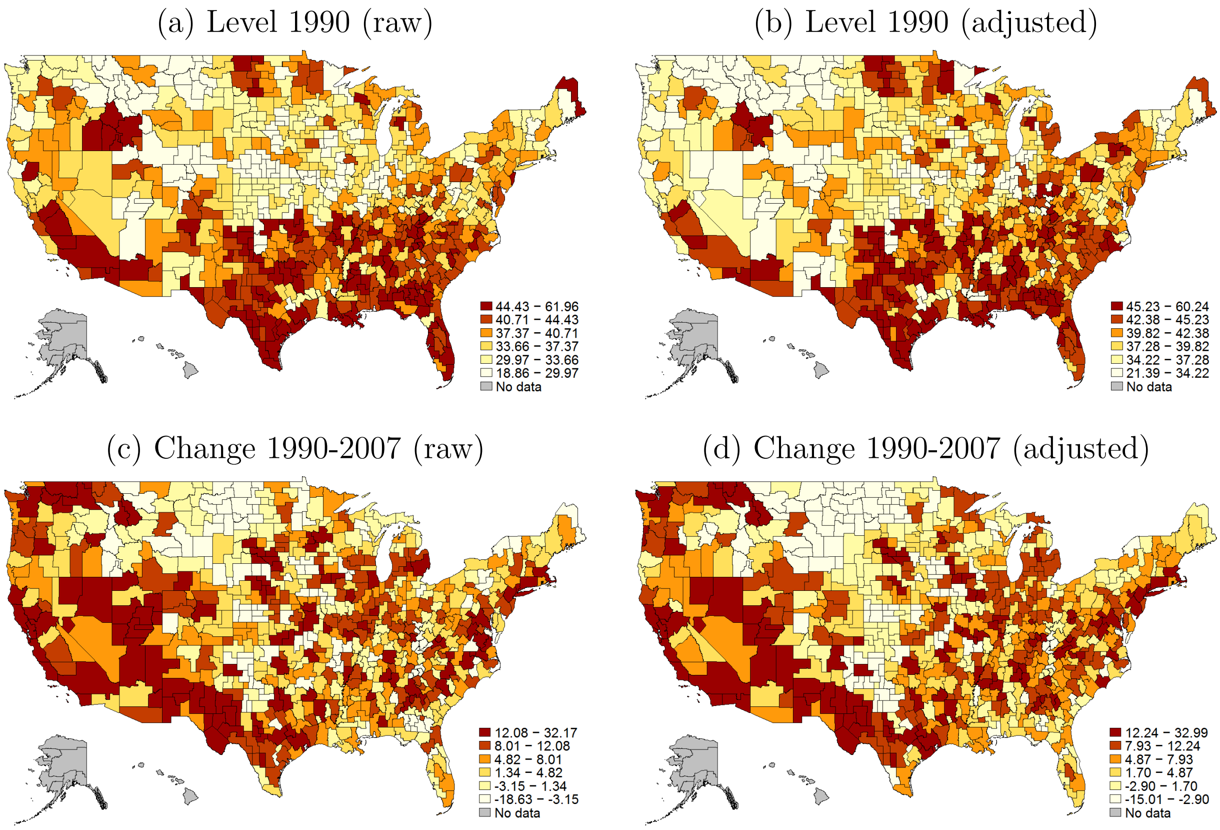
A closer look at the maps in figure 1 suggests that the CWP in 1990 tends to be higher in the south part of the country, including for example areas in Texas, Florida, Oklahoma, Mississippi, and Alabama. The change in the CWP over time is more dispersed across the country. Particularly high increases in the CWP are visible in California, parts of Texas, New Mexico, New York, New Jersey, Massachusetts, Alabama, and Mississippi. Table G2 provides a list of the 30 largest commuting zones as of 1990 and their respective change in the CWP. The increase in the CWP tends to be above the national average in these commuting zones. For example, the commuting zones of San Francisco CA, San Jose CA, and Washington DC experienced an increase in the adjusted CWP of more than 20 log points.

Figure 2 plots the change in the adjusted CWP from 1990 to 2007 against the initial log population and illustrates that the heterogeneity in the inequality trends goes beyond a mere divide between larger and smaller cities or commuting zones. Baum-Snow and Pavan (2012) for example provide evidence that wage inequality increased more strongly in larger and more densely populated areas. A potential explanation for this phenomenon is that agglomeration economies in larger cities tend to favor more skilled workers (e.g. De La Roca and Puga 2017; Baum-Snow et al. 2018).[11] Figure 2 confirms a positive relationship between initial size and the subsequent evolution of the CWP. However, figure 2 also shows that the change in the adjusted CWP also differs substantially, conditional on a given initial size. Consider for example the commuting zones of Cleveland and Pittsburgh. As of 1990, they are very similar in terms of their population count (around 2.6 million individuals). While the adjusted CWP increased by 7.86 log points in Cleveland between 1990 and 2007, it increased by 2.42 log points in Pittsburgh during that period. While the heterogeneity illustrated in 1 and table 1 might have a myriad of different causes, figure 2 implies that it is necessary to go beyond initial city size in explaining the diverging

[11] De La Roca and Puga (2017) for example provide evidence that the returns to city-specific experience are larger for more skilled individuals.

inequality trends across regions.

Figure 1: Heterogeneity in the CWP across commuting zones



Notes: The figures plot the level of the college wage premium (CWP) in 1990 and its change from 1990 to 2007, separately for 722 U.S. commuting zones. The raw CWP is computed as the difference in mean log hourly wages between individuals with a bachelor's degree and individuals with a high school degree. The adjusted CWP stems from a regression of log hourly wages on a dummy for bachelor's degree, controlling for all possible interactions between variables for sex (male and female), race (white, black, and other), potential experience (<10, 10-20, 20-30, 30-40, >40), and immigration status (foreign-born or not), separately by commuting zone and year. Sample is restricted on all workers with either a high school or a bachelor's degree with 20-60 years of age in dependent employment outside the military. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007).

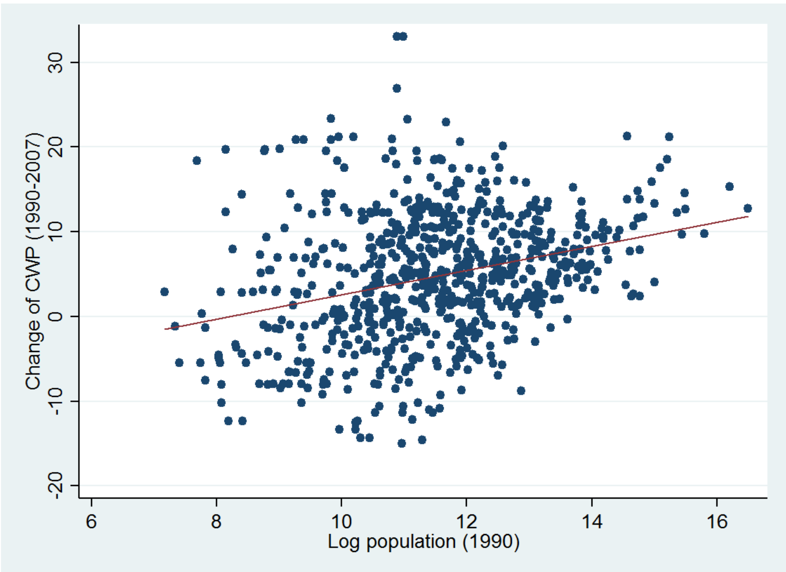
Figure 2 also provides evidence that a restriction of the attention to mostly urban areas leads to an understatement of the true heterogeneity in inequality trends. The figure suggests that the estimated CWP decreased in a non-negligible number of commuting zones between 1990 and 2007. As these commuting zones tend to be smaller on average, most of them are not captured by the commonly used definition of local labor markets based on MSAs. Focusing on MSAs, Black et al. (2008) and Moretti (2013) estimate the change in the local CWP from 1990 to 2010 or from 1980 to 2000, respectively. Indeed, in both studies, most MSAs exhibit a positive change in the estimated CWP during that period. Figure 2 in contrast suggests that it is important to be able to rationalize a decrease in the CWP in a substantial share of regions.

Table 1: Heterogeneity in CWP across commuting zones, summary statistics

	min	p10	p25	p50	p75	p90	max
				(a) Level (1990)			
Raw CWP	18.86	32.71	36.14	38.95	43.89	46.04	61.96
Adjusted CWP	21.39	36.30	38.88	41.93	44.68	46.85	60.24
				(b) Change (1990-2007)			
Raw CWP	-18.63	1.38	4.87	10.53	14.85	18.53	32.17
Adjusted CWP	-15.01	1.95	4.95	9.69	12.75	15.33	32.99

Notes: The table displays summary statistics on the college wage premium (CWP) within 722 U.S. commuting zones. The raw CWP is computed as the difference in mean log hourly wages between individuals with a bachelor's degree and individuals with a high school degree in the respective commuting zone and year. The adjusted CWP stems from a regression of log hourly wages on a dummy for bachelor's degree, controlling for all possible interactions between variables for sex (male and female), race (white, black, and other), potential experience (<10, 10-20, 20-30, 30-40, >40), and immigration status (foreign-born or not), separately by commuting zone and year. Sample is restricted on all workers with either a high school or a bachelor's degree with 20-60 years of age in dependent employment outside the military. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007).

Figure 2: Population size and the increase in the CWP



Notes: The graph plots the change in the adjusted CWP from 1990 to 2007 on the vertical axis and the log population in 1990 on the horizontal axis, separately for 722 U.S. commuting zones. The adjusted CWP stems from a regression of log hourly wages on a dummy for bachelor's degree, controlling for all possible interactions between variables for sex (male and female), race (white, black, and other), potential experience (<10, 10-20, 20-30, 30-40, >40), and immigration status (foreign-born or not), separately for each commuting zone and year. Sample is restricted on all workers with either a high school or a bachelor's degree with 20-60 years of age in dependent employment outside the military. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007).

4.3 Model

Motivated by the results in the previous section, this section presents a model in which a decrease in the relative price of manufacturing goods in response to the integration of China into the world economy affects the CWP differently across regions. I lay out a parametric Ricardo-Roy model along the lines of Costinot and Vogel (2010) and Costinot and Vogel (2015). In this model, the productivity of workers in a given sector exhibits unobserved heterogeneity, as reflected by a draw from an underlying productivity distribution. Regions are populated by workers in different skill groups who are perfectly mobile across industries within a region, but immobile across regions. The model yields two main insights. First, it rationalizes regional differences between college and non-college workers in the allocation to the manufacturing and non-manufacturing sector. Second, the model emphasizes the role that these differences play for the effect of a decrease in the relative manufacturing price on the CWP in a region. Depending on the initial allocation, the local CWP can either increase or decrease in response to the change in relative goods prices.

4.3.1 Set up

I assume that there exists a number of locations indexed by $\gamma \in \Gamma$. Each location is endowed with a continuum of workers indexed by $\omega \in \Omega(\gamma)$. Each worker inelastically supplies one unit of labor and her wage is given by $w(\omega, \gamma)$. I divide workers into a number of skill groups λ. One can think of λ as the observed level of formal education, for example a college degree. The set of workers in λ is given by $\Omega(\lambda, \gamma) \subseteq \Omega(\gamma)$ and has a mass of $L(\lambda, \gamma)$.

Further, each location is endowed with a number of sectors indexed by $\sigma \in \Sigma$. Each sector produces a homogeneous good of price $\mathrm{p}(\sigma)$ under perfect competition. I assume that locations are small open economies and therefore each industry σ takes $\mathrm{p}(\sigma)$ as given. Workers are perfectly mobile across sectors and immobile across locations.

I assume the production functions to be linear:

$$Q(\sigma, \gamma) = \int_{\Omega(\gamma)} A(\omega, \sigma, \gamma) L(\omega, \sigma, \gamma) d\omega \tag{1}$$

$Q(\sigma, \gamma)$ denotes the output in sector σ in location γ, $A(\omega, \sigma, \gamma)$ is the productivity of worker ω in sector σ and location γ and $L(\omega, \sigma, \gamma)$ is a binary variable which indicates whether worker ω is employed in sector σ in location γ or not.

I assume that regions γ, sectors σ, and skill groups λ are perfectly observable to the econometrician, while the exact productivity of a worker ω in region γ and sector σ, $A(\omega, \sigma, \gamma)$, is not. $A(\omega, \sigma, \gamma)$ is drawn from the following Fréchet distribution:

$$Pr(A(\omega, \sigma, \gamma) \leq a|\lambda) = exp\left[-[a/T(\lambda, \sigma, \gamma)]^{-\theta(\lambda)}\right] \tag{2}$$

Equation 2 introduces unobserved heterogeneity within skill groups as it implies that workers in the same observable skill group λ differ in terms of their productivity in sector σ in region γ, depending on their productivity draw from the Fréchet distribution. This implies for example that, in a given location, some college workers are more productive in the manufacturing sector than others.

Equation 2 contains two important parameters. $T(\lambda, \sigma, \gamma)$ is the scale parameter of the distribution. The higher the value of $T(\lambda, \sigma, \gamma)$, the more productive workers in skill group λ on average are in sector σ in location γ. $\theta(\lambda) > 1$ governs the dispersion of the distribution. The lower $\theta(\lambda)$, the more dispersed are the productivity draws within skill group λ.

Conditional on their productivity draw $A(\omega, \sigma, \gamma)$, workers endogenously select into one sector to maximize the value of their marginal product given by:

$$w(\omega, \gamma) = \max_{\sigma \in \Sigma} \{p(\sigma) A(\omega, \sigma, \gamma)\} \tag{3}$$

In this setting, workers with identical observable characteristics λ, such as the level of education, are employed in different sectors due to unobserved productivity differences.[12] This way of modeling unobserved heterogeneity within skill groups is in the spirit of Eaton and Kortum (2002).[13] It has been applied recently for example by Costinot et al. (2016), Galle et al. (2017), Fajgelbaum and Redding (2018), Hsieh et al. (2019), and Burstein et al. (2019).

Consumers in each location γ have the same CES preferences:

$$U(\gamma) = \left[\sum_{\sigma} D(\sigma, \gamma)^{\frac{\epsilon - 1}{\epsilon}} d\sigma \right]^{\frac{\epsilon}{\epsilon - 1}} \tag{4}$$

$D(\sigma, \gamma)$ denotes consumption of good σ in location γ and ϵ is the elasticity of substitution across goods. With utility maximization, demand for good σ is given by $D(\sigma, \gamma) = \frac{p(\sigma)^{-\epsilon} I(\gamma)}{P^{1-\epsilon}}$, where $I(\gamma) = \int_{\Omega(\gamma)} w(\omega, \gamma) L(\omega, \gamma) d\omega$ denotes total income in location γ and $P = (\sum_{\sigma} p(\sigma)^{1-\epsilon} d\sigma)^{\frac{1}{1-\epsilon}}$ denotes the CES price index.

Additionally, consider the labor market clearing condition:

$$\int_{\Sigma} L(\lambda, \sigma, \gamma) d\sigma = L(\lambda, \gamma), \quad \forall \lambda, \gamma \tag{5}$$

[12] See Costinot and Vogel (2010) for a similar model with a large number of observable skill groups. That setup typically gives rise to perfect assortative matching of skill groups across sectors. However, in practice, the econometrician only observes a limited number of skill groups with, potentially, substantial unobserved heterogeneity within a given skill group. Additionally, perfect assortative matching across sectors never holds exactly in the data. To bring the model closer to the data, I follow the approach outlined above.

[13] In the original model by Eaton and Kortum (2002), there is one factor of production and one industry that exhibits a continuum of goods. A country's productivity in producing a good is drawn from a Fréchet distribution. See also the multi-sector extensions by Costinot et al. (2012), Caliendo et al. (2015), or Krebs and Pflueger (2018).

Full employment implies that the mass of workers in skill group λ employed in sector σ of a location, $L(\lambda, \sigma, \gamma)$, summed up across all sectors, is equal to the mass of workers in skill group λ in a location. Finally, note that all regions are small open economies which take goods prices $p(\sigma)$ as given.

To sum up, the model takes as exogenous the sectors in a location, workforce composition in a location including the productivity draw for each worker from the Fréchet distribution with scale and dispersion parameter, and goods prices. The main endogenous outcomes of the model are the allocation of workers across sectors and their wage.

4.3.2 Cross-sectional prediction: allocation across sectors

As emphasized by equation 3, workers self-select into sectors to maximize their wage. Using the features of the Fréchet distribution, one can derive the probability that a worker in skill group λ in location γ maximizes her wage in sector σ:

$$\pi(\lambda, \sigma, \gamma) = \frac{[p(\sigma)T(\lambda, \sigma, \gamma)]^{\theta(\lambda)}}{\sum_{\sigma'} [p(\sigma')T(\lambda, \sigma', \gamma)]^{\theta(\lambda)}} \tag{6}$$

$\pi(\lambda, \sigma, \gamma)$ reflects the share of workers in skill group λ who are employed in sector σ in location γ. As all workers with observable characteristics λ in location γ face the same distribution of factor prices across sectors, $\pi(\lambda, \sigma, \gamma)$ also reflects the share of skill group λ's labor income which is being earned in sector σ in location γ. In what follows, I will denote $\pi(\lambda, \sigma, \gamma)$ as the wage or labor income share of skill group λ in sector σ and location γ. This share is higher for workers in skill groups that on average are very productive in sector σ (high $T(\lambda, \sigma, \gamma)$). It also increases with the price of the good produced by sector σ.[14]

In this environment, relative productivities shape the relative factor allocation across sectors. To illustrate this, I assume that the dispersion parameter of the Fréchet distribution is the same across skill groups: $\theta(\lambda) = \theta$.[15] Consider a location γ with two skill groups, college (C) and non-college (NC) workers, and two sectors, manufacturing (M) and non-manufacturing (N). Using equation 6, one can show that relative factor allocation is closely linked to relative productivities:

$$\frac{T(C, N, \gamma)}{T(NC, N, \gamma)} \Big/ \frac{T(C, M, \gamma)}{T(NC, M, \gamma)} = \left[\frac{\pi(C, N, \gamma)}{\pi(NC, N, \gamma)} \Big/ \frac{\pi(C, M, \gamma)}{\pi(NC, M, \gamma)}\right]^{1/\theta} \tag{7}$$

The left-hand side of equation 7 is a stochastic version of the well-known condition for comparative advantage. If it is larger than 1, college workers are relatively more productive in the non-manufacturing sector than non-college workers and therefore have

[14] See the following section 4.3.3 for a detailed interpretation of the role of $\theta(\lambda)$.

[15] See for example Burstein et al. (2019) or Hsieh et al. (2019) who also make this assumption. In the quantitative exercise, however, I will allow the dispersion parameter to differ across skill groups.

a comparative advantage in the non-manufacturing sector.[16] A look at the right-hand side of the equation shows that, if this is the case, college-workers should earn a relatively higher share of their labor income in the non-manufacturing sector. An increase in relative productivity across sectors translates into an increase in relative labor income shares with an elasticity of $1/\theta$.

Building on this logic, one can rationalize regional differences in factor allocation across sectors as a consequence of regional differences in workforce composition within the groups of college and non-college workers. Consider two locations, γ and γ'. Suppose that both locations host identical sectors, manufacturing and non-manufacturing. Both locations are populated by college and non-college workers. Suppose that location γ hosts college workers who exhibit a higher relative productivity in the non-manufacturing sector than college workers in location γ':

$$\frac{T(C,N,\gamma)}{T(NC,N,\gamma)} \Big/ \frac{T(C,M,\gamma)}{T(NC,M,\gamma)} > \frac{T(C,N,\gamma')}{T(NC,N,\gamma')} \Big/ \frac{T(C,M,\gamma')}{T(NC,M,\gamma')} \tag{8}$$

It then follows from equation 7 that college workers in location γ should earn a relatively higher share of their labor income in the non-manufacturing sector than those in γ':

$$\frac{\pi(C,N,\gamma)}{\pi(NC,N,\gamma)} \Big/ \frac{\pi(C,M,\gamma)}{\pi(NC,M,\gamma)} > \frac{\pi(C,N,\gamma')}{\pi(NC,N,\gamma')} \Big/ \frac{\pi(C,M,\gamma')}{\pi(NC,M,\gamma')} \tag{9}$$

To see a stylized example for this result, consider a world in which college workers consist of two groups, lawyers and engineers. Suppose that, due to their specific skills and training, lawyers on average are more productive in the non-manufacturing sector (e.g. in companies specializing in legal services) in every region: $T(Law,N,\gamma) > T(Eng,N,\gamma)$. In contrast, engineers on average are more productive in the manufacturing sector (e.g. in automobile firms) in every region: $T(Eng,M,\gamma) > T(Law,M,\gamma)$. Through the lens of the model, this implies that lawyers, relative to engineers, have a comparative advantage in the non-manufacturing sector and therefore should exhibit a relatively higher employment and labor income share in non-manufacturing. A look at the data supports this idea. For example, as of 2000, the employment share of lawyers (engineers) in the non-manufacturing sector amounts to 98.2% (49.8%). To see how differences in workforce composition within the groups of college and non-college workers can translate into differences in allocation across sectors, suppose that college workers in location γ exclusively consist of lawyers, whereas college workers in location γ' exclusively consist of engineers. Holding constant the composition of non-college workers across regions, college workers in γ then are relatively more productive in the non-manufacturing sector than college

[16] As productivities are drawn with a given distribution, this is of course not the case for all workers. The deterministic version is given by $\frac{A(C,N,\gamma)}{A(NC,N,\gamma)} / \frac{A(C,M,\gamma)}{A(NC,M,\gamma)} > 1$.

workers in γ' (equation 8) and therefore should exhibit relatively higher employment and labor income shares than college workers in γ' (equation 9).[17]

Panel (a) of figure 3 provides evidence that commuting zones indeed differ in their share of lawyers and engineers. The figure plots the share of lawyers and engineers as of 2000 separately for commuting zones. To increase the precision of the estimates, the figure focuses on commuting zones with at least 500,000 residents. Commuting zones like New York City or Washington DC have a relatively high share of lawyers (above 1%) and a relatively low share of engineers. In contrast, the commuting zones of Detroit and Seattle exhibit a relatively high share of engineers (above 3%) and a lower share of lawyers. One can apply the same logic to differences within the group of engineers. Panel (b) differentiates between civil and computer engineers and industrial and mechanical engineers. Civil and computer engineers are very specific to the non-manufacturing sector. As of 2000, 91% of them are employed in the non-manufacturing sector. The opposite is true for mechanical and industrial engineers. As of 2000, 76% of them work in the manufacturing sector.[18] Commuting zones like Detroit and Cleveland have a high share of mechanical and industrial engineers, but a comparatively lower share of civil and computer engineers. In contrast, the share of civil and computer engineers is higher in San Francisco and Sacramento.[19] While occupational groups like lawyers or engineers can be observed in the data, this logic also applies to unobserved or unobservable regional differences in workforce composition within the groups of college and non-college workers.

Finally, it can be shown that the average wage for workers in skill group λ in location γ in the cross section is given by:

$$w(\lambda, \gamma) = \chi \left[\sum_{\sigma} [p(\sigma)T(\lambda, \sigma, \gamma)]^{\theta(\lambda)} \right]^{1/\theta(\lambda)} \tag{10}$$

where $\chi = \Gamma(\frac{\theta(\lambda)-1}{\theta(\lambda)})$ is the gamma function: $\Gamma(a) = \int_0^\infty x^{a-1}e^{-x}dx$.[20]

4.3.3 Comparative-static prediction: sectoral reallocation and CWP

In the model, changes in relative goods prices affect the allocation of workers across sectors and the CWP in a region. The empirical exercise will focus on the 'China shock'. In the

[17] To see this, note that $T(C, N, \gamma) = T(Law, N, \gamma) > T(C, N, \gamma') = T(Eng, N, \gamma')$ and $T(C, M, \gamma) = T(Law, M, \gamma) < T(C, M, \gamma') = T(Eng, M, \gamma')$.

[18] Civil engineers are clustered in the construction sector, while computer engineers tend to work in industries providing computer and data processing services. Industrial and mechanical engineers, in contrast, are clustered in manufacturing industries like the automobile industry.

[19] In panel (b), the outlier with a share of mechanical and industrial engineers of more than 2% is Detroit. San Francisco is leading the ranking in terms of computer engineers, while Sacramento is leading the ranking in terms of civil engineers.

[20] Equation 10 refers to nominal wages. However, since the interest of this paper is exclusively on relative wages of skill groups and preferences are assumed to be homothetic, relative wages $\frac{w(\lambda,\gamma)}{w(\lambda',\gamma)}$ can be interpreted in real terms.

course of its transition to a market economy which triggered substantial productivity growth in the manufacturing sector, China became a large manufacturing exporter (e.g. Naughton 2007; Hsieh and Klenow 2009; Hsieh and Song 2015; Autor et al. 2016). I will treat this event as a positive supply shock of manufacturing goods which triggers a decrease in the relative price of manufacturing goods on the world market.[21]

To illustrate the effects of price changes on factor allocation and wages, I follow the method in Dekle et al. (2007) and write down the system of equations in proportional changes between two periods, where $\hat{x} = x_1/x_0$ is the proportional change of a variable between period t_0 and t_1. I assume that fundamental productivities remain unchanged, i.e. $\hat{T}(\cdot) = 1$. Consider the two main equations in changes:

$$\hat{\pi}(\lambda, \sigma, \gamma) = \frac{\hat{p}(\sigma)^{\theta(\lambda)}}{\sum_{\sigma'} \hat{p}(\sigma')^{\theta(\lambda)} \pi_0(\lambda, \sigma', \gamma)} \tag{11}$$

$$\hat{w}(\lambda, \gamma) = \left[\sum_{\sigma} \hat{p}(\sigma)^{\theta(\lambda)} \pi_0(\lambda, \sigma, \gamma)\right]^{1/\theta(\lambda)} \tag{12}$$

Appendix F provides a derivation of equations 11 and 12. From equation 11, it becomes clear that an increase in the price of the good produced in a sector, ceteris paribus, triggers a reallocation of workers in all skill groups towards this sector. The strength of the reallocation crucially depends on $\theta(\lambda)$ which governs the dispersion of productivity draws within skill group λ. A higher dispersion of productivity draws (lower level of $\theta(\lambda)$) means that there are more workers with an unfavorable productivity draw for sector σ. For some of them, a given relative increase in p(σ) is not sufficient to maximize their marginal product value in that sector and this is why they remain employed in a different sector. For a given change in relative prices, a lower level of $\theta(\lambda)$ therefore goes along with a lower reallocation of workers towards the sector that experiences an increase in its relative price.

Equation 12 illustrates that the change in the average wage that a skill group experiences in response to a given price change depends on its initial allocation across sectors. Suppose that the price of the good of a given sector decreases. According to equation 12, the fall in the wage is higher for skill groups which earn a higher share of their labor income in that sector. The intuition of that result is similar to the one in the specific-factors model. As workers self-select into a sector according to their productivity draw, they become partly specific to that sector. Skill groups with a higher labor income share in a given sector

[21] See for example Costinot and Vogel (2010) who show that productivity growth in the foreign labor-abundant country is equivalent to an increase in the size of the foreign country. This makes the world relatively less skill-abundant and the relative price of the low-skill intensive manufacturing good should decrease. In the setting of this model which focused on locations as small open economies, one would have to assume that China consists of a large group of locations which is large enough to have an effect on world market prices. The empirical exercise in the following chapters will focus on the impact on U.S. commuting zones, for which the assumption of a small open economy is maintained.

have a particularly favorable productivity draw for that sector. For them, reallocation into a different sector goes along with a large decrease in productivity. This is why they are more negatively affected from a price decrease in that sector than other skill groups are.

How does a given change in relative prices in this environment affect the CWP? Again, for simplicity, assume that the dispersion parameter is equal across skill groups: $\theta(\lambda) = \theta$. Return to the setting with two skill groups (college and non-college), and two sectors (manufacturing and non-manufacturing). Suppose that the price of the manufacturing good decreases, $\hat{p}(M) < 1$. With the price of the non-manufacturing good normalized to 1, this corresponds to a decrease in the relative price of the manufacturing good. With two sectors and full employment, it holds that $\pi_0(NC, M, \gamma) = 1 - \pi_0(NC, N, \gamma)$ and $\pi_0(C, M, \gamma) = 1 - \pi_0(C, N, \gamma)$. Therefore, the resulting change in the CWP can be expressed as follows:

$$\frac{\hat{w}(C,\gamma)}{\hat{w}(NC,\gamma)} = \left[\frac{1 - \pi_0(C, M, \gamma)(1 - \hat{p}(M)^{\theta})}{1 - \pi_0(NC, M, \gamma)(1 - \hat{p}(M)^{\theta})}\right]^{1/\theta} \tag{13}$$

Equation 13 shows that the CWP increases in response to a decrease in the relative manufacturing price ($0 < \hat{p}(M) < 1$) if non-college workers earn a higher share of their labor income in the manufacturing sector than college workers, i.e. if $\pi_0(NC, M, \gamma) > \pi_0(C, M, \gamma)$. This is the case if non-college workers have a comparative advantage in the manufacturing sector, i.e. if $\frac{\pi_0(C,N,\gamma)}{\pi_0(NC,N,\gamma)} / \frac{\pi_0(C,M,\gamma)}{\pi_0(NC,M,\gamma)} > 1$. In contrast, if college workers have a comparative advantage in the manufacturing sector, they earn a higher share of their income in the manufacturing sector than non-college workers and the CWP decreases in response to a decrease in the relative manufacturing price. Consider again the example with lawyers and engineers. Holding constant the productivity of non-college workers in both regions γ and γ', if lawyers (engineers) have a sufficiently high productivity in the non-manufacturing (manufacturing) sector, the CWP would increase in region γ and would decrease in region γ'.[22]

More generally, equation 13 suggests that, for a given $\pi_0(NC, M, \gamma)$, the increase in the CWP is higher for lower levels of $\pi_0(C, M, \gamma)$. Analogously, for a given $\pi_0(C, M, \gamma)$, the increase in the CWP is lower for lower levels of $\pi_0(NC, M, \gamma)$. Additionally, equation 13 shows that, for given $\pi_0(NC, M, \gamma)$ and $\pi_0(C, M, \gamma)$, the effect on the CWP increases with the extent to which the relative price of the manufacturing good decreases.

At this point, a note on the assumption of immobility of workers across locations is in order. One could construct settings in which worker mobility across locations equalizes the wage for workers with given characteristics. With the assumption of regional immobility in this model, one should think of the estimates in the quantitative exercise as effects

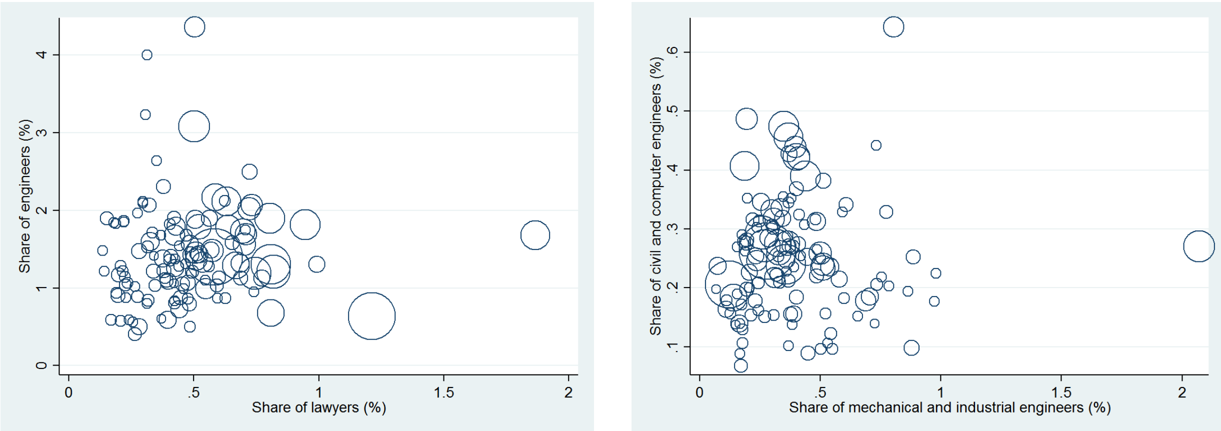
[22] Formally, this would require $\frac{\pi_0(C,N,\gamma)}{\pi_0(NC,N,\gamma)} / \frac{\pi_0(C,M,\gamma)}{\pi_0(NC,M,\gamma)} > 1$ and $\frac{\pi_0(C,N,\gamma')}{\pi_0(NC,N,\gamma')} / \frac{\pi_0(C,M,\gamma')}{\pi_0(NC,M,\gamma')} < 1$.

before any potential mobility across locations that might equalize wages for workers with given characteristics across locations.

Figure 3: Allocation of engineers and lawyers across commuting zones

(a) Engineers and lawyers

(b) Types of engineers



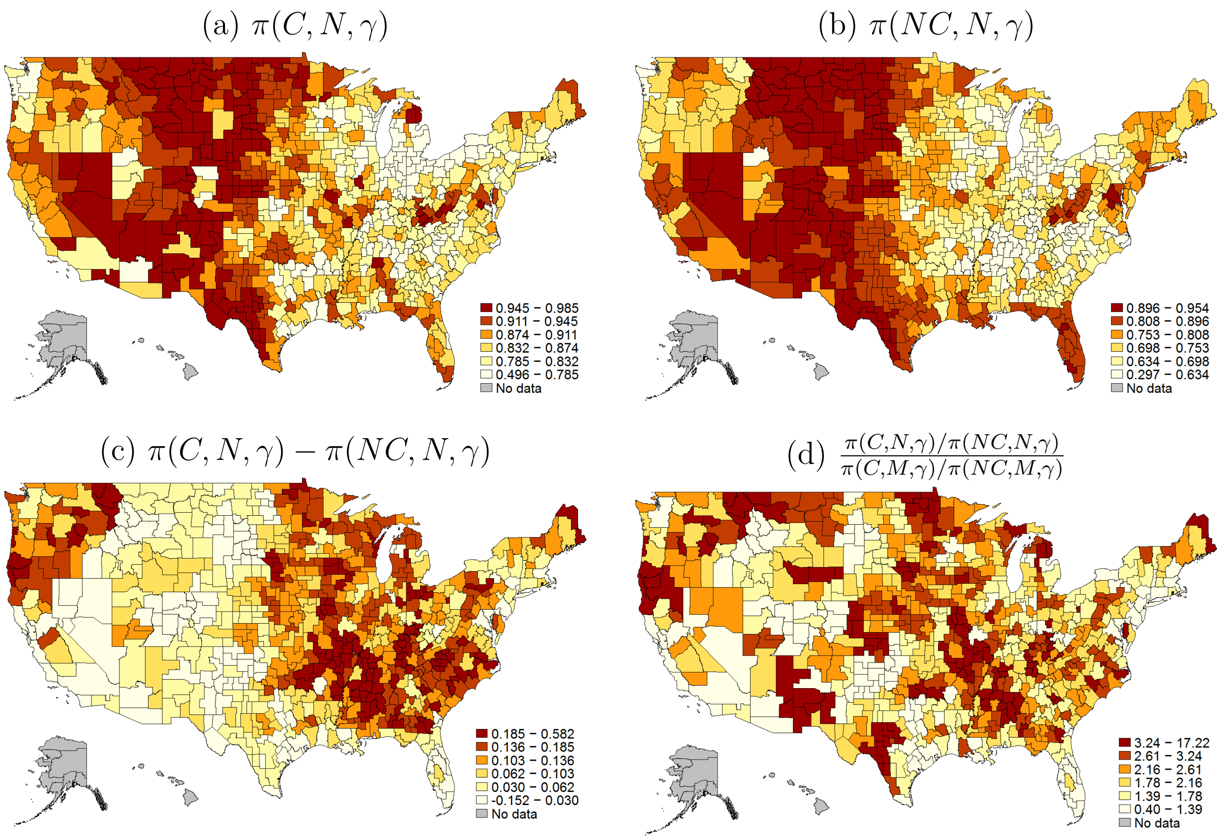
Notes: Panel (a) plots the share of engineers and the share of lawyers in the respective commuting zone in 2000. To increase precision of the estimated shares, the figures focus on 122 commuting zones with a population larger than 500,000 as of 2000. In total, 50.2% of all engineers and 1.2% of all lawyers are employed in the manufacturing sector. Analogously, panel (b) plots the share of civil and computer engineers on the vertical axis and the share of industrial and mechanical engineers on the horizontal axis. In total, 76.5% of all mechanical and industrial engineers and 9.1% of all civil and computer engineers are employed in the manufacturing sector. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007).

4.4 Allocation of skill groups across sectors - regional differences

The theoretical model presented in the previous section rationalizes regional differences in the allocation of college and non-college workers across sectors and suggests that these differences play a role for the way in which changes in relative prices affect the CWP. Table 2 and figure 4 focus on the year 1990 and provide evidence that there are indeed substantial differences across regions in the extent to which college and non-college workers select into the manufacturing and non-manufacturing sector.

Consistent with the important role that the non-manufacturing sector plays for the overall U.S. economy, the non-manufacturing sector on average provides the main source of labor income for college and non-college workers. According to the first two lines of table 2, the share of their labor income that college (non-college) workers earn in the non-manufacturing sector amounts to 85% (79%) in the median commuting zone. This share ranges from 50% (30%) in very manufacturing-intensive commuting zones to 99% (97%) in very non-manufacturing-intensive commuting zones. Panels (a) and (b) of figure 4 suggest the existence of an east-west divide. In particular, the maps illustrate that the non-manufacturing labor income share of college and non-college workers is lower in traditional manufacturing-intensive regions in the western part of the country, including the states of Michigan, Ohio, Indiana, New York, Pennsylvania and in parts of Kentucky, Mississippi, and Alabama. The non-manufacturing labor income share tends to be lower in commuting zones surrounding manufacturing-intensive cities like Buffalo NY, Detroit MI, and Cleveland OH. For example, Detroit MI belongs to the bottom 10% of commuting zones with a non-manufacturing wage share of college (non-college) workers of 72% (64%).

Figure 4: Allocation of skill groups across sectors - regional differences



Notes: $\pi(C,N,\gamma)$ ($\pi(NC,N,\gamma)$) denotes the share of their labor income that college (non-college) workers earn in the non-manufacturing sector in a commuting zone in 1990. Sample is restricted on all workers with either a high school or a bachelor's degree with 20-60 years of age in dependent employment outside the military. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007).

More importantly for the purpose of this paper, table 2 and figure 4 document substantial regional differences in the extent to which college and non-college workers *differentially* select into the non-manufacturing sector. Lines 3 and 4 of table 2 focus on two alternative measures, the simple difference in non-manufacturing labor income shares $\pi(C,N,\gamma) - \pi(NC,N,\gamma)$ and the relative non-manufacturing labor income share $\frac{\pi(C,N,\gamma)/\pi(NC,N,\gamma)}{\pi(C,M,\gamma)/\pi(NC,M,\gamma)}$. In the median commuting zone, college workers earn 5 percentage points more of their labor income in the non-manufacturing sector than non-college workers. This difference rises to 16 percentage points in a commuting zone at the 90th percentile. In a commuting zone at the 10th percentile, non-college workers in fact earn a higher share of their labor income in the non-manufacturing sector. The relative labor income shares in line 4 provide a qualitatively similar picture in terms of the variation across commuting zones. Through the lens of the model, the value of 1.41 (>1) suggests that in the median commuting zone, college workers have a comparative advantage in the non-manufacturing sector. In contrast, in the commuting zone at the 10th percentile, college workers have a comparative advantage in the manufacturing sector - as reflected by the value of 0.92 (<1).

Panels (c) and (d) of figure 4 provide evidence that college workers on average select more strongly into the non-manufacturing sector than non-college workers for example in parts of Wisconsin, Missouri, Mississippi, Alabama, Montana, North Dakota, California, and Texas. While the two alternative measures, $\pi(C,N,\gamma)-\pi(NC,N,\gamma)$ and $\frac{\pi(C,N,\gamma)/\pi(NC,N,\gamma)}{\pi(C,M,\gamma)/\pi(NC,M,\gamma)}$, do not provide the exact same pattern, the correlation is high with a correlation coefficient of 0.75. Figure G2 in the appendix provides a very similar picture for the year 2000.

Table 2: Allocation of skill groups across sectors, descriptives

	min	p10	p25	p50	p75	p90	max
$\pi(C,N,\gamma)$	0.50	0.75	0.80	0.85	0.88	0.91	0.99
$\pi(NC,N,\gamma)$	0.30	0.64	0.71	0.79	0.83	0.88	0.97
$\pi(C,N,\gamma)-\pi(NC,N,\gamma)$	-0.32	-0.01	0.02	0.05	0.11	0.16	0.58
$\frac{\pi(C,N,\gamma)/\pi(NC,N,\gamma)}{\pi(C,M,\gamma)/\pi(NC,M,\gamma)}$	0.16	0.92	1.14	1.41	1.93	2.68	17.22

Notes: $\pi(C,N,\gamma)$ ($\pi(NC,N,\gamma)$) denotes the share of their labor income that college (non-college) workers earn in the non-manufacturing sector in a commuting zone in 1990. Sample is restricted on all workers with either a high school or a bachelor's degree with 20-60 years of age in dependent employment outside the military. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007).

4.5 Model-supported estimates of the China Shock

Between 1991 and 2007, U.S. imports of Chinese manufacturing goods increased from 26.3 billions of USD to 330 billions of USD. This corresponds to a rise of more than 1,150%. In contrast, U.S. manufacturing exports to China increased less strongly from 10.3 billions of USD to 57.4 billions of USD during that period (Autor et al. 2013). Part of this phenomenon is driven by China's transformation into a market economy which resulted in productivity growth in the manufacturing sector and triggered a positive supply shock of manufacturing goods on the world market (e.g. Naughton 2007; Hsieh and Klenow 2009; Hsieh and Song 2015; Autor et al. 2016).

I build on the model structure, in particular on equations 11 and 12, to end up with estimates on the effect of this supply shock on the CWP within U.S. commuting zones. Equation 12 suggests that the change in average wages of skill groups, and therefore the change in the CWP, depends on the initial labor income shares $\pi_0(C, N, \gamma)$ and $\pi_0(NC, N, \gamma)$, the change in (relative) prices, and $\theta(\lambda)$. While $\pi_0(C, N, \gamma)$ and $\pi_0(NC, N, \gamma)$ are readily observable in the data, relative price changes and $\theta(\lambda)$s are not and need to be estimated.

4.5.1 Estimation of the dispersion parameters

I make use of the fact that, given the assumption of productivity draws from a Fréchet distribution, wages within a sector for a given skill group λ follow a Fréchet distribution with dispersion parameter $\theta(\lambda)$ (Hsieh et al. 2019).[23] The dispersion parameter for a given skill group therefore can be inferred from the within-sector distribution of wages of workers in the respective skill group. Analogously to Hsieh et al. (2019), I obtain the within-sector distribution of wages by residualizing wages from a manufacturing dummy.[24] I then estimate the dispersion parameter by maximum likelihood estimation (MLE), separately by skill group, for the year 1990. MLE yields the most likely result for the dispersion parameter, given the distribution of residualized wages.

Table 3 provides the estimates. The results suggest a higher level of $\hat{\theta}$ for non-college workers than for college workers, implying a higher dispersion of productivity draws for college workers. This result is in line with the finding that groups with higher levels of education exhibit a higher dispersion of residual wages (Lemieux 2006). The point estimates are precisely estimated.

Table 3: Maximum likelihood estimation of $\theta(\lambda)$

	(1) College	(2) Non-college	(3) Both
$\hat{\theta}(\lambda)$	1.6443	1.7668	1.6959
	(0.0005)	(0.0003)	(0.0003)
N	1,032,735	2,574,837	3,607,572

Notes: The table shows maximum likelihood estimates of the dispersion parameter of the Fréchet distribution. I first residualize log hourly wages from a dummy for manufacturing employment. I then fit the estimated dispersion parameter to the distribution of residual wages, separately for each group. Estimates are for the year 1990. Standard errors in parentheses. Sample is restricted on all workers with either a high school or a bachelor's degree with 20-60 years of age in dependent employment outside the military. Data sources: Census Integrated Public Use Micro Samples (IPUMS) (1990).

[23] See page 1452 in Hsieh et al. (2019). In their model, individuals in three age groups select into occupations rather than sectors. Note that their estimation additionally includes a parameter for the elasticity of human capital with respect to human capital spending - a parameter which is not relevant for the model in this paper.

[24] Due to their different focus (selection into occupations rather than sectors), Hsieh et al. (2019) residualize log wages from occupation dummies instead.

4.5.2 Estimating price changes

Empirical strategy. In a next step, I estimate the change in the relative manufacturing price in a commuting zone in response to the China shock. Equation 11 provides a link between price changes ($\hat{p}(\sigma)$), labor reallocation between sectors ($\hat{\pi}(\lambda, \sigma, \gamma)$), the initial labor income shares ($\pi_0(\lambda, \sigma', \gamma)$), and the dispersion parameter ($\theta(\lambda)$), separately for each skill group in a region. I focus on a setting with two sectors, manufacturing and non-manufacturing, where the price of the non-manufacturing good is normalized to one. This means that $\hat{p}(M)$ reflects the change in the relative price of manufacturing goods.

In what follows, I first estimate labor reallocation across sectors in a commuting zone in response to the China shock. Building on equation 11, I then use this estimate, together with data on initial labor income shares and the estimated dispersion parameter, to back out the implied change in the relative manufacturing price.

To end up with an estimate of labor reallocation across sectors in response to the China shock, I build on the empirical strategy in Autor et al. (2013) and estimate the following reduced-form specification:

$$\Delta\pi_t(NC, M, \gamma) = \beta\Delta Imp_{\gamma t} + \xi X'_{\gamma t} + \delta_t + \epsilon_{\gamma t} \tag{14}$$

$\Delta\pi_t(NC, M, \gamma)$ denotes the change in the manufacturing labor income share of non-college workers in commuting zone γ. Following Autor et al. (2013), I compute this change for two ten-year equivalent periods (1990-2000 and 2000-2007), where t refers to the first year of the period.

The main explanatory variable is a Bartik-style measure of the change in Chinese manufacturing import exposure in commuting zone γ during the respective period:

$$\Delta Imp_{\gamma t} = \sum_j \frac{L_{\gamma jt}}{L_{jt}} \frac{\Delta M_{jt}}{L_{\gamma t}} \tag{15}$$

ΔM_{jt} denotes the total observed increase in U.S. manufacturing imports in industry j from China during the ten-year equivalent period. $L_{\gamma jt}$ denotes industry j's employment in commuting zone γ in year t and L_{jt} reflects industry j's total U.S. employment in year t. In equation 15, the total observed increase in imports in a given industry is allocated across commuting zones according to the respective commuting zone's share in the industry's total employment. The resulting value is then normalized by the respective commuting zone's total manufacturing employment $L_{\gamma t}$. Variation in the estimated change in local import exposure in equation 15 stems from variation in the industry structure within the manufacturing sector across commuting zones in year t. The measured increase in import exposure in a commuting zone is high if its employment is concentrated in industries which experience a high inflow of Chinese imports.[25]

[25] Additionally, the estimated increase in import exposure varies depending on differences in total man-

To isolate the supply-driven component of the increase in imports which is caused by China's rise in productivity, I follow Autor et al. (2013) and employ the following instrument:

$$\Delta Imp_{\gamma ot} = \sum_j \frac{L_{\gamma jt-10}}{L_{ujt-10}} \frac{\Delta M_{ojt}}{L_{\gamma t-10}} \tag{16}$$

ΔM_{ojt} reflects industry j's increase in imports from China in a set of instrument countries: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. To the extent that China became more competitive in a given industry, this should not only translate into higher U.S. imports in that industry, but also into higher imports in that industry in other high-income countries. This approach purges the estimates from bias due to unobserved manufacturing import demand shocks which might lead to an understatement of the true effect on reallocation under two main conditions. First, product-level demand shocks should not be strongly correlated across high-income countries. Second, other high income countries' imports from China should not affect the outcome through any other channel than the import exposure in equation 14. See also Autor et al. (2013) for a detailed discussion. Equation 16 uses employment levels lagged by ten years to mitigate problems due to changes in employment in a given commuting zone in anticipation of future trade with China.

$X'_{\gamma t}$ includes a battery of controls, held constant at year t. It includes the initial manufacturing labor income share, the manufacturing employment share, the share of females, the share of foreign-born individuals, the share of whites, and the share of workers in five potential experience groups (<10, 10-19, 20-29,30-39,>39 years) within non-college workers, dummies for eight census divisions, controls for the routine intensity and offshorability of occupations in a commuting zone as in Autor and Dorn (2013), and the log population count. δ_t is a dummy to differentiate between the two periods 1990-2000 and 2000-2007. This specification is similar to the one in Autor et al. (2013). However, it employs the labor income shares in manufacturing rather than employment or the employment to population ratio as dependent variable. One can estimate this equation for every skill group. I focus on the estimates for non-college workers. The reason is that less educated workers tend to be less geographically mobile and therefore the assumption of commuting zones not being connected by migration and commuting flows which is immanent to this kind of specification is less crucial. Table G4 provides basic summary statistics on the regression sample.

Having estimated equation 14, I compute the predicted labor reallocation into the non-manufacturing sector in response to the China shock by multiplying the observed change in import exposure by the estimated coefficient $\hat{\beta}$:

ufacturing employment across commuting zones. However, controlling for the manufacturing employment share in t, the empirical approach focuses on variation in import exposure stemming from within-manufacturing variation in the employment structure.

$$\widetilde{\Delta\pi}_t(NC, M, \gamma) = \hat{\beta}\Delta Imp_{\gamma t} \tag{17}$$

Equation 17 yields the predicted change in the labor income share during the respective ten-year equivalent period in a commuting zone. To remain consistent with equation 11, I transform the value into the implied proportional change over the ten-year period in the respective commuting zone $\hat{\pi}(NC, M, \gamma)$.[26] Finally, I plug $\hat{\pi}(NC, M, \gamma)$ as well as $\pi_0(NC, M, \gamma)$ and the estimated $\theta(NC)$ into equation 11 to obtain the implied change in the relative manufacturing price. With this approach, I obtain different relative manufacturing price changes for different commuting zones. Empirically, these differences stem from regional differences in industry composition within the manufacturing sector. This is however not consistent with the model which abstracts from regional differences in industry composition. To remain consistent with the model, I will also provide results from a counterfactual which assumes that all commuting zones exhibit the same relative price change, namely the average of $\widetilde{\Delta\pi}_t(NC, M, \gamma)$ across all commuting zones.

Results. Table 4 provides the regression results from estimating equation 14. According to the results, growing Chinese import exposure went along with labor reallocation from the manufacturing into the non-manufacturing sector. Consistent with the presence unobserved demand shocks for imports correlated with the increase in import exposure and manufacturing employment, the OLS estimates are smaller in absolute size than the 2SLS estimates. According to the preferred specification in column (6), a one-unit increase in import exposure goes along with a decrease in the manufacturing labor income share by 0.74 percentage points for non-college workers. To set this point estimate into perspective, consider the mean increase in import exposure in the sample of 1.88 (measured in \$1000 per worker) and the mean observed decrease in the manufacturing labor income share of 4.47 percentage points (see table G4). Evaluated at the sample mean, the increase in import exposure explains around 31% of the decrease in the manufacturing labor income share of non-college workers ((1.88 x 0.0074)/0.0447 $\approx$ 0.31). The result also holds in a specification which regresses the dependent variable directly on the instrument (column 7). Table G5 in the appendix provides the first-stage estimates and figure G3 visualizes the first stage graphically. It turns out that the first stage is strong, with a statistically significant point estimate and F-statistics between 100 and 200.

As a robustness check, I carry out the same regression with employment shares rather than labor income shares in the dependent variable. Table G6 shows that the estimated effects are larger in magnitude in this specification. Estimating equation 17 for college rather than non-college workers yields qualitatively very similar results, however with point esti-

[26] $\hat{\pi}(NC, M, \gamma) = \frac{\pi_0(NC,M,\gamma)+\widetilde{\Delta\pi}_{it}(NC,M,\gamma)}{\pi_0(NC,M,\gamma)}$, where $\pi_0(NC, M, \gamma)$ denotes the initial manufacturing labor income share in the first year of the period (year t).

mates which are slightly smaller in magnitude (see tables G7 and G8). This specification is less reliable because college workers are expected to be more geographically mobile - a feature with goes against the empirical approach which assumes commuting zones to be closed economies. Finally, table G9 shows that the results are robust to using net import exposure as the explanatory variable. Overall, the results are in line with findings of the previous literature which documents that rising Chinese import exposure went along with structural change in the form of a shift of employment out of the manufacturing sector (e.g. Autor et al. 2013; Dauth et al. 2014).

Table 4: Import exposure and labor reallocation

	Dependent variable: $\Delta\pi_t(NC, M, \gamma)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	IV	IV	IV	OLS
$\Delta Imp_{\gamma t}$	0.0004	-0.0019^b	-0.0019^b	-0.0019	-0.0074^c	-0.0072^c	
	(0.0009)	(0.0009)	(0.0009)	(0.0017)	(0.0022)	(0.0023)	
$\Delta Imp_{\gamma ot}$							-0.0045^c
							(0.0012)
Basic controls		$\surd$	$\surd$		$\surd$	$\surd$	$\surd$
Adv. controls			$\surd$			$\surd$	$\surd$
Obs.	1444	1444	1444	1444	1444	1444	1444
Adj. R^2	0.23	0.31	0.31	0.23	0.29	0.29	0.32

Notes: Dependent variable is the ten-year equivalent change in the manufacturing labor income share of non-college workers in a commuting zone (1990-2000, 2000-2007). See equations 15 and 16 for the definition of $\Delta Imp_{\gamma t}$ and $\Delta Imp_{\gamma ot}$. Basic controls include the initial manufacturing labor income share, the manufacturing employment share, the share of individuals with a bachelor's degree, the share of individuals with a high school degree as well as the share of foreigners, females, whites, 5 experience groups, and the share of unemployed. Advanced controls include the share of employment in routine occupations and an average offshorability index of occupations. All specifications additionally include dummies for 8 census divisions, and a dummy to differentiate between the two periods. Standard errors clustered by census division in parentheses. Data sources: IPUMS Census (1990 and 2000), American Community Survey (2006 and 2007) and Autor et al. (2013). ^{a} $p < 0.10$, ^{b} $p < 0.05$, ^{c} $p < 0.01$.

The first line of table 5 summarizes the estimates on the predicted labor reallocation. On average across all commuting zones, the China shock triggered a decrease of non-college workers' labor income earned in the manufacturing sector by 6% ($\hat{\pi}(NC, M) = 0.94$) over a period of ten years.[27] The reallocation of non-college workers out of the manufacturing sector occurred to a different extent across commuting zones. In a commuting zone at the 90th (10th) percentile, the manufacturing labor income share of non-college workers decreased by 3% (10%) over ten years. Analogously, I compute the predicted reallocation

[27]The table uses the average over both ten-year equivalent periods for each commuting zone.

of college workers.[28] The second line shows that the estimated labor reallocation of college workers is slightly smaller, with a sample mean of $\hat{\pi}(C, M) = 0.95$. It also varies substantially across commuting zones. The smaller reallocation response of college workers is consistent with the smaller dispersion parameter estimated for college workers.

Table 5: Predicted effects on labor allocation, prices, and CWP

	mean	min	p10	p25	p50	p75	p90	max
			(a) Main estimates					
$\hat{\pi}(NC, M)$	0.94	0.21	0.90	0.92	0.94	0.96	0.97	1.00
$\hat{\pi}(C, M)$	0.95	0.27	0.92	0.94	0.95	0.97	0.97	1.01
$\hat{P}(M)$	0.95	0.27	0.93	0.94	0.96	0.97	0.98	1.00
Δ CWP (log points)	0.30	-1.27	-0.04	0.08	0.16	0.43	0.71	4.96
			(b) Counterfactuals					
Δ CWP ($\hat{P}(M) = 0.95$)	0.27	-0.60	-0.05	0.06	0.21	0.48	0.66	1.79
Δ CWP ($\theta = 1.6959$)	0.28	-1.33	-0.06	0.07	0.14	0.41	0.67	5.54
Δ CWP ($\hat{P}(M) = 0.95$ and $\theta = 1.6959$)	0.29	-0.58	-0.04	0.08	0.24	0.50	0.68	1.83

Notes: $\hat{\pi}(NC, M)$ reflects the proportional change in the manufacturing labor income share of non-college workers. $\hat{\pi}(C, M)$ is the corresponding change for college workers. $\hat{P}(M)$ is the proportional change in the (relative) price of the manufacturing good. ΔCWP is the predicted impact on the CWP in log points. Panel (b) refers to various counterfactual results, equalizing the relative price change across commuting zones ($\hat{P}(M) = 0.95$), equalizing the dispersion of productivity draws for skill groups ($\theta = 1.6959$), or both. All estimates refer to the mean over both ten-year equivalent intervals (1990-2000 and 2000-2007) for a given commuting zone. Table shows population-weighted statistics. See section 4.5 for an explanation of the estimation procedure. Data sources: IPUMS Census (1990 and 2000), American Community Survey (2006 and 2007), and Autor et al. (2013).

The third line of table 5 shows the implied change in the relative manufacturing price in the commuting zones. On average across all commuting zones, the estimates imply a decline of the relative manufacturing price by 5% over ten years in response to the China shock ($\hat{P}(M) = 0.95$). The estimated decline in the relative manufacturing price is consistent with estimated labor reallocation out of the manufacturing sector in response to the shock, as documented by table 4. In general, it is consistent with the idea that the rise of China as a major manufacturing exporter constituted a positive supply shock of manufacturing goods which resulted in a decline in the relative manufacturing price. Again, the estimates exhibit regional differences. For example, in a commuting zone at the 10th percentile, the estimated decrease in the relative manufacturing price amounts to 7%.

[28] To compute these values, I use the regression estimate from column (4) of table G7 and the corresponding values for initial allocation and the estimated dispersion parameter for college workers, analogously to the procedure described above.

4.5.3 Impact on the regional college wage premium

Main estimates. Finally, to obtain an estimate for the change in the CWP implied by the rise of China, I make use of equation 12 which allows to compute the proportional change in average wages in a skill group as a function of the relative manufacturing price change, the initial labor income shares, and the dispersion parameters.

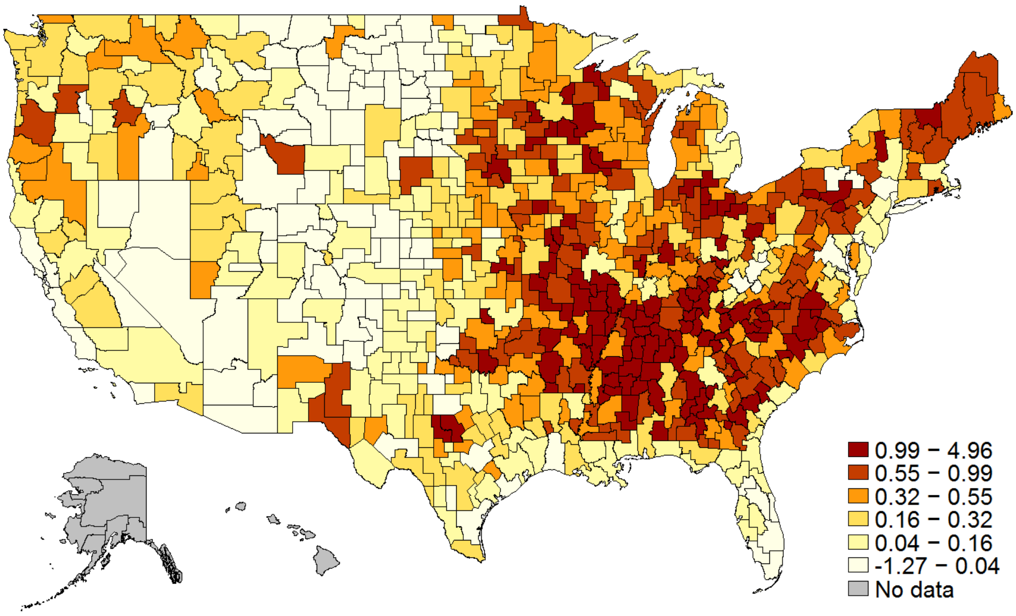
According to the estimates displayed in table 5, the CWP on average increased by 0.30 log points in response to the China shock. The inequality-increasing impact on aggregate is consistent with non-college workers on average earning a higher share of their labor income in the manufacturing sector than college workers (see figure 4). In the light of the mean increase in the observed CWP over the respective ten-year intervals of 5.39 log points, this is a modest average effect.

However, importantly, the predicted impact on the CWP displayed in table 5 differs substantially across commuting zones. According to the estimates, the impact on the CWP ranges from 4.96 log points to minus 1.27 log points. In a commuting zone at the 90th percentile, the CWP increases by 0.71 log points, whereas a commuting zone at the 10th percentile experiences a small decrease in the CWP in response to the China shock. Relative to the mean observed increase in the CWP of 5.39 log points, the heterogeneity in the estimated impact is not negligible. Importantly, this result suggests that studies which impose a single elasticity between their measure of trade exposure and the local CWP mask a substantial regional heterogeneity.

Figure 5 gives an impression of the spatial distribution of the predicted impact on the CWP. The estimated impact on the CWP is largest in parts of the Midwest and the south-east of the country, including the states of Missouri, Alabama, Mississippi, Arkansas, and Tennessee. A comparison with figure 4 shows that the predicted impact is closely connected to the initial allocation of college and non-college workers across sectors. Commuting zones in which non-college workers initially select more strongly into the manufacturing sector than college workers experience a larger impact. Panel (a) of figure 6 confirms this link with a binscatter plot that has the difference in non-manufacturing labor income shares at the horizontal axis $(\pi_0(C, N, \gamma) - \pi_0(NC, N, \gamma))$ and the predicted impact on the CWP at the vertical axis.

Panel (b) of figure 6 plots the observed change in the CWP in the respective ten-year equivalent interval in a commuting zone against the predicted impact. In the light of numerous potential drivers of the observed changes in the CWP, one cannot expect a one-to-one mapping between the predicted impact and the actual change in the CWP. Nevertheless, the figure which shows that commuting zones which experience a higher increase in the CWP on average also are the commuting zones for which the estimation predicts a higher effect of the China shock. On average, therefore, the China shock contributes to the regional heterogeneity in the evolution of the CWP.

Figure 5: Predicted impact on the college wage premium



Notes: The map displays the mean predicted impact on the CWP over both ten-year equivalent periods (1990-2000 and 2000-2007) in a commuting zone. Data sources: IPUMS Census (1990 and 2000), American Community Survey (2006 and 2007) and Autor et al. (2013).

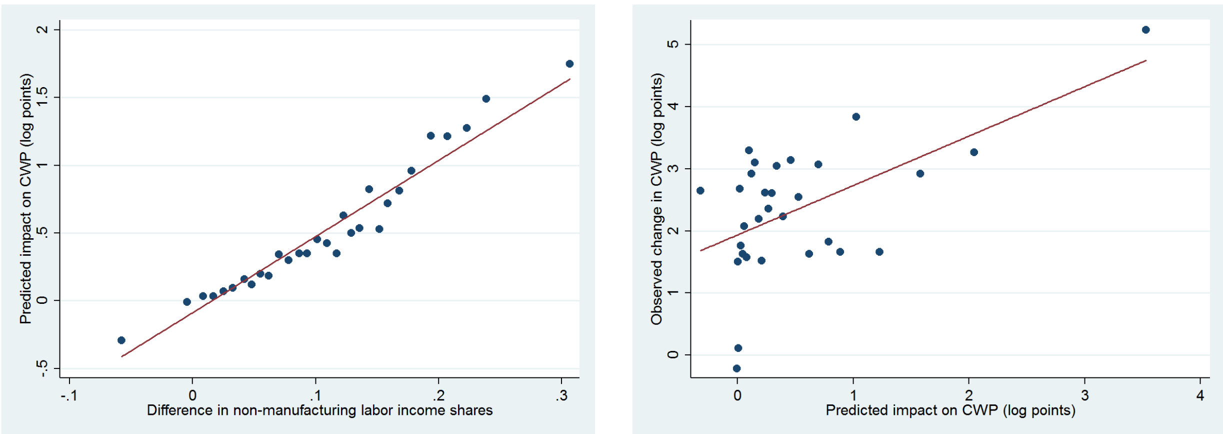
Counterfactuals. The predicted impact of the China shock on the CWP and its heterogeneity across commuting zones is a function of changes in relative manufacturing prices, initial allocations of skill groups across sectors, and the the dispersion of productivity draws within skill groups. The graphs presented so far point to an important role played by the initial allocation of workers across sectors. To more formally analyze the relative importance of the factors for the heterogeneity of the effects, I perform various counterfactual exercises. The results are displayed in panel (b) of table 5.

To get an idea about the extent to which the heterogeneous effects hinge on regional differences in the change in the relative manufacturing price, I first switch off the regional dispersion in price changes. More specifically, rather than employing the predicted change in the manufacturing price for each commuting zone, I assume that the price change in each commuting zone equals the average national price change. As suggested by panel (a) of table 5, the manufacturing price on average decreases by 5% across all commuting zones ($\hat{P}(M) = 0.95$). The first line of panel (b) shows that the minimum and the maximum of the predicted impact become smaller in absolute terms when imposing the same relative price change. However, most of the estimated regional heterogeneity in the impact on the CWP is not driven by regional variation in price changes. For example, the difference between the commuting zones at the 90th and 10th percentile remains almost unchanged.

Alternatively, I shut down the differences between skill groups in the dispersion of productivity draws. Rather than using the estimated θs from the maximum likelihood estimation which differ between college and non-college workers, I use the joint dispersion parameter of both skill groups of θ (1.6959) and assign it to both skill groups. The second line of panel (b) suggests that most of the observed heterogeneity in the impact is not driven by differences between skill groups in the productivity dispersion. In fact, the minimum and maximum become even larger when equalizing the dispersion parameter across skill groups. The third line of panel (b) shows that a similar picture emerges when shutting down both the heterogeneity in price changes and the heterogeneity in productivity dispersion. Overall, these results point to the importance of the initial allocation of skill groups across sectors for the way in which the local CWP is affected.

Figure 6: Initial allocation, predicted impact, and actual impact

(a) (b)



Notes: Panel (a) is a binscatter plot (30 bins) with the initial difference in non-manufacturing labor income shares ($\pi_0(C, N, \gamma) - \pi_0(NC, N, \gamma)$) on the horizontal axis and the predicted impact on the CWP on the vertical axis. Panel (b) is a binscatter plot (30 bins) with the predicted impact on the CWP on the horizontal axis and the observed change in the CWP on the vertical axis. All estimates refer to ten-year equivalent changes (1990-2000 and 2000-2007). Data sources: IPUMS Census (1990 and 2000), American Community Survey (2006 and 2007) and Autor et al. (2013).

Extension to more than two skill groups. To get a more comprehensive picture on the heterogeneous effects, I extend the analysis to eight education groups. I keep the estimated change in the manufacturing price in a commuting zone from the previous section, but estimate the productivity dispersion parameter separately for each education group. Together with the initial allocation shares, I obtain estimates for the predicted impact on wages for each skill group.

Table 6 provides the results for the change in the wage gap between 7 education groups and high school graduates as the reference. The results suggest that skill groups with a higher mean log wage are in general more positively affected, implying an increase in the skill premium along the full spectrum of educational groups. The wage gap between individuals with a professional degree and those with a high school degree increases most strongly on average. This wage gap also has the highest regional dispersion, with a maximum of 18.22 log points and a minimum of minus 0.58 log points. Importantly, table 6 shows that the regional heterogeneity in the predicted impact is also present in the case of more than two skill groups. Figure G4 in the appendix illustrates the geographic distribution of predicted impact on the respective wage gap measure. The predicted effects for the respective measures are positively but not perfectly correlated.

Table 6: Extension to more than two skill groups

	mean	min	p10	p25	p50	p75	p90	max
Less than high school vs. high school	0.01	-1.39	-0.41	-0.08	0.05	0.14	0.30	3.54
Some college vs. high school	0.26	-0.79	0.06	0.11	0.20	0.29	0.56	3.05
Associate vs. high school	0.28	-3.96	0.02	0.10	0.22	0.37	0.67	3.91
Bachelor vs. high school	0.30	-1.27	-0.04	0.08	0.16	0.43	0.71	4.96
Master vs. high school	0.41	-1.70	-0.03	0.14	0.21	0.58	1.08	10.02
Professional vs. high school	0.91	-0.58	0.31	0.48	0.70	1.04	1.76	18.22
Doctoral vs. high school	0.47	-3.31	-0.06	0.10	0.33	0.61	1.29	12.39

Notes: Table plots summary statistics of the predicted impact on the wage gap between various education groups. See section 4.5 for an explanation of the estimation procedure. Estimated dispersion parameters: Less than high school 1.7992, Some college 1.7173, Associate 1.7129, Master 1.6246, Professional 1.4863, Doctoral 1.5750. Data sources: IPUMS Census (1990 and 2000), American Community Survey (2006 and 2007) and Autor et al. (2013).

4.6 Conclusion

The large heterogeneity in the evolution of the college wage premium across regions gives rise to the question to what extent the effects of globalization or technological progress on wage inequality differ across regions. This paper takes one step into this direction by asking whether the effects of China's integration into the world economy on the college wage premium differed across U.S. commuting zone. It turns out that this is indeed the case. The analysis in this paper emphasizes one factor which shapes the size and the direction of the impact in a given region, namely the initial allocation of skill groups across sectors. Depending on this allocation, the effect of a given change in the trade environment on the college wage premium can be large and positive or even negative. With this insight, the paper contributes to the understanding of the distributional effects of globalization.

The results in this paper have implications for empirical studies on the regional effects of international trade. Studies that focus on regional outcomes such as wages or employment, for example Autor et al. (2013), typically force the effect of a given trade exposure to be equal across regions. In this setting, differences in outcomes across regions can only by explained by variation in trade exposure that results from region differences in industry composition. The analysis in this paper emphasizes that the college wage premium is differently affected across regions even for a given industry composition or a given change in relative prices. This means that estimates that focus on a single elasticity between regional outcomes and a Bartik-style measure of trade exposure mask a substantial heterogeneity across regions.

A limitation of the analysis in this paper is that it does not allow for worker mobility across locations in response to a given shock. This means that the results of the quantitative exercise need to be understood as effects before any worker mobility across regions in response to the shock occurs. Recently, the literature has made progress on the question to what extent aggregate and disaggregate shocks trigger worker mobility across regions in terms of migration or commuting and to what extent these flows shape the resulting regional outcomes (e.g. Monte et al. 2018; Krebs and Pflueger 2019). While the focus of these studies is on aggregate regional outcomes such as employment, a fruitful avenue for future research could be to extend the present analysis to an environment in which regions are connected by commuting and migration flows. A second limitation is that this paper exclusively focuses on the college wage premium. Numerous studies point out that a large part of the rise in wage inequality in fact happened within conventional skill groups (e.g. Acemoglu and Autor 2011). It would therefore be interesting to see to what extent the heterogeneous effects pointed out in this paper also occur for residual wage inequality.

4.7 Appendix E: Construction of commuting zones

To provide a regional perspective on the evolution of the college wage premium, this paper relies on commuting zones as the concept of a local labor market. This appendix serves to give a short overview on the underlying idea behind the use of commuting zones as well as on the procedure to construct commuting zones within the Census and ACS data. The following explanations are based on the data appendix in Dorn (2009). While the data appendix in Dorn (2009) provides a detailed explanation of all steps, this appendix gives a short summary, focusing on the main intuition behind the approach.

The most commonly used concept of a local labor market in recent research is the Metropolitan Statistical Area (MSA) (e.g. Moretti 2010; Baum-Snow and Pavan 2012; Moretti 2013). MSAs cover major population centers in the USA, mostly larger cities and the surrounding suburbs. A disadvantage of the use of MSAs is that this concept of a local labor market does not include rural areas. Additional complications arise because the definition of MSAs changes over time. In fact, the delineations of MSAs change in every wave of the Census and therefore a given MSA code might correspond to different areas in different years. For example, the gradual inclusion of outlying suburbs to MSAs over time leads to mechanical changes in the composition of MSAs if the population in suburbs systematically differs from the population in the city center. In the context of this paper, a potential concern is that changes over time in the delineation of MSAs might lead to mechanical changes in the observed college wage premium in MSAs. I therefore follow Dorn (2009) and Autor and Dorn (2013), and use time-consistent commuting zones instead of MSAs as the main concept of a local labor market. In creating commuting zones within the IPUMS and ACS data, I closely follow the procedure described by Dorn (2009).

The definition of commuting zones dates back to Tolbert and Killian (1987) and Tolbert and Sizer (1996). Based on commuting data from the 1980 and 1990 census, they compute the strength of commuting ties between two counties as the sum of commuters in both directions relative to the population in the smaller one of both counties. They create commuting zones as clusters of counties such that the average strength of commuting ties within commuting zones is above 0.02. In other words, this procedure ensures that commuting ties between commuting zones are so weak that increasing the level of aggregation (i.e. combning more counties into one commuting zone) would push the average strength of commuting ties within commuting zones below 0.02. For the year 1990, Tolbert and Sizer (1996) define 741 commuting zones, with the average commuting zone consisting of four counties.

A complication that arises with the use of commuting zones is that they are not directly reported in the Census and ACS data. This has to do with data confidentiality restrictions which require that the data must not report geographic units with a population below

100,000. As some commuting zones host less than 100,000 residents, directly reporting commuting zones or counties in the data would violate the confidentiality restrictions. For the years 1990, 2000, and 2006/2007, the most detailed geographic unit reported in the data is the Public Use Microdata Area (PUMA). A typical PUMA consists of 100,000-200,000 residents. States and MSAs are multiples of PUMAs.

Dorn (2009) and Autor and Dorn (2013) develop a procedure to match every individual in the Census and ACS data to a given commuting zone. To understand the approach, first note that the data allow to observe the PUMA in which a given individual lives, but it does not allow to observe the county and commuting zone in which the individual lives. Second, note that the Census Bureau provides information on the counties that overlap with a given PUMA as well as on the population count of every PUMA-county overlap in 1990 and 2000. Finally, note that every county belongs to a given commuting zone by definition of Tolbert and Killian (1987).

Matching individuals to commuting zones is simple in cases where individuals live in a PUMA that overlaps only with counties that all belong to the same commuting zone. In that case, the mapping from PUMAs to commuting zones is unambiguous and the probability that an individual in a given PUMA lives in a given commuting zone is either 0 or 1. This is the case for around 80% of all PUMAs in a given year.

Matching individuals to commuting zones is more difficult in cases where PUMAs overlap with counties that do not all belong to the same commuting zone. Consider the following example of individuals living in PUMA j_1. Suppose that 50% of j_1's population overlaps with county c_1, 30% overlaps with county c_2, and 20% overlaps with county c_3. Additionally, assume that counties c_1 and c_2 belong to commuting zone k_1, whereas county c_3 belongs to commuting zone k_2. In that case, the probability that an individual in PUMA j_1 lives in commuting zone k_1 is 0.8 (0.5+0.3) and the probability that the individual lives in commuting zone k_2 is 0.2. In these ambiguous cases, individuals are split into multiple parts. For the specific example, every individual living in PUMA j_1 would be split into two observations, one observation allocated to commuting zone k_1 and one observation allocated to commuting zone k_2. In the course of this procedure, the sample weights provided by the data are being multiplied by the respective probabilities. For the observation allocated to k_1 (k_2) sample weights would be multiplied by 0.8 (0.2). In the analysis throughout the paper, I use these adjusted weights. The adjusted weights sum up to the original sample weights for each individual. As the Census Bureau does not report the population count for PUMA-county overlaps in years after 2000, Dorn (2009) and Autor and Dorn (2013) use the matching for 2000 for these years.

The crosswalks from PUMAs to commuting zones are provided on David Dorn's homepage and can be accessed via https://www.ddorn.net/data.htm. The crosswalk also includes the respective probabilities ('afactor') which need to be multiplied by the sample weights to obtain the adjusted weights.

4.8 Appendix F: Theory

Derivation of equation 11: $\hat{\pi}(\lambda,\sigma,\gamma) = \frac{\hat{p}(\sigma)^{\theta(\lambda)}}{\sum_{\sigma'} \hat{p}(\sigma')^{\theta(\lambda)}\pi_0(\lambda,\sigma',\gamma)}$

Start with equation 6: $\pi(\lambda,\sigma,\gamma) = \frac{[p(\sigma)T(\lambda,\sigma,\gamma)]^{\theta(\lambda)}}{\sum_{\sigma'}[p(\sigma')T(\lambda,\sigma',\gamma)]^{\theta(\lambda)}}$

Define proportional change over time as $\hat{x} = x_1/x_0$ and note that $\hat{T}(\cdot) = 1$

$$\hat{\pi}(\lambda,\sigma,\gamma) = \frac{\hat{p}(\sigma)^{\theta(\lambda)}}{\sum_{\sigma'}[p_1(\sigma')T_1(\lambda,\sigma',\gamma)]^{\theta(\lambda)}/\sum_{\sigma''}[p_0(\sigma'')T_0(\lambda,\sigma'',\gamma)]^{\theta(\lambda)}}$$

$$\hat{\pi}(\lambda,\sigma,\gamma) = \frac{\hat{p}(\sigma)^{\theta(\lambda)}}{\sum_{\sigma'}\hat{p}(\sigma')^{\theta(\lambda)}[p_0(\sigma')T_0(\lambda,\sigma',\gamma)]^{\theta(\lambda)}/\sum_{\sigma''}[p_0(\sigma'')T_0(\lambda,\sigma'',\gamma)]^{\theta(\lambda)}}$$

$$\hat{\pi}(\lambda,\sigma,\gamma) = \frac{\hat{p}(\sigma)^{\theta(\lambda)}}{\sum_{\sigma'}\hat{p}(\sigma')^{\theta(\lambda)}\pi_0(\lambda,\sigma',\gamma)}$$

Derivation of equation 12: $\hat{w}(\lambda,\gamma) = \left[\sum_\sigma \hat{p}(\sigma)^{\theta(\lambda)}\pi_0(\lambda,\sigma,\gamma)\right]^{1/\theta(\lambda)}$

Start with equation 10: $w(\lambda,\gamma) = \chi\left[\sum_\sigma [p(\sigma)T(\lambda,\sigma,\gamma)]^{\theta(\lambda)}\right]^{1/\theta(\lambda)}$

Define proportional change over time as $\hat{x} = x_1/x_0$ and note that $\hat{T}(\cdot) = 1$

$$\hat{w}(\lambda,\gamma)^{\theta(\lambda)} = \frac{\sum_\sigma[p_1(\sigma)T_1(\lambda,\sigma,\gamma)]^{\theta(\lambda)}}{\sum_{\sigma'}[p_0(\sigma')T_0(\lambda,\sigma',\gamma)]^{\theta(\lambda)}}$$

$$\hat{w}(\lambda,\gamma)^{\theta(\lambda)} = \frac{\sum_\sigma \hat{p}(\sigma)^{\theta(\lambda)}[p_0(\sigma)T_0(\lambda,\sigma,\gamma)]^{\theta(\lambda)}}{\sum_{\sigma'}[p_0(\sigma')T_0(\lambda,\sigma',\gamma)]^{\theta(\lambda)}}$$

$$\hat{w}(\lambda,\gamma)^{\theta(\lambda)} = \left[\sum_\sigma \hat{p}(\sigma)^{\theta(\lambda)}\pi_0(\lambda,\sigma,\gamma)\right]$$

$$\hat{w}(\lambda,\gamma) = \left[\sum_\sigma \hat{p}(\sigma)^{\theta(\lambda)}\pi_0(\lambda,\sigma,\gamma)\right]^{1/\theta(\lambda)}$$

4.9 Appendix G: Tables and figures

Table G1: Sample descriptives - individual level

	mean	p10	p25	p50	p75	p90
			(a) 1990			
Annual labor income	36,310.38	7,613.16	15,860.75	30,084.67	47,582.25	68,201.22
Hourly wage	20.51	7.32	10.25	15.55	23.64	33.55
Log hourly wage	2.77	1.99	2.33	2.74	3.16	3.51
College (bachelor)	0.34	0.00	0.00	0.00	1.00	1.00
Manufacturing	0.21	0.00	0.00	0.00	0.00	1.00
Female	0.48	0.00	0.00	0.00	1.00	1.00
White	0.85	0.00	1.00	1.00	1.00	1.00
Black	0.10	0.00	0.00	0.00	0.00	0.00
Foreign-born	0.07	0.00	0.00	0.00	0.00	0.00
			(b) 2000			
Annual labor income	41,796.92	9,630.66	18,057.49	32,503.48	50,560.98	78,249.13
Hourly wage	23.13	7.74	11.04	16.54	25.08	37.62
Log hourly wage	2.85	2.05	2.40	2.81	3.22	3.63
College (bachelor)	0.40	0.00	0.00	0.00	1.00	1.00
Manufacturing	0.18	0.00	0.00	0.00	0.00	1.00
Female	0.48	0.00	0.00	0.00	1.00	1.00
White	0.80	0.00	1.00	1.00	1.00	1.00
Black	0.11	0.00	0.00	0.00	0.00	1.00
Foreign-born	0.11	0.00	0.00	0.00	0.00	1.00
			(c) 2006/2007			
Annual labor income	40,677.86	7,403.57	16,966.52	30,848.21	50,385.42	80,000.00
Hourly wage	23.17	7.20	10.28	15.91	25.00	38.46
Log hourly wage	2.81	1.97	2.33	2.77	3.22	3.65
College (bachelor)	0.40	0.00	0.00	0.00	1.00	1.00
Manufacturing	0.14	0.00	0.00	0.00	0.00	1.00
Female	0.47	0.00	0.00	0.00	1.00	1.00
White	0.77	0.00	1.00	1.00	1.00	1.00
Black	0.12	0.00	0.00	0.00	0.00	1.00
Foreign-born	0.14	0.00	0.00	0.00	0.00	1.00

Notes: The table displays summary statistics on the sample at the individual worker level, before collapsing the data to to commuting zone-year level. Sample is restricted on all workers with either a high school or a bachelor's degree with 20-60 years of age in dependent employment outside the military. I drop all observations with an hourly wage lower than 75% of the federal minimum wage in the respective year. Labor income and hourly wages are deflated by the consumer price index in the respective year in order to reflect constant year-2007-USD. Hourly wages are computed as annual labor income divided by weeks worked and usual work hours. All computations use sample weights. Sample includes 3,607,572 observations in 1990, 3,968,548 observations in 2000, and 1,730,749 observations in 2006-2007. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007).

Table G2: Adjusted CWP in 30 largest commuting zones

	(1) CWP 1990	(2) CWP 2007	(3) Change 1990-2007
Atlanta GA	43.42	55.18	11.76
Baltimore MD	42.26	52.97	10.71
Boston MA	38.47	50.74	12.27
Bridgeport CT	41.36	54.71	13.35
Buffalo NY	42.65	45.33	2.68
Chicago IL	41.22	50.99	9.78
Cincinnati OH	45.24	54.55	9.31
Cleveland OH	43.13	50.99	7.86
Dallas TX	47.46	61.26	13.80
Denver CO	40.09	50.29	10.20
Detroit MI	44.56	54.25	9.69
Houston TX	47.18	64.7	17.52
Kansas City MO	39.35	49.54	10.18
Los Angeles CA	44.68	57.43	12.75
Miami FL	43.29	47.36	4.069
Milwaukee WI	38.79	45.49	6.70
Minneapolis MN	38.03	49.61	11.58
New York City NY	41.93	57.26	15.33
Newark NJ	43.26	57.82	14.56
Philadelphia PA	40.71	53.34	12.64
Phoenix AZ	46.74	49.16	2.42
Pittsburgh PA	48.54	50.96	2.42
Sacramento CA	37.76	51.57	13.81
San Diego CA	41.15	56.00	14.85
San Francisco CA	37.05	58.21	21.16
San Jose CA	43.99	65.3	21.31
Seattle WA	34.31	50.22	15.91
St. Louis MO	41.53	49.2	7.70
Tampa FL	48.05	51.77	3.72
Washington DC	38.88	57.41	18.53

Notes: The table displays the estimated adjusted CWP in the 30 largest commuting zones in terms of their overall population as of 1990, in alphabetical order. The adjusted CWP stems from a regression of log hourly wages on a dummy for bachelor's degree, controlling for all possible interactions between variables for sex (male and female), race (white, black, and other), potential experience (<10, 10-20, 20-30, 30-40, >40), and immigration status (foreign-born or not), separately for each commuting zone and year. Sample is restricted on all workers with either a high school or a bachelor's degree with 20-60 years of age in dependent employment outside the military. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007).

Table G3: Heterogeneity in CWP across commuting zones, summary statistics (restricted sample)

	min	p10	p25	p50	p75	p90	max
				(a) Level (1990)			
Raw CWP	7.16	30.39	34.21	38.53	43.39	47.74	59.42
Adjusted CWP	11.29	35.15	39.12	43.01	47.73	51.24	62.09
				(b) Change (1990-2007)			
Raw CWP	-21.55	0.70	4.47	9.74	16.14	20.41	30.03
Adjusted CWP	-18.87	2.90	6.59	11.12	13.87	17.41	37.07

Notes: The table displays summary statistics on the college wage premium (CWP) within 722 U.S. commuting zones. In contrast to the corresponding table in the main text, this table restricts the sample on individuals who have worker at least 40 weeks and 35 hours per week. The raw CWP is computed as the difference in mean log hourly wages between individuals with a bachelor's degree and individuals with a high school degree in the respective commuting zone and year. The adjusted CWP stems from a regression of log hourly wages on a dummy for bachelor's degree, controlling for all possible interactions between variables for sex (male and female), race (white, black, and other), potential experience (<10, 10-20, 20-30, 30-40, >40), and immigration status (foreign-born or not), separately for each commuting zone and year. Sample is restricted on all workers with either a high school or a bachelor's degree with 20-60 years of age in dependent employment outside the military. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007).

Table G4: Regression sample descriptives at commuting zone level

	(1)					
	mean	p10	p25	p50	p75	p90
$\Delta Imp_{\gamma t}$ (in \$1000 per worker)	1.88	0.51	0.81	1.46	2.40	3.59
$\Delta Imp_{\gamma ot}$ (in \$1000 per worker)	1.79	0.47	0.78	1.36	2.52	3.31
$\Delta\pi_t(NC, M, \gamma)$	-0.0447	-0.0980	-0.0631	-0.0412	-0.0252	-0.0007
Share non-college	0.64	0.51	0.57	0.63	0.71	0.78
Share college	0.36	0.22	0.29	0.37	0.43	0.49
Share immigrants (non-college)	0.10	0.01	0.02	0.05	0.14	0.25
Share immigrants (college)	0.10	0.02	0.04	0.06	0.12	0.24
Share females (non-college)	0.47	0.45	0.46	0.48	0.49	0.50
Share females (college)	0.48	0.44	0.46	0.48	0.49	0.51
Share white (non-college)	0.79	0.60	0.69	0.80	0.91	0.96
Share white (college)	0.86	0.74	0.80	0.88	0.94	0.97
Share black (non-college)	0.12	0.01	0.04	0.09	0.19	0.26
Share black (college)	0.07	0.01	0.02	0.05	0.10	0.14
Log population	14.05	11.97	13.02	14.17	15.21	16.20
Manufacturing share of population	18.46	9.31	12.58	16.66	22.46	29.84
Share unemployed	4.54	3.40	3.84	4.46	5.12	5.53
Routine task measure	32.05	28.23	30.50	32.52	34.04	34.90
Outsourcing measure	0.05	-0.67	-0.29	0.15	0.41	0.62

Notes: The table displays summary statistics at the level of 722 U.S. commuting zones for the base years of the regression, 1990 and 2000. Computations make use of sample weights. See section 4.5 for details on the construction of the variables. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007) and Autor et al. (2013).

Table G5: First stage estimates

	(1)	(2)	(3)
	Dep.var.: $\Delta Imp_{\gamma t}$		
Δ Imp$_{\gamma ot}$	0.70^c	0.62^c	0.62^c
	(0.09)	(0.09)	(0.09)
N	1444	1444	1444
Adj. R^2	0.56	0.59	0.59
F	115.45	169.78	191.18

Notes: The table displays the first-stage results corresponding to columns (4)-(6) of table 4. Standard errors clustered by census division. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007) and Autor et al. (2013). ^{a} $p < 0.10$, ^{b} $p < 0.05$, ^{c} $p < 0.01$.

Table G6: Import exposure and labor reallocation (employment shares)

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV	(7) OLS
$\Delta Imp_{\gamma t}$	-0.0026^c	-0.0034^c	-0.0034^c	-0.0063^c	-0.0090^c	-0.0091^c	
	(0.00046)	(0.00051)	(0.00051)	(0.0011)	(0.0015)	(0.0016)	
$\Delta Imp_{\gamma ot}$							-0.0056^c
							(0.00064)
Obs.	1444	1444	1444	1444	1444	1444	1444
Adj. R^2	0.48	0.53	0.53	0.45	0.47	0.47	0.55

Notes: Dependent variable is the ten-year equivalent change in the employment share of non-college workers in the manufacturing sector in a commuting zone (1990-2000, 2000-2007). See equations 15 and 16 for the definition of $\Delta Imp_{\gamma t}$ and $\Delta Imp_{\gamma ot}$. Basic controls include the initial share of income earned in the manufacturing sector, the manufacturing employment share, the share of individuals with a bachelor's degree, the share of individuals with a high school degree as well as the share of foreigners, females, whites, 5 experience groups, and the share of unemployed in the commuting zone. Advanced controls include the share of employment in routine occupations and an average offshorability index of occupations. All specifications additionally include dummies for 8 census divisions, and a dummy to differentiate between the two periods. Standard errors clustered by census division in parentheses. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007) and Autor et al. (2013). ^{a} $p < 0.10$, ^{b} $p < 0.05$, ^{c} $p < 0.01$.

Table G7: Import exposure and labor reallocation (college)

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV	(7) OLS
$\Delta Imp_{\gamma t}$	-0.0012	-0.0029^a	-0.0029^a	-0.0017	-0.0038	-0.0044	
	(0.0017)	(0.0015)	(0.0015)	(0.0033)	(0.0028)	(0.0031)	
$\Delta Imp_{\gamma ot}$							-0.0028
							(0.0019)
Obs.	1444	1444	1444	1444	1444	1444	1444
Adj. R^2	0.12	0.14	0.14	0.12	0.14	0.14	0.14

Notes: Dependent variable is the ten-year equivalent change in the share of college workers' wage sum which is earned in the manufacturing sector in a commuting zone (1990-2000, 2000-2007). See equations 15 and 16 for the definition of $\Delta Imp_{\gamma t}$ and $\Delta Imp_{\gamma ot}$. Basic controls include the initial share of income earned in the manufacturing sector, the manufacturing employment share, the share of individuals with a bachelor's degree, the share of individuals with a high school degree as well as the share of foreigners, females, whites, 5 experience groups, and the share of unemployed in the commuting zone. Advanced controls include the share of employment in routine occupations and an average offshorability index of occupations. All specifications additionally include dummies for 8 census divisions, and a dummy to differentiate between the two periods. Standard errors clustered by census division in parentheses. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007) and Autor et al. (2013). ^{a} $p < 0.10$, ^{b} $p < 0.05$, ^{c} $p < 0.01$.

Table G8: Import exposure and labor reallocation (college, employment shares)

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV	(7) OLS
$\Delta Imp_{\gamma t}$	0.00032	-0.00070	-0.00071	-0.0013	-0.0036^c	-0.0036^c	
	(0.00066)	(0.00048)	(0.00048)	(0.0014)	(0.0014)	(0.0014)	
$\Delta Imp_{\gamma ot}$							-0.0023^c
							(0.00074)
Obs.	1444	1444	1444	1444	1444	1444	1444
Adj. R^2	0.30	0.34	0.34	0.29	0.32	0.32	0.35

Notes: Dependent variable is the ten-year equivalent change in the employment share of college workers in the manufacturing sector in a commuting zone (1990-2000, 2000-2007). See equations 15 and 16 for the definition of $\Delta Imp_{\gamma t}$ and $\Delta Imp_{\gamma ot}$. Basic controls include the initial share of income earned in the manufacturing sector, the manufacturing employment share, the share of individuals with a bachelor's degree, the share of individuals with a high school degree as well as the share of foreigners, females, whites, 5 experience groups, and the share of unemployed in the commuting zone. Advanced controls include the share of employment in routine occupations and an average offshorability index of occupations. All specifications additionally include dummies for 8 census divisions, and a dummy to differentiate between the two periods. Standard errors clustered by census division in parentheses. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007) and Autor et al. (2013). ^{a} $p < 0.10$, ^{b} $p < 0.05$, ^{c} $p < 0.01$.

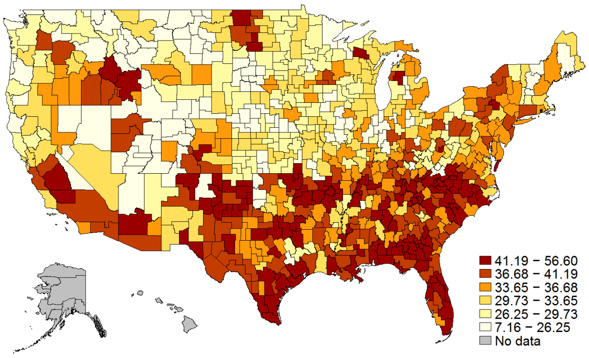
Table G9: Import exposure and labor reallocation (Net import exposure)

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV	(7) IV
$\Delta NetImp_{\gamma t}$	0.0005	-0.0016^a	-0.0016^a	-0.0012	-0.0063^c	-0.0063^c	
	(0.0010)	(0.0009)	(0.0009)	(0.0019)	(0.0021)	(0.0021)	
$\Delta NetImp_{\gamma ot}$							-0.0042^c
							(0.0012)
Obs.	1444	1444	1444	1444	1444	1444	1444
Adj. R^2	0.23	0.31	0.31	0.23	0.29	0.30	0.32

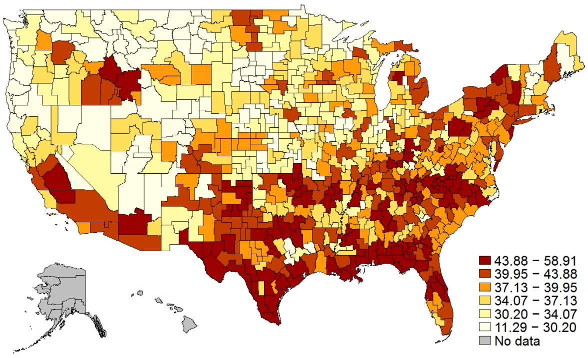
Notes: Dependent variable is the ten-year equivalent change in the share of non-college workers' wage sum which is earned in the manufacturing sector in a commuting zone (1990-2000, 2000-2007). $\Delta NetImp_{\gamma t}$ denotes the change in net import exposure in a commuting zone and $\Delta NetImp_{\gamma ot}$ denotes the corresponding instrument. Basic controls include the initial share of income earned in the manufacturing sector, the manufacturing employment share, the share of individuals with a bachelor's degree, the share of individuals with a high school degree as well as the share of foreigners, females, whites, 5 experience groups, and the share of unemployed in the commuting zone. Advanced controls include the share of employment in routine occupations and an average offshorability index of occupations. All specifications additionally include dummies for 8 census divisions, and a dummy to differentiate between the two periods. Standard errors clustered by census division in parentheses. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007) and Autor et al. (2013). ^{a} $p < 0.10$, ^{b} $p < 0.05$, ^{c} $p < 0.01$.

Figure G1: Heterogeneity in the CWP across commuting zones (restricted sample)

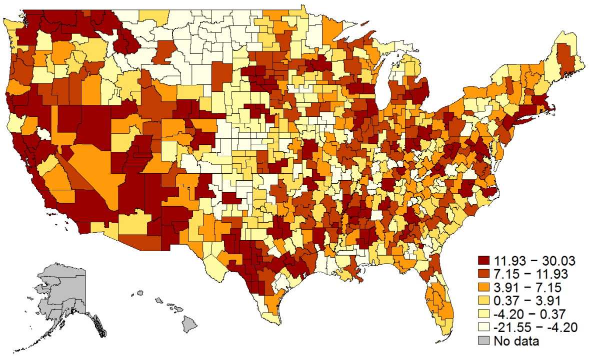
(a) Level 1990 (raw)



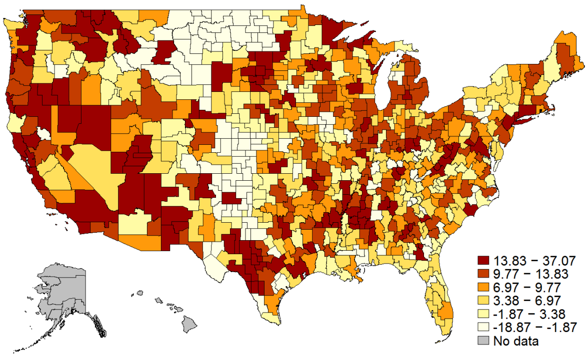
(b) Level 1990 (adjusted)



(c) Change 1990-2007 (raw)

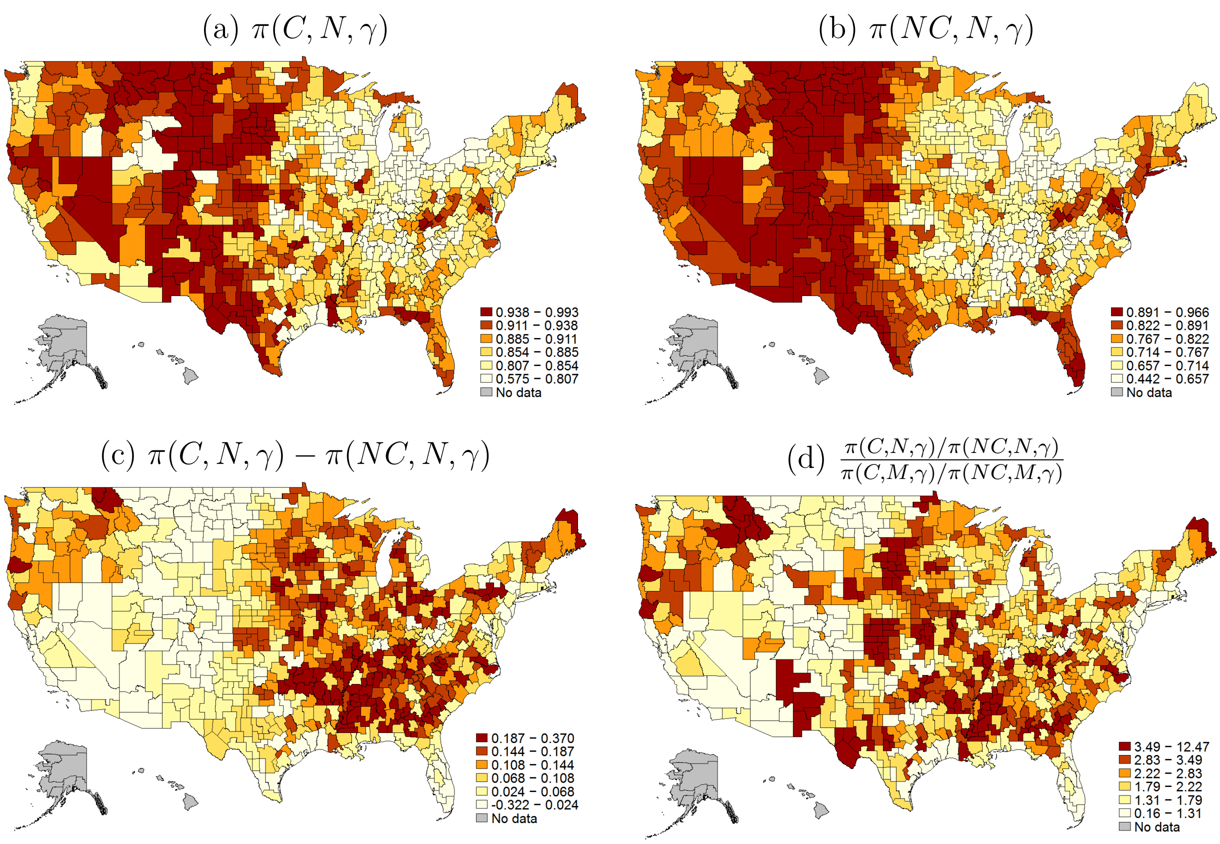


(d) Change 1990-2007 (adjusted)



Notes: The figures plot the level of the college wage premium (CWP) in 1990 and its change from 1990 to 2007, separately for 722 U.S. commuting zones. The raw CWP is computed as the difference in mean log hourly wages between individuals with a bachelor's degree and individuals with a high school degree in the respective commuting zone and year. The adjusted CWP stems from a regression of log hourly wages on a dummy for bachelor's degree, controlling for all possible interactions between variables for gender (male and female), race (white, black, and other), potential experience (<10, 10-20, 20-30, 30-40, >40), and immigration status (foreign-born or not), separately for each commuting zone and year. Sample is restricted on all workers with either a high school or a bachelor's degree with 20-60 years of age in dependent employment outside the military. In contrast to the figure in the main text, this figure additionally restricts the sample on workers who workeed at least 40 weeks and 35 hours per week. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007).

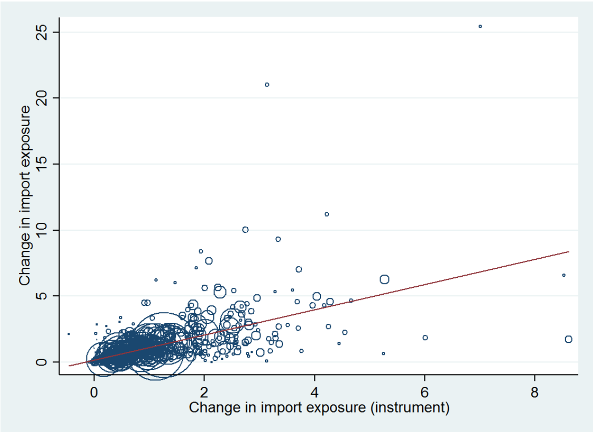
Figure G2: Allocation of skill groups across sectors 2000 - regional differences



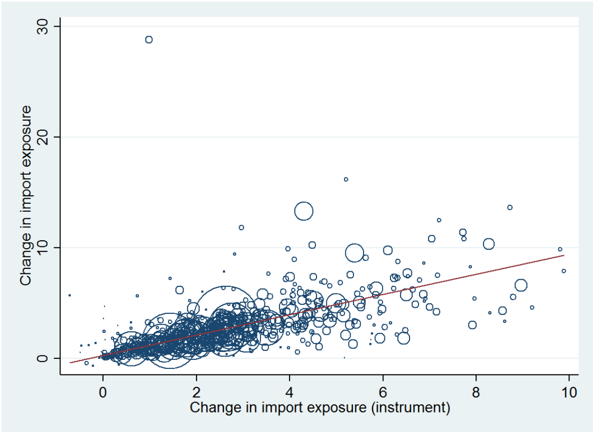
Notes: $\pi(C, N, \gamma)$ ($\pi(NC, N, \gamma)$) denotes the share of their labor income that college (non-college) workers earn in the non-manufacturing sector in a commuting zone in 2000. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007).

Figure G3: Graphical representation of first stage

(a) 1990-2000



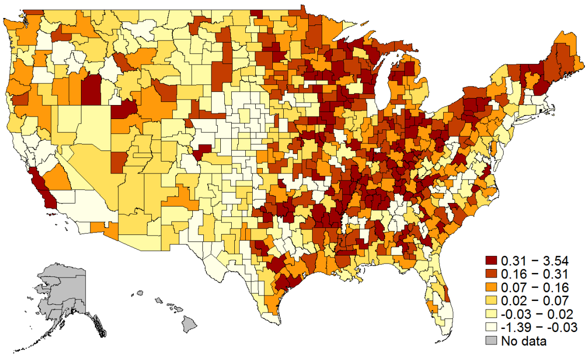
(b) 2000-2007



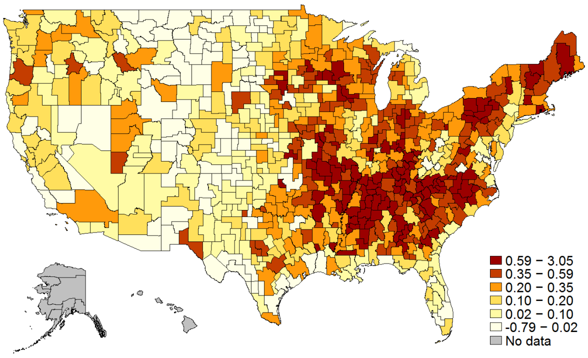
Notes: The graphs plot the change in import exposure in a commuting zone at the vertical axis and the corresponding instrument on the horizontal axis. The size of the bubbles reflect the size of the commuting zone in terms of population in 1990 or 2000, respectively. The figures drop observations with instrument value>10 for better visibility. Data sources: IPUMS Census (1990 and 2000) and American Community Survey (2006 and 2007) and Autor et al. (2013).

Figure G4: Predicted impact on skill premium, relative to high school graduates

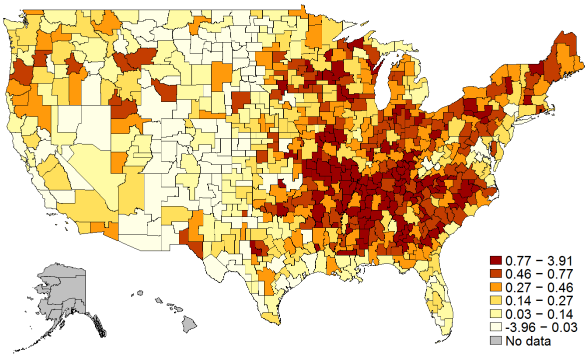
(a) Less than high school



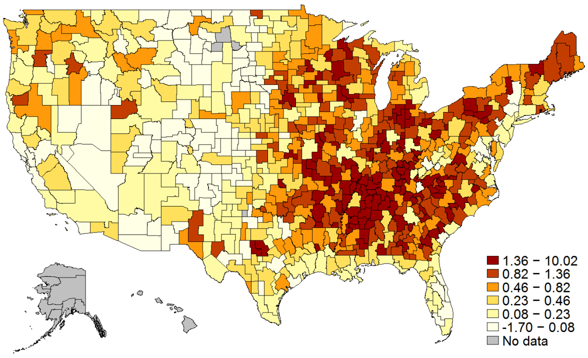
(b) Some college



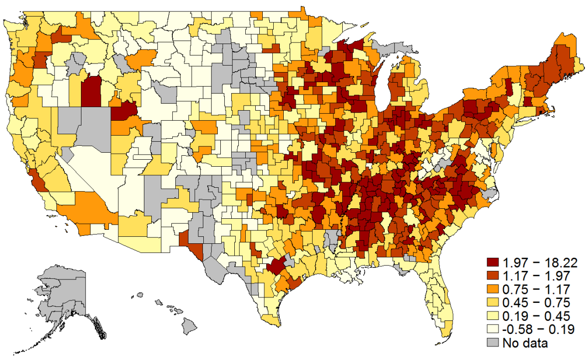
(c) Associate



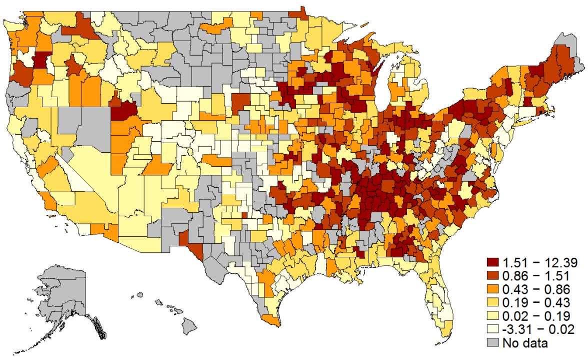
(d) Master



(e) Professional



(f) Doctoral



Notes: The maps plot the predcited impact on the skill premium, always with high school graduates as the reference group. Data sources: Census Integrated Public Use Micro Samples (IPUMS) (1990 and 2000) and American Community Survey (2006-2008). In some commuting zones, I do not observe individuals with a professional degree and a doctoral degree.

4.10 Acknowledgments and remarks

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5 Exporters and wage inequality during the Great Recession - Evidence from Germany

Exporters and wage inequality during the Great Recession - Evidence from Germany

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We show that the exporter wage premium decreased at the dawn of the Great Recession and stagnated afterwards. Our decomposition suggests that the decline of the premium explains 24-43% of the decrease in residual wage inequality between 2007 and 2008.

JEL-Classification: F16, J31
Keywords: exporter wage premium, wage-inequality, Great Recession, international trade, matched employer-employee data.

5.1 Introduction

The German labor market proved to be robust to the negative shocks associated with the recent financial crisis. Explanations for this so called "German Job Miracle" comprise institutional factors, such as working time accounts and short-time work, which created a strong buffering capacity among firms and allowed them to cushion the shock (Moeller 2010). We argue that research on the "exporter wage premium" (EWP) suggests another margin of adjustment for firms that seek to decrease labor costs in times of low demand. Such a wage premium can be rationalized by fair wage preferences of workers (Egger and Kreickemeier 2012) and importantly, Hauptmann and Schmerer (2013) show that it mainly stems from a larger wage drift in exporting firms. Since cutting the wage drift (e.g. in the form of lower bonus payments) is a comparatively painless way to quickly reduce labor costs, German firms might have taken advantage of this instrument to compensate the costs of labor-hoarding. Given that export-oriented firms have been hit more intensively by the crisis than purely domestic firms (Moeller 2010), one would expect the wage adjustment to be stronger for exporters and the EWP to fall. Since the upward-trend of the EWP during the 2000s has proven to be inequality-increasing (Baumgarten 2013), a decrease of the EWP should work in the opposite direction.

Our contribution to the existing literature is to provide evidence that both, exporters and non-exporters reduced wage payments during the crisis. Since exporters started to adjust their wage setting one year earlier than non-exporters, the EWP decreased at the dawn of the crisis and stagnated thereafter. Finally, our decomposition results show that the decline of the EWP had a negative and persistent impact on wage inequality during the crisis, especially on residual wage inequality.

5.2 Data and methods

We use the LIAB (version LIAB QM2 9310 v1), a matched employer-employee dataset provided by the Institute for Employment Research, and follow Baumgarten (2013) in terms of data preparation and empirical specification. We thus restrict the sample to male full-time workers in the manufacturing sector at the age between 18 and 65 in regular employment.

The specification we estimate separately for each year, is:

$$ln(w)_{ift} = \beta_{0t} + \beta_{1t} exp_{ft} + X'_{ift}\beta_{2t} + P'_{ft}\beta_{3t} + I'_{ft}\beta_{4t} + F'_{ft}\beta_{5t} + \epsilon_{ift}, \tag{1}$$

where $ln(w)_{ift}$ denotes the logarithm of worker i's daily real wage including bonus payments, working in firm f in year t (imputed because of top-coding at the social security contribution ceiling).[1] exp_{ft} is a dummy variable indicating firm f's exporter status in

[1]The data are sampled at the end of June and thus include all workers employed by the firm at this

t. X'_{ift} denotes a rich set of controls for worker characteristics, including 20 skill group dummies (interactions of five age and four education dummies), foreign nationality, a quadratic term in tenure and a dummy for being a master craftsman or foreman. The vector of firm characteristics P'_{ft} varies by specification: dummies for IT-investments and technological state (tech), firm or industry level wage agreements (bargain), a quadratic term of ln employment (size), and all plant controls jointly plus dummies for works council and 1-plant firm (full).[2] The baseline specification does not include any firm-level controls apart from the export dummy. I'_{ft} and F'_{ft} denote industry and federal state dummies and are included in all models. Note that we are interested in the contribution of changes in the EWP to changes in wage inequality and therefore do not rely on capturing the causal effect of exporting on wages in the cross-section. For our purpose it is more important that the bias (if there is one) is constant over time. The fact that we obtain similar results from five different specifications confirms the validity of this approach.

Making use of the OLS estimates, we employ the method described by Lemieux (2002) and decompose the change in residual wage inequality between two years t_0 and t_1 into different components. We measure residual wage inequality as the standard error of a regression of log wages on the 20 skill group dummies. The construction of several counterfactual distributions allows us to disentangle the impact of changes of 1) the EWP, 2) other coefficients, 3) covariates, and 4) residuals on residual wage inequality by sequentially changing the components of the OLS models. Whereas a change of coefficients is easily obtained from the OLS estimates, a change of covariates is performed via reweighting.

5.3 The EWP during the financial crisis

5.3.1 Baseline results

Figure 1 shows the EWP's change over time. Each line represents a different specification of equation (1).[3] The estimates indicate that the EWP increased since the beginning of the 2000s, probably due to trade liberalization (Baumgarten 2013).[4] Between 2007 and 2008, the premium fell by around two percentage points in all specifications. This timing is closely in line with the decline in incoming orders shown in figure 2. Interestingly, the EWP did not further decline during the peak of the crisis, between 2008 and 2009. The pooled estimates in the next section shed light on statistical significance of the changes and, more importantly, the differential patterns of wage adjustment during the crisis.

point in time.

[2]See table H1 for summary statistics of the main variables.

[3]Tables H2-H5 in the appendix present the full tables for all covariates.

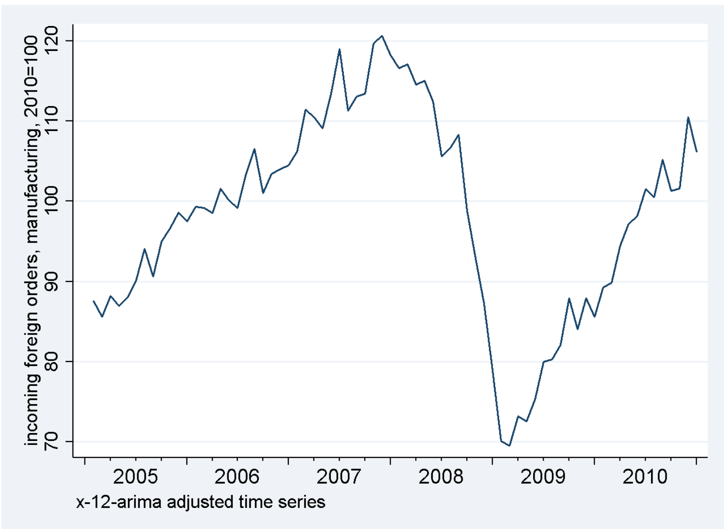
[4]When controlling for plant size, the rise of the EWP starts in 2005 and is insignificant before. However, the point estimates likely are downwards biased in this specification, since exporters grow larger and pay higher wages at the same time (Baumgarten 2013).

Figure 1: Baseline Results: Coefficients of the exporter dummy in various specifications

(a) (b)

Notes: See equation (1). "base" includes 20 skill group dummies (interactions of five age and four education dummies), foreign nationality, a quadratic term in tenure and a dummy for being a master craftsman or foreman, as well as industry and federal state dummies. "tech" additionally includes dummies for IT investment and technological state, "bargain" additionally controls for firm- or industry-level collective bargaining agreements, "size" additionally controls for a quadratic term of log firm employment, and "full" additionally includes dummies for the existence of a works council and for 1-plant firms. Data source: LIAB.

Figure 2: Incoming foreign orders



Notes: The figure shows an index of incoming foreign orders in the German manufacturing sector. Data source: German Statistical Office.

5.3.2 Mechanics of EWP changes

In order to analyze wage adjustments of exporters and non-exporters, we pool the data for two subsequent years and re-estimate the baseline and full specifications of equation 1 with a dummy indicating the latter year and an interaction with the exporter dummy.

Having included all the control variables from equation (1), the time dummy reflects the change in the average wage-setting in non-exporting firms, whereas the interaction term indicates by how much more or less exporting firms have changed their average wage-setting as compared to non-exporters.[5]

The coefficient on the interaction term indicates that the decrease of the EWP between 2007 and 2008 is statistically significant and the subsequent increase is not. The first two columns of table 1 show that between 2007 and 2008, wages in non-exporting firms rose by about 2.5 p.p. However, wages in exporting firms (time dummy plus interaction term) remained constant and this is in stark contrast to the wage increases since 2004, which are shown in table H6 in the appendix. This suggests that exporters did not further increase wages due to the decline in foreign orders and likely also in expectation of a long-lasting negative shock. The estimates in columns 3 and 4 suggest that between 2008 and 2009, wages declined in exporting and non-exporting firms. Apparently, non-exporters have been hit by the crisis one year later, possibly via input/output linkages. Between 2009 and 2010, a period of economic recovery, nominal wages increased in both firm types.[6]

Table 1: Mechanics of EWP changes

	Dependent variable: ln daily wage (imputed)					
	(t=2007)		(t=2008)		(t=2009)	
	(1)	(2)	(3)	(4)	(5)	(6)
Dummy, exporter	0.1618***	0.0247**	0.1456***	0.0099	0.1451***	0.0217**
	(0.014)	(0.010)	(0.014)	(0.010)	(0.016)	(0.011)
Dummy, t+1	0.0269***	0.0241***	-0.0172	-0.0167**	0.0269**	0.0215***
	(0.009)	(0.007)	(0.011)	(0.007)	(0.012)	(0.007)
Exporter in t+1	-0.0239**	-0.0203**	-0.0042	0.0079	-0.0032	0.0059
	(0.011)	(0.008)	(0.012)	(0.009)	(0.015)	(0.009)
Firm controls	-	yes	-	yes	-	yes
F (dummy+interaction)	0.20	0.67	16.21***	2.88*	8.80***	22.19***
N	1,003,074	997,413	970,022	963,954	842,753	835,206
Plants	4006	3993	4030	4017	3991	3978
Adj. R^2	0.509	0.581	0.499	0.570	0.493	0.564

Notes: Estimates are based on the baseline specification in columns 1, 3, 6, and the full specification in columns 2, 4, 6. "t" denotes the earlier one of the two years in the estimation. Standard errors in parentheses, clustered at plant level. Levels of significance: *** 1 %, ** 5 %, * 10 %.

[5] Note that we use nominal wages, since this is the relevant measure from the firm's perspective.

[6] One concern might be that these effects stem from firms exiting or entering the sample. In appendix table H7, we therefore restrict the sample to firms that are observed in two consecutive years, which does not qualitatively alter our results.

5.4 Impact on residual wage inequality

In order to disentangle the impact the fall of the EWP had on residual wage inequality, we apply the decomposition outlined in section 2. The results in table 2 suggest that overall residual wage inequality first decreased between 2007 and 2008 and then remained constant afterwards. Alternatively, summing up the total changes over all years yields a negligible change of inequality between 2007 and 2010. Both is in stark contrast to the strong increase during the decade before (Baumgarten 2013). Our decomposition shows that between 24% and 43% of the initial decline in wage inequality can be attributed to the simultaneous decline of the EWP between 2007 and 2008. After 2008, the changes of the EWP had a negligible and insignificant effect on wage inequality which is not surprising since the magnitude of the EWP-changes between 2008 and 2010 was low. The results in general suggest that the decrease of the EWP contributed to the fact that residual wage inequality did not further increase during the crisis.[7]

Table 2: Impact on Residual Wage Inequality

	Base	Tech	Bargain	Size	Full
Change in residual wage inequality, 2007-2008					
Total Change	-0.0074^{*}	-0.0074^{*}	-0.0074^{*}	-0.0074^{*}	-0.0074^{*}
	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0039)
EWP Effect	-0.0023	-0.0018	-0.0026^{*}	-0.0032^{***}	-0.0028^{**}
	(0.0015)	(0.0014)	(0.0013)	(0.0012)	(0.0012)
% of Total	31.1	24.3	35.1	43.2	37.8
Change in residual wage inequality, 2008-2009					
Total Change	0.0060	0.0060	0.0060	0.0060	0.0060
	(0.0042)	(0.0042)	(0.0042)	(0.0042)	(0.0042)
EWP Effect	0.0006	0.0010	0.0015	0.0019	0.0020
	(0.0015)	(0.0016)	(0.0015)	(0.0013)	(0.0013)
% of Total	10.0	16.7	25.0	31.7	33.3
Change in residual wage inequality, 2009-2010					
Total Change	0.0031	0.0031	0.0031	0.0031	0.0031
	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)
EWP Effect	-0.0005	-0.0008	-0.0000	-0.0002	0.0006
	(0.0019)	(0.0017)	(0.0017)	(0.0014)	(0.0013)
% of Total	-16.1	-25.8	-2.3	-6.5	19.4

Notes: "Total Change" denotes the change of overall residual wage inequality (measured by the standard deviation) between two periods. 'EWP Effect' denotes the change in residual wage inequality which can be attributed to the change of the EWP. Standard errors in parentheses, based on 200 bootstrap replications. Levels of significance: *** 1 %, ** 5 %, * 10 %.

[7] Table H8 in the appendix confirms the result for overall rather than residual wage inequality. However, the results are not as large and statistically significant.

5.5 Conclusion

Our analysis provides evidence that German firms have reacted to the crisis by adjusting wages. Exporting firms started to adjust wages one year earlier than non-exporters and this leads the EWP to fall in 2007. Our decomposition shows that the drop of the EWP worked towards a decrease in wage inequality. Consequently, after the EWP has proven to be an important driver of wage inequality in case of trade liberalization, we show that the same mechanism can work into the opposite direction in case of a major trade shock.

5.6 Appendix H

Table H1: Summary statistics

year	2007		2008		2009		2010	
exporter	no	yes	no	yes	no	yes	no	yes
ln daily wage	4.45	4.74	4.48	4.74	4.45	4.72	4.50	4.74
	(0.45)	(0.43)	(0.44)	(0.42)	(0.44)	(0.43)	(0.48)	(0.43)
Age	41.86	42.98	41.85	43.08	42.25	43.57	42.71	43.98
	(10.88)	(10.44)	(10.91)	(10.63)	(11.08)	(10.54)	(11.20)	(10.57)
Tenure	9.75	12.04	9.62	12.22	10.28	12.67	10.32	12.94
	(8.08)	(8.97)	(8.25)	(9.27)	(8.49)	(9.31)	(8.46)	(9.27)
Foreign	0.06	0.08	0.06	0.08	0.06	0.08	0.05	0.08
	(0.23)	(0.27)	(0.23)	(0.27)	(0.23)	(0.27)	(0.22)	(0.27)
Skill miss.	0.11	0.06	0.12	0.06	0.13	0.07	0.12	0.07
	(0.31)	(0.23)	(0.32)	(0.24)	(0.33)	(0.25)	(0.33)	(0.25)
Skill low	0.09	0.12	0.09	0.12	0.08	0.12	0.08	0.12
	(0.29)	(0.33)	(0.28)	(0.33)	(0.28)	(0.32)	(0.27)	(0.32)
Skill med.	0.75	0.70	0.75	0.70	0.74	0.69	0.73	0.70
	(0.44)	(0.46)	(0.43)	(0.46)	(0.44)	(0.46)	(0.45)	(0.46)
Skill high	0.05	0.12	0.05	0.12	0.05	0.12	0.07	0.12
	(0.23)	(0.33)	(0.21)	(0.33)	(0.21)	(0.33)	(0.25)	(0.33)
plant size	222.54	2446.96	269.37	2802.91	269.34	2538.91	403.71	2121.68
	(525.33)	(6030.41)	(615.27)	(7479.77)	(631.08)	(7605.47)	(910.13)	(5958.33)
N	64,795	439,256	64,842	474,944	56,493	409,203	48,666	361,621
Plants	1,780	1,627	1,706	1,606	1,635	1,748	1,608	1,678

Average values, standard errors in parentheses.

Table H2: Baseline Results: 2007

	Dependent variable: ln daily wage (imputed)				
	Base	Tech	Bargain	Size	Full
dummy, exporter	0.1601***	0.1350***	0.1422***	0.0281***	0.0238**
	(0.014)	(0.013)	(0.012)	(0.011)	(0.010)
dummy, foreign	-0.0268***	-0.0283***	-0.0330***	-0.0464***	-0.0479***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
tenure	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tenure squared	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
dummy, foreman	0.1779***	0.1792***	0.1798***	0.2064***	0.2066***
	(0.012)	(0.011)	(0.011)	(0.009)	(0.009)
dummy, technology state of the art		0.0614***			0.0490***
		(0.020)			(0.014)
dummy, investments in IT		0.0992***			0.0189*
		(0.013)			(0.010)
dummy, industry level coll. agreement			0.1545***		0.0526***
			(0.014)		(0.011)
dummy, firm level coll. agreement			0.1169***		0.0121
			(0.018)		(0.015)
ln plant size				0.1213***	0.0762***
				(0.013)	(0.014)
ln plant size squared				-0.0048***	-0.0029**
				(0.001)	(0.001)
dummy, not part of larger group					0.0497***
					(0.011)
dummy, works council					0.0796***
					(0.013)
N	483,639	482,024	483,413	483,639	481,832
Plants	3,385	3,376	3,379	3,385	3,371
Adj. R^2	0.513	0.524	0.533	0.570	0.582

Models include dummy variables for industries and federal states. Standard errors, clustered at the firm-level, in parentheses. Regressions employ sample weights. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Table H3: Baseline Results: 2008

	Dependent variable: ln daily wage (imputed)				
	Base	Tech	Bargain	Size	Full
dummy, exporter	0.1419***	0.1246***	0.1225***	0.0031	0.0057
	(0.014)	(0.013)	(0.012)	(0.011)	(0.010)
dummy, foreign	-0.0347***	-0.0345***	-0.0398***	-0.0538***	-0.0529***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)
tenure	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tenure squared	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
dummy, foreman	0.1804***	0.1843***	0.1883***	0.2061***	0.2080***
	(0.011)	(0.010)	(0.010)	(0.009)	(0.009)
dummy, technology state of the art		0.0646***			0.0422***
		(0.017)			(0.013)
dummy, investments in IT		0.0855***			0.0231**
		(0.011)			(0.011)
dummy, industry level coll. agreement			0.1648***		0.0631***
			(0.013)		(0.010)
dummy, firm level coll. agreement			0.1489***		0.0457***
			(0.020)		(0.015)
ln plant size				0.1311***	0.0851***
				(0.012)	(0.013)
ln plant size squared				-0.0055***	-0.0036***
				(0.001)	(0.001)
dummy, not part of larger group					0.0517***
					(0.011)
dummy, works council					0.0678***
					(0.013)
N	519,435	516,162	518,819	519,435	515,581
Plants	3,283	3,272	3,275	3,283	3,265
Adj. R^2	0.507	0.518	0.532	0.568	0.581

Models include dummy variables for industries and federal states. Standard errors, clustered at the firm-level, in parentheses. Regressions employ sample weights. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Table H4: Baseline Results: 2009

	Dependent variable: ln daily wage (imputed)				
	Base	Tech	Bargain	Size	Full
dummy, exporter	0.1458***	0.1332***	0.1335***	0.0187*	0.0232**
	(0.016)	(0.015)	(0.014)	(0.011)	(0.011)
dummy, foreign	-0.0541***	-0.0545***	-0.0585***	-0.0747***	-0.0773***
	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)
tenure	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tenure squared	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
dummy, foreman	0.1875***	0.1871***	0.1932***	0.2184***	0.2181***
	(0.012)	(0.012)	(0.012)	(0.009)	(0.009)
dummy, technology state of the art		0.0603***			0.0317**
		(0.018)			(0.012)
dummy, investments in IT		0.0698***			0.0149
		(0.012)			(0.010)
dummy, industry level coll. agreement			0.1449***		0.0470***
			(0.013)		(0.011)
dummy, firm level coll. agreement			0.1394***		0.0279
			(0.023)		(0.018)
ln plant size				0.1038***	0.0549***
				(0.012)	(0.013)
ln plant size squared				-0.0032***	-0.0007
				(0.001)	(0.001)
dummy, not part of larger group					0.0556***
					(0.011)
dummy, works council					0.0698***
					(0.014)
N	450,587	448,381	450,546	450,587	448,373
Plants	3,362	3,349	3,359	3,362	3,347
Adj. R^2	0.492	0.501	0.512	0.550	0.561

Models include dummy variables for industries and federal states. Standard errors, clustered at the firm-level, in parentheses. Regressions employ sample weights. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Table H5: Baseline Results: 2010

	Dependent variable: ln daily wage (imputed)				
	Base	Tech	Bargain	Size	Full
dummy, exporter	0.1410***	0.1270***	0.1298***	0.0172	0.0261**
	(0.017)	(0.016)	(0.016)	(0.013)	(0.012)
dummy, foreign	-0.0436***	-0.0423***	-0.0480***	-0.0607***	-0.0630***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
tenure	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tenure squared	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
dummy, foreman	0.1906***	0.1906***	0.1987***	0.2066***	0.2105***
	(0.013)	(0.013)	(0.012)	(0.010)	(0.010)
dummy, technology state of the art		0.0426**			0.0315***
		(0.019)			(0.012)
dummy, investments in IT		0.0710***			0.0113
		(0.012)			(0.009)
dummy, industry level coll. agreement			0.1687***		0.0525***
			(0.013)		(0.011)
dummy, firm level coll. agreement			0.1459***		0.0230
			(0.019)		(0.017)
ln plant size				0.1381***	0.0866***
				(0.013)	(0.013)
ln plant size squared				-0.0062***	-0.0040***
				(0.001)	(0.001)
dummy, not part of larger group					0.0714***
					(0.010)
dummy, works council					0.0835***
					(0.015)
N	392,166	389,117	389,848	392,166	386,833
Plants	3,258	3,249	3,201	3,258	3,193
Adj. R^2	0.495	0.502	0.519	0.555	0.568

Models include dummy variables for industries and federal states. Standard errors, clustered at the firm-level, in parentheses. Regressions employ sample weights. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Table H6: Mechanics of EWP changes

	Dependent variable: ln daily wage (imputed)					
	(t=2004)		(t=2005)		(t=2006)	
	(1)	(2)	(3)	(4)	(5)	(6)
Dummy, exporter	0.1268***	0.0069	0.1404***	0.0223**	0.1519***	0.0229**
	(0.012)	(0.010)	(0.012)	(0.010)	(0.012)	(0.010)
Dummy, t+1	0.0036	-0.0007	0.0065	0.0126*	0.0228**	0.0180**
	(0.009)	(0.007)	(0.009)	(0.007)	(0.010)	(0.007)
Exporter in t+1	0.0138	0.0177**	0.0193*	0.0139	0.0150	0.0107
	(0.011)	(0.008)	(0.012)	(0.009)	(0.012)	(0.009)
Firm controls	-	yes	-	yes	-	yes
F (dummy+interaction)	9.17***	14.41***	16.19***	24.56***	29.51***	42.40***
N	1,086,973	1,082,841	1,021,948	1,017,483	971,297	967,459
Plants	4,199	4,187	4,037	4,027	4,030	4,021
Adj. R^2	0.484	0.551	0.487	0.554	0.504	0.572

Notes: Estimates are based on the baseline specification in clumns 1, 3, 6, and the full specification in columns 2, 4, 6. "t" denotes the earlier one of the two years in the estimation. Standard errors in parentheses, clustered at plant level. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Table H7: Mechanics of EWP changes - Balanced Firm Panel

	Dependent variable: ln daily wage (imputed)					
	(t=2007)		(t=2008)		(t=2009)	
	(1)	(2)	(3)	(4)	(5)	(6)
Dummy, exporter	0.1616***	0.0316***	0.1431***	0.0071	0.1411***	0.0242*
	(0.015)	(0.011)	(0.016)	(0.011)	(0.017)	(0.012)
Dummy, t+1	0.0204***	0.0220***	-0.0198**	-0.0149**	0.0331**	0.0231***
	(0.007)	(0.006)	(0.009)	(0.007)	(0.013)	(0.007)
Exporter in t+1	-0.0175*	-0.0191**	0.0083	0.0110	-0.0001	0.0115
	(0.010)	(0.008)	(0.011)	(0.009)	(0.014)	(0.008)
Firm controls	-	yes	-	yes	-	yes
F (dummy+interaction)	0.27	0.47	6.37***	0.65	45.94***	66.87***
N	793,375	788,195	773,919	770,422	619,861	613,073
Plants	2,670	2,667	2,623	2,620	2,634	2,632
Adj. R^2	0.519	0.585	0.506	0.576	0.496	0.565

Notes: Notes: Estimates are based on the baseline specification in columns 1, 3, 6, and the full specification in columns 2, 4, 6. Firms that are not observed in both years of a regression are dropped. "t" denotes the earlier one of the two years in the estimation. Standard errors in parentheses, clustered at plant level. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Table H8: Impact on Wage Inequality

	Base	Tech	Bargain	Size	Full
Change in wage inequality, 2007-2008					
Total Change	-0.0124^{**}	-0.0122^{*}	-0.0122^{*}	-0.0124^{**}	-0.0132^{**}
	(0.0063)	(0.0064)	(0.0064)	(0.0063)	(0.0065)
EWP Effect	-0.0024	-0.0019	-0.0015	-0.0029^{**}	-0.0027^{**}
	(0.0016)	(0.0016)	(0.0014)	(0.0013)	(0.0013)
% of Total	19.4	15.6	12.3	23.4	20.6
Change in wage inequality, 2008-2009					
Total Change	0.0089^{*}	0.0089^{*}	0.0089^{*}	0.0089^{*}	0.0089^{*}
	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)
EWP Effect	0.0007	0.0011	0.0016	0.0021	0.0021
	(0.0017)	(0.0018)	(0.0017)	(0.0015)	(0.0014)
% of Total	7.9	12.4	18.0	23.6	23.6
Change in wage inequality, 2009-2010					
Total Change	0.0040	0.0040	0.0040	0.0040	0.0040
	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)
EWP Effect	-0.0006	-0.0010	-0.0001	-0.0002	0.0006
	(0.0021)	(0.0020)	(0.0019)	(0.0015)	(0.0015)
% of Total	15.0	25.0	2.5	5.0	15.0

Notes: "Total Change" denotes the change of overall wage inequality (measured by the standard deviation) between two periods. 'EWP Effect' denotes the change in wage inequality which can be attributed to the change of the EWP. Standard errors in parentheses, based on 200 bootstrap replications. Levels of significance: *** 1 %, ** 5 %, * 10 %.

5.7 Acknowledgments and remarks

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6 Concluding Remarks

This thesis consists of four essays which contribute to the understanding of the labor market effects of international trade, with a focus on the nexus between trade, structural change, and inequality. The essays tackle the question about the labor market effects of international trade from different perspectives. The first essay puts a focus on the household level. It asks to what extent the heterogeneous labor market effects of trade integration materialize in the form of differences in labor income between households. Workers and firms are at the center of the second and the fourth essay. In particular, these essays aim to shed light on the adjustment of workers and firms to changes in the trade environment and the consequences for wage inequality between workers. The third essay, in contrast, provides a region-level perspective. The goal of this essay is to illustrate that the inequality effects of trade integration differ between regions within a country. A unifying theme of all essays is that the labor market effects of international trade are vastly heterogeneous.

What should be kept in mind when reflecting on the essays and their results is that they do not question the idea that the opportunity to engage in international trade of goods and services is beneficial to countries. Instead, the essays emphasize that not everybody within a country benefits to the same extent from the opportunity to engage in international trade. To a large extent, the heterogeneity of the effects materialize on the labor market. To design and implement policies which ensure that the gains from trade are shared by the broad population, it is vital to get a detailed picture about the factors which govern the way in which an individual or household is affected by a change in the trade environment. By emphasizing in detail the role of skills, firms, households, industries, and regions, this thesis aims to take one step forward into this direction.

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Deutschsprachige Zusammenfassung

Diese Dissertationsschrift befasst sich mit den Auswirkungen von internationalem Handel auf den Arbeitsmarkt. Ein besonderer Fokus wird hierbei auf die Effekte auf Lohn- und Einkommensungleichheit gelegt. Gesunkene Zölle und Transportkosten haben in den letzten Jahrzehnten zu einem starken Anstieg des internationalen Handels von Gütern und Dienstleistungen geführt. Der gestiegene Handel ist inbesondere durch den Aufstieg Chinas zum größten Exporteur von Gütern aus dem verarbeitenden Gewerbe gekennzeichnet. Aus Sicht von Deutschland hat in den letzten Jahrzehnten neben dem Handel mit China auch der Handel mit diversen osteuropäischen Ländern an Bedeutung gewonnen. Zeitgleich haben sich in den letzten Jahrzehnten in vielen Industrieländern die Gegebenheiten auf dem Arbeitsmarkt verändert. Zahlreiche Länder, darunter auch Deutschland, verzeichneten einen Anstieg der Lohn- und Einkommensungleichheit. Darüber hinaus vollzog sich auf dem Arbeitsmarkt ein Strukturwandel in der Form einer Verlagerung der Beschäftigung vom verarbeitenden Gewerbe in den Dienstleistungssektor. Im Zentrum dieser Dissertationsschrift steht deshalb die Wechselwirkung zwischen gestiegenem internationalem Handel, insbesondere mit China und Osteuropa, Strukturwandel und Lohn- bzw. Einkommensungleichheit. Die Dissertationsschrift gliedert sich in vier Aufsätze, die jeweils einen unabhängigen Forschungsbeitrag zu diesem Thema liefern.

Der erste Aufsatz, mit dem Titel “All you need is love? Trade shocks, inequality, and risk sharing between partners”, beschäftigt sich mit den Effekten von internationalem Handel mit China und Osteuropa auf Ungleichheit von Arbeitseinkommen zwischen Personen und zwischen Haushalten in Deutschland. Die zentrale neue Erkenntnis dieses Aufsatzes ist, dass ein Teil der Ungleichheitseffekte von internationalem Handel, welche auf Personenebene auftreten, auf Haushaltsebene abgefangen werden können. Dies liegt an einem Versicherungseffekt, welcher sich daraus ergibt, dass Partner innerhalb von Haushalten oftmals in verschiedenen Branchen tätig sind und ein unterschiedliches Bildungsniveau haben und deswegen unterschiedlich von internationalem Handel betroffen sind. Dieser Aufsatz ist zusammen mit Katrin Huber von der Universität Passau entstanden und ist in der Zeitschrift *European Economic Review* publiziert.

Der zweite Aufsatz trägt den Titel “Diverging paths: Labor reallocation, sorting, and wage inequality”. Dieser Aufsatz zeigt, dass handelsinduzierter Strukturwandel in der Form einer Verlagerung von Beschäftigten aus dem verarbeitenden Gewerbe in den Dienstleistungssektor in Deutschland zu einem Anstieg von Lohnungleichheit führt. Dies liegt daran, dass hochqualifizierte Arbeitnehmer, welche in den Dienstleistungssektor wechseln, häufiger in Firmen wechseln, welche hohe Löhne bezahlen, während Geringqualifizierte häufiger in Firmen wechseln, welche niedrige Löhne bezahlen. Strukturwandel erklärt somit auch einen beträchtlichen Teil des gestiegenen *Sortings* zwischen Arbeitnehmern und Firmen, welches in Deutschland in den letzten Jahrzehnten zu beobachten ist.

Der dritte Aufsatz mit dem Titel “International trade and its heterogeneous effect on the college wage premium across regions” zeigt mit Hilfe eines Modells und einer quantitativen Schätzung für die USA, dass die Auswirkungen von internationalem Handel mit China auf die Lohnprämie für einen College-Abschluss (“college wage premium”) regional unterschiedlich sind. In manchen Regionen steigt die Lohnprämie, in anderen Regionen sinkt die Lohnprämie in Folge des gestiegenen Handels.

Der vierte Aufsatz mit dem Titel “Exporters and wage inequality during the Great Recession - Evidence from Germany” beschäftigt sich mit den Auswirkungen der Lohnprämie, welche exportierende Firmen bazahlen (“exporter wage premium”) auf die Lohnungleichheit während der globalen Finanz- und Wirtschaftskrise von 2007 bis 2009. Die zentrale Erkenntnis des Aufsatzes ist, dass der Rückgang der Export-Lohnprämie einen beträchtlichen Teil der gesunkenen Lohnunungleichheit während der Finanz- und Wirtschaftskrise erklärt. Dieser Aufsatz ist zusammen mit Hans-Jörg Schmerer (FernUniversität Hagen) und Wolgang Dauth (Universität Würzburg) entstanden und ist in der Zeitschrift *Economics Letters* publiziert.

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