# Four Essays in Empirical Trade and Labor Economics

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*to my parents*

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# Introduction

The access to high quality individual data has drastically increased in the last 20 years. The possibility to observe individuals across time, space and employer has a high value for researchers, both for describing the status quo and producing stylized facts about the economy as well as designing research studies and identifying causal effects. It can help understand major political events and subsequently to give informed policy advice. The abundant information has to be structured and reduced to be usable.

In my work I focus on two things. Firstly, I make use of a large individual panel data set and retrieve additional information on the workers by observing their behavior and realized labor market variables, such as wages, occupations and unemployment information. In particular, I use the network structure of the data to estimate latent characteristics of workers and firms. The use of large and almost full samples of the workforce allows to observe a tight network between them.

Secondly, I develop empirical hypotheses and connect them to economic theory. In particular I am interested in empirical studies on the relation of trade, technological change and wage inequality in Germany as well as the reasons for internal migration in Germany. For this purpose I connect the information on workers and firms to other sources of data. In particular, information on global trade flows and automation of production, which are main drivers of wage inequality.

In our study in the first chapter we use a large sample of German workers to analyze the effect of low-wage competition with China and Eastern Europe (the East) on the wage structure within German manufacturing industries. Utilizing the method by Abowd, Kramarz, and Margolis (1999) (hereafter AKM), we decompose wages into firm and worker components. We find that the rise of market access and competitiveness of the East has a substantial impact on the dispersion of the worker wage component and in part on positive assortative matching. Trade fails to explain changes in the firm wage premium. The rising dispersion in worker-specific wages can be attributed to increasing skill premia and to changes in the extensive margin of the workforce, leading to a wage polarization for the remaining within-industry workers. We also account for technological change by considering how many routine-intensive jobs are substituted within an industry. The more routine jobs are cut, the higher is the effect on wage inequality, especially on the dispersion of worker-specific wages. Overall, trade explains up to 19% of the recent increase in wage inequality and slightly exceeds the technology effect that accounts for approximately 17%. In chapter 2 we present supporting empirical evidence and a new theoretical explanation for the negative selection into planned return migration between similar regions in Germany. In our model costly temporary and permanent migration are used as imperfect signals to indicate workers' high but otherwise unobservable skills. Production thereby takes place in teams with individual skills as strategic complements. Wages therefore are determined by team performance and not by individual skill, which is why migration inflicts a wage loss on all workers, who expect the quality of their co-workers to decline. In order to internalise this negative migration externality, which leads to sub-optimally high levels of temporary and permanent migration in a *laissez-faire* equilibrium, we propose a mix of two policy instruments, which reduce initial outmigration while at the same time inducing later return migration. While we show a theoretical explanation for internal migration in chapter 2, in chapter 3 we use a large German administrative dataset and assess sorting patterns of workers between high-density regions in Germany. With detailed wage information we predict the selection of workers into well defined mobility patterns such as permanent, return and move-on migration. We assess latent heterogeneity in the wage data by estimating premia to unobservable skill for workers and firm pay premia (Card, Heining, and Kline, 2013, hereafter CHK). We show that being matched to a low-paying firm strongly increases the probability to return migrate. In terms of unobservable skill we find that initially migrants are positively selected. Given migration occurred, return migrants are negatively and move-on migrants are highly positive selected. Move-on migrants benefit from additional moves both in terms of skill and firm premium.

Finally, in the fourth paper we again turn to a large random sample of the German workforce to assess sorting patterns in a matched employer-employee framework. We compare different econometric models to estimate bipartite latent heterogeneity of workers and firms using recent methods proposed by Card, Heining, and Kline (2013) and Bonhomme, Lamadon, and Manresa (2017) (hereafter BLM). With the latter generalizing the baseline model for a broader scope for complementarities and addressing prominent shortcomings due to limited mobility bias. We discuss the model results and compare the assumptions given the results that we find. We decompose the log wages across time with the two methods and compare the trends in wage inequality, in particular concerning the increase in Germany between 1995 and 2005. We are able to replicate BLM's baseline results and find a stark underestimation of sorting of the additive CHK model, likely caused by limited mobility bias. No improvement of fit can be found by allowing for firm-type specific (conditional random) worker effects, i.e. differing complementarities in production.

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# Chapter 1

# Trade, Technology and Channels of Wage Inequality in Germany

*Co-authored with Linda Borrs*

## 1.1 Introduction

Over the last 30 years wage inequality has grown significantly in many industrialized economies, among them Germany and the US (e.g., Dustmann, Ludsteck, and Schönberg, 2009; Autor, Dorn, Hanson, and Song, 2014).

Extensive research has shown that this rise in wage inequality can be attributed to a large extend to skill-biased technological change (SBTC), and automation or computerization as well as to globalization, in particular offshoring and low-wage competition (e.g. Katz, David, et al., 1999; Autor, Dorn, and Hanson, 2013; Krugman, 2008).[1][2] Another strand of the literature has attempted to examine the relative importance of worker- and firm-specific factors that determine individual wages (e.g., Abowd, Kramarz, and Margolis, 1999). These studies show that growing heterogeneity of workers and increasing differences in firm-specific pay premia as well as more assortative matching of high(low)-wage workers to high(low)-wage firms[3] explain large parts of rising wage inequality (e.g, Card, Heining, and Kline, 2013, for Germany).

We are the first to combine the prominent literature assessing the effects of trade and technology on the wage structure pioneered by Autor, Dorn, and Hanson (2013) and the methods on wage formation pioneered by Abowd, Kramarz, and Margolis (1999), finding that the skill premium, or worker component, is the most important channel of wage inequality and is equally affected by trade and technology. The assortative matching component is also affected by international trade. We do not find a strong role for the proportional firm pay premium in explaining the trends in inequality in wages in Germany.

Initially, decompose wages into their worker and firm component. Then we regress changes in trade exposure on changes in the distribution of the wage components separately. We measure trade exposure as the rise in Chinese and Eastern European market access and competitiveness. Figure 1 depicts Germany's parallel rise in wage dispersion and in import and export volumes of Germany with China and Eastern

[1] Other important factors behind the increase in wage inequality are changes in labor market institutions (e.g., Dustmann, Ludsteck, and Schönberg, 2009), immigration, especially, of less-educated workers (Antonczyk, Fitzenberger, and Sommerfeld, 2010)

[2] For a broad overview of wage inequality in Germany see Antonczyk, DeLeire, and Fitzenberger (2018).

[3] In fact, the data at hand is at the establishment level, we use the terms firm, establishment and plant interchangeably in this paper.

Europe[4] (the East). Over the course of these years China joined the World Trade Organization (WTO) in 2001 and the Eastern Enlargement of the European Union (EU) took place in 2004. In this paper we use these trade shocks to analyze the impact of increased import competition from the East on the distributional changes in wage components within manufacturing industries in Germany. We control for concurrent developments in the automation of tasks and technological change by considering changes in the number of an industry's routine jobs. This approach enables us to make a causal statement how changes in trade and technology exposure of industries affect wage inequality.

First, trade might impact the distribution of the worker wage component, which reflects the wage share a worker receives independent of the employer—where the skill premium is the mayor part of the worker wage component. According to long standing ideas in trade theory, a rise in international trade leads to an increase in the relative demand for skilled labor and thus an increase in the skill premium in developed economies, which are skill abundant. If trade affects raw wage inequality through this channel, we expect to see an effect of trade on the increase the inequality of the worker fixed effect of wages.

Second, we assume that trade may have an impact on the inequality in the firm pay premium. According to trade theories with heterogenous firms (e.g., Melitz, 2003), only the most productive firms engage in international trade. These firms benefit from the openness of the East as they export to these markets. If exporters share their additional foreign profits with their employees, their firm wage premium will be higher (see theories that combine heterogenous firms with labor market frictions, e.g., Egger and Kreickemeier, 2009; Amiti and Davis, 2011). If this is a relevant channel how trade impacts wage inequality, our analysis will show an increase in the inequality of the firm pay premium as some firms become exports and others do not. In addition, the rise of trade with the East is largely based on a strong increase in the Eastern firms competitiveness. Western firms that cannot resist the import competition are crowded out. As a consequence, the inequality in the firm fixed effect decreases because the least productive firms exit the market. On the contrary, it is also possible that these firms do not disappear completely, but have to reduce their firm pay premium to withstand competition. In this case, inequality

[4] The Eastern European countries in our analysis include Bulgaria, the Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, the Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan.

in the firm wage premium increases. Altogether, the impact of trade on the firm pay premium is theoretically unclear and can go in both directions.

Skill-biased technological change affects the relative demand for skills in the economy. Especially, automation technologies are developed to substitute routine tasks of workers. These tasks are mainly performed by low- and medium-skilled labor. High-skilled workers, on the contrary, complement these technologies as they develop and operate the new machines. Hence, we presume to find an effect of technological progress, measured as a decrease in an industrys routine jobs, on the deviation of the worker wage component.

To identify the causal effect of rising trade exposure on wage inequality, we have to account for potential endogeneity in trade because unobserved product demand shocks may simultaneously affect imports and wages. Therefore, we use gravity residuals that measure the relative change in competitiveness of the East compared with German industries through changes in productivity and transport costs.[5].

We find strong evidence that rising competitiveness of the East (i) led to an increase in the dispersion of the skill premium, measured by the deviation of individual fixed effects, and (ii) we find no effect on the dispersion of the firm wage component. Furthermore, we find some evidence that import pressure leads to increased assortative matching between better firms and better workers. Looking at the within skill-group distribution, we show that trade affects the wage dispersion of medium-skilled workers—again, only through the individual wage component. Our sample period is marked by an absolute decline of the manufacturing workforce. The largest share of jobs is lost in the low-skilled category, but there are substantial relative gains of high-skilled jobs. Within these two skill groups we see large increases in wage dispersion, which are not connected to trade.

Generally, our findings favor models of heterogeneous workers with assortative matching (e.g., Yeaple, 2005; Helpman, Itskhoki, and Redding, 2010; Sampson, 2014; Grossman, Helpman, and Kircher, 2017) and models that are able to explain the positive skill premium, by higher returns to scale in larger markets (e.g., Epifani and

[5]Gravity residuals were previously used by Autor, Dorn, and Hanson (2013) and Dauth, Findeisen, and Südekum (2014). The concept draws on the general equilibrium theory, e.g., byAnderson and Van Wincoop (2003) We measure technology exposure as the decrease in the share of routine jobs in an industry (see also, Autor, Dorn, and Hanson, 2015)

Gancia, 2008; Monte, 2011)[6] over models emphasizing the role of firm-wage premia in determining wage inequality (e.g., Egger and Kreickemeier, 2009).

For our empirical analysis, we use a 50% sample of administrative data for all full-time working men in West Germany between 1985 and 2010 and add trade volumes of the United Nations Commodity Trade Statistics Database (Comtrade). By linking the two data sets, we are able to measure the worker and firm contribution to wage inequality within industries, which are heterogeneously exposed to trade.

Our paper contributes to the literature on distributional effects of trade and technological change. ADH find that increased import exposure from China leads to lower manufacturing employment in the United States. They do not find a wage effect in the manufacturing sector. For Germany, DFS show that an increase in export exposure of a region is followed by a small increase in the regional wage level. However, they do not find any impact of the regional import exposure on wages. In contrast to ADH and DFS, we focus on the industry but not regional effects of trade. Ebenstein, Harrison, McMillan, and Phillips (2014) do not find any effect of increased import exposure on the industry level for the US. However, they find that workers in exposed occupations are pushed out of the manufacturing sector to find themselves in lower-paying sectors and occupations.

Apart from trade, computerization impacts labor demand. Autor et al. (2003) describe that new technologies are often substitutes for routine job-tasks. Because a lot of those routine jobs are performed by medium-qualified workers, the task-based approach (see, e.g, Acemoglu and Autor (2011) for the US and Spitz-Oener (2006) for Germany) is able to explain an increase in wage inequality as a consequence of wage polarization due to technological progress. Changes in wage inequality are also attributable to institutional changes and labor market reforms (see, e.g., Dustmann, Ludsteck, and Schönberg (2009). Felbermayr, Hauptmann, and Schmerer (2014) find an interdependence between unionization and the exporter wage premium for Germany. Therefore, we also consider different effects of trade with regard to changes in the union coverage rate of industries.

Similar to our approach, previous papers have used results of the AKM decomposition to analyze the impact of international trade on wages. For example, Frias, Kaplan, and Verhoogen (2009) and Macis and Schivardi (2016) find evidence for a

[6] Theories that assume a monotonic effect on skill cannot explain more complex changes of the wage distribution, e.g., a polarization of wages, mainly driven by a decrease in medium-skilled occupations (see, e.g., Autor, Katz, and Kearney, 2008; Acemoglu, 2003; Acemoglu and Autor, 2011) or the increase of wage inequality on both ends of the wage distribution.

positive exporter wage premium by examining the relationship between export status of a firm and the firm fixed effect. The study by Baziki, Ginja, and Borota Milicevic (2016) is closely related to our approach. They provide evidence that increased assortative matching occurs in industries with a high Chinese trade exposure and that use information and communication technologies intensively. We extend their focus on the worker-to-firm sorting process by looking at the effects of international trade and technological change on all decomposed wage components separately.
The paper is structured as follows. In section 1.2, we present the data sets used for our empirical analysis and describe the wage decomposition. In the same section we provide some descriptive results and stylized facts about the inequality of wage components. In section 1.3 we introduce our estimation strategy and explain the construction of the independent variables. The estimation results on the impact of trade on wage components are presented in section 1.4. Section 1.5 concludes.

## 1.2 Data and Variable Calculation

### 1.2.1 Data Sources

Our main data source are the Employee History data (BeH V.09.05.00) of the Institute for Employment Research (IAB) from which we draw wages and all relevant worker-level information. The BeH are comprehensive administrative data that contain all employees subject to social security in Germany. We use a 50% random sample of the BeH between 1985 and 2010 of all full-time working men aged 20 to 60 in West Germany.[7] All estimations are based on person-year observations that include the highest paid job of a worker in every year. As the data originally is used to calculate social security contributions, it is highly reliable and complete. We correct missing and inconsistent education data by using the routine described in Fitzenberger, Osikominu, and Völter (2005). Apart from that, wages above the threshold level for social security notifications are not recorded and need to be imputed. The imputation procedure follows the method by Card, Heining, and Kline (2013). For information on the firm level, e.g., firm size, we use the aggregated data

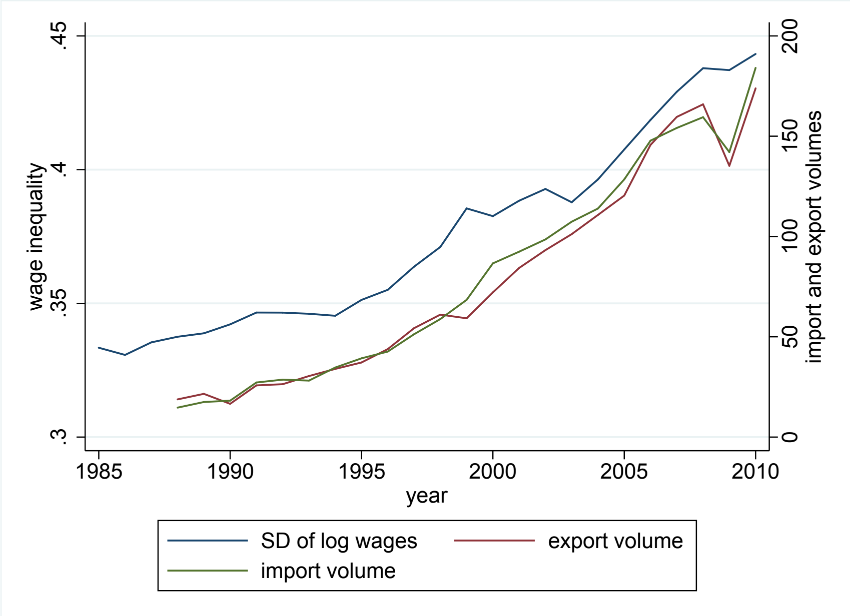
[7]We restrict our analysis to full-time jobs and exclude trainees. The reason is that non-standard work, like part-time jobs, are different sources of wage inequality that we do not want to measure. Thus, we avoid that changes in the use of non-standard work drive our results. Moreover, the data set does not provide exact information on working hours to make full- and part-time daily wages comparable.

of the Establishment History Panel (BHP).
To calculate an industry's exposure to trade, we use the UN Comtrade database from 1985 to 2010. Following DFS, we look at Germany, China, various Eastern European countries and their bilateral trading partners. We restrict our analysis to manufacturing industries. We match the data along four-digit product codes to the German Classification of Economic Activities 1993 by using correspondence tables of the UN Statistics Division and correct for inflation.
From the BIBB-IAB Employment Surveys 1979 to 1999 and the BIBB/BAuA Employment Survey 2006 (for more informations on the surveys see Hall, 2006), we draw information on tasks that we need to construct our measure of technological change (see section 1.3.2). Additionally, we use the IAB Establishment Panel for industry information on collective wage agreements.

### 1.2.2 Stylized Facts about Wage Inequality and Rising Trade Exposure

In the public perception, there is a strong connection between globalization and rising income inequality. Indeed, Germany has experienced a strong increase in wage dispersion, especially from the 2000s onwards. Over the same period several trade liberalizations took place that led world trade volumes increase quickly: The fall of the Iron Curtain in 1990, China joining the World Trade Organization (WTO) in 2001 and the Eastern Enlargement of the European Union (EU) in 2004.
Figure 1.1 depicts the parallel rise in wage dispersion in Germany and in import and export values of Germany the East. In this paper we use these trade shocks to analyze the impact of increased import competition from the East on the distributional changes in wage components within manufacturing industries in Germany.
In our empirical model, described in detail in section 1.3, we analyze whether industry-specific shocks in trade and technology can explain the increase in wage dispersion within sectors. Sectors are differently exposed to import competition and export opportunities of the East and we expect to see different effects on wage inequality within industries. The question arises how much of the overall wage variation in Germany is actually explained by the dispersion within and across sectors. Figure 1.2 shows that although the between share is on the rise, the within-industry part explains by far the largest share, namely between 81% and 88% of wage inequality in Germany. These figures are in line with other papers' findings, like

Figure 1.1: Wage Inequality and Trade Volumes in Germany, 1985–2010



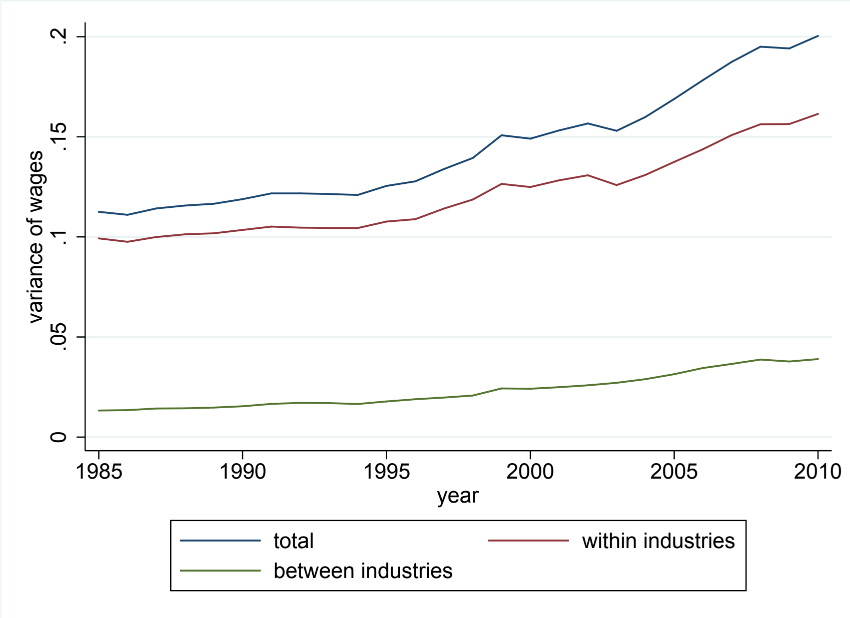

Notes: The left axis depicts the standard deviation of log wages of full-time working men between 20 to 60 in West Germany between 1985 and 2010. The right axis depicts import and export volumes in billion Euros between Germany and China as well as Germany and Eastern Europe between 1988 and 2010.
Source: Own calculations, BeH and Comtrade.

Helpman (2014) and Baumgarten (2013). Consequently, it is likely that the major part of wage dispersion can be explained by changes in inequality within three-digit industries.

Figure 1.3 shows that wage inequality develops differently between industries.[8] The graphs present shifts of the wage distribution for selected industries between the first interval, 1990 to 1995, and the last one, 2005 to 2010, i.e. a while before and after China entered the WTO in 2001 and the 2004 eastern enlargement of the EU. Panel A depicts the German textile sector, a typical import sector. The wage distribution widens over time. At the end of our observational period, there are more workers at the lower and the upper end of the distribution, whereas relatively few people are in the middle. Interestingly, the median wage does not change—the median employer earns approximately the same in the first and last interval. Wage inequality also increases within the publishing, printing and reproduction

[8]For more information on all manufacturing sectors in our sample see also table 1.1 in section 1.3.

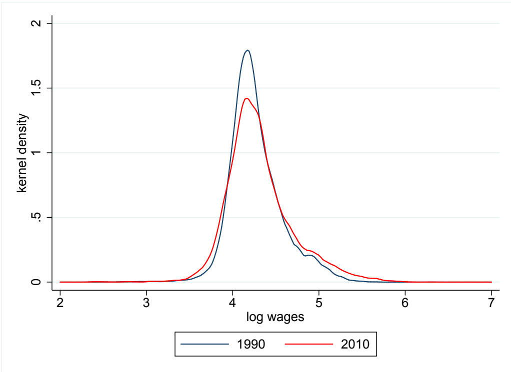
Figure 1.2: Within- and Between-Industry Variance of Log Wages, 1985–2010



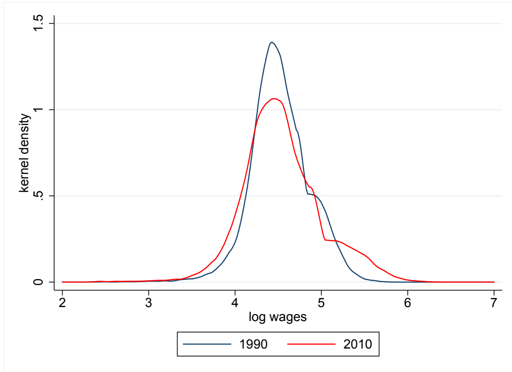

Notes: The graph depicts the variance of log wages (total) and the variance within and between three-digit manufacturing industries. The sample includes full-time working men between 20 and 60 in the manufacturing sector in West Germany between 1985 and 2010.
Source: Own calculations, BeH.

of recorded media sector(see panel B), which is among the sectors with the highest increase in both wage inequality and import exposure (see also table 1.1). Moreover, we find increasing wage inequality in export-intensive industries in Germany—the machinery industry, panel C, and the automobile sector, panel D. Compared with panels A and B, the distributions of the export-intensive industries shift more to the right, indicating that most of the employees in these sectors experience a wage gain. The automobile industry has the most equal distribution of wages and is also closest to a pattern of first-order stochastic dominance among the four sectors presented here. In general, figure 1.3 shows an increase in wage inequality with considerably less mass in the middle of the distribution in the later period for all industries.

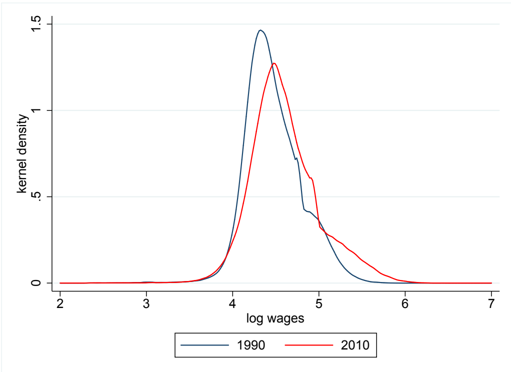
Figure 1.3: Distributions of Log Wages in selected Industries, 1990–1995 and 2005–2010



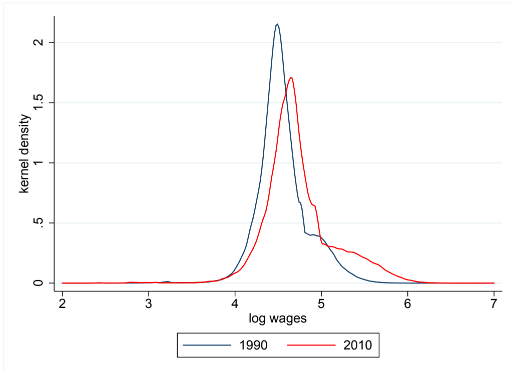

PANEL A: Textiles




PANEL B: Publishing




PANEL C: Machinery




PANEL D: Automobile

Notes: The graphs depict distributions of log wages within four major two-digit industries in Germany in interval 2 (1990-1995) and interval 5 (2005-2010). The sample includes full-time working men between 20 and 60 in the manufacturing sector in West Germany between 1985 and 2010.
Source: Own calculations, BeH.

### 1.2.3 Estimating the Wage Components

The aim of this paper is to explore how trade and technology influence wages in Germany through changes in either the firm or worker wage component. In a first step we therefore have to decompose wages. We do this by applying the decomposition method introduced by AKM. Their aim was to determine how much of the wage is worker- and how much of it is firm-specific. According to AKM, the individual log wage, $y_{it}$, can be fully described as an additive separable system of worker and firm fixed effects:

$$y_{it} = \alpha_i + \psi_{\mathbf{J}_{(it)}} + x'_{it}\beta + r_{it} \quad with \quad r_{it} = \eta_{i\mathbf{J}(it)} + \zeta_{it} + \varepsilon_{it}. \tag{1.1}$$

Here, the worker fixed effect $\alpha_i$ can be interpreted as the worker-specific wage component. It comprises all characteristics of a worker that are equally valuable across firms, i.e. independent of the job a worker holds. The worker fixed effect captures time-invariant observable characteristics, like formal education, as well as unobservable traits, such as motivation and specific (e.g., interpersonal) skills. $\psi_{\mathbf{J}_{(it)}}$ is the establishment component. It comprises the wage that is equally paid by a firm to all of its employees independent of their characteristics. The firm effect also covers region- and industry-specific fixed effects, because generally firms do not change the region or industry in our sample. $x'_{it}$ is a vector of observable worker characteristics. Following Card, Heining, and Kline (2013), the vector includes year dummies as well as quadratic and cubic terms in age fully interacted with education dummies. By construction, $x'_{it}$ captures education specific tenure. The impact of formal education is mainly included in the worker fixed effect. The reason is that the education information hardly changes over time for most workers in our sample. Typically, people within the age group of our sample (20 to 60) have already completed education when they start full-time regular work.

Last, $r_{it}$ is the error term. As described in Card, Heining, and Kline (2013), it includes three independent random effects: $\eta_{i\mathbf{J}(it)}$ is the match component, i.e. an individual wage a worker $i$ receives only at firm $j$. $\zeta_{it}$ is a unit root component of the error term. It captures a potential drift in employees' wages, e.g., any form of human capital accumulation or job mobility within the firm. $\varepsilon_{it}$ is the transitory error term and includes, e.g., bonuses. We need to assume that all error components are orthogonal to the wage components and have mean zero, conditional on the controls. According to AKM, this assumption requires exogenous mobility. Workers should not sort into firms depending on how good they match with the firm. If workers receive different wages depending on the match quality of their characteristics with the ones of the firm, the firm effect will be estimated with bias. Card, Heining, and Kline (2013) show that the exogenous mobility assumption holds for the German labor market. They conclude that match effects are not important by providing evidence that the match-specific wage premium is not considered by workers who switch employers. Moreover, they show that adding a match-specific component in form of a job fixed effect to equation 1.1 only increases the model fit marginally, implying that endogenous mobility does not play a major role in Germany.

Some work has been done on the relation of endogenous mobility and globalization. According to Helpman, Itskhoki, and Redding (2010), more productive firms screen the labor market more successfully and intensively for potential employees because their high productivity is complementary to employees with high abilities. This leads to worker-firm matches of higher quality. Krishna, Poole, and Senses (2014) conclude that the matching of employees in more productive exporting firms (in comparison to less productive non-exporters) is not random, and consequently, worker and firm effects are estimated with bias. Ashournia, Munch, and Nguyen (2014) argue that import penetration might change workers' mobility following an unobservable match effect with the firm. Following these arguments, one could assume that the match effect on wages increases in trade exposed sectors in comparison to less export- and import-intensive industries. However, we rely on previous evidence by Card, Heining, and Kline (2013), who do not find any evidence for sizeable match effects in Germany.

### 1.2.4 Descriptive Results of the Wage Components

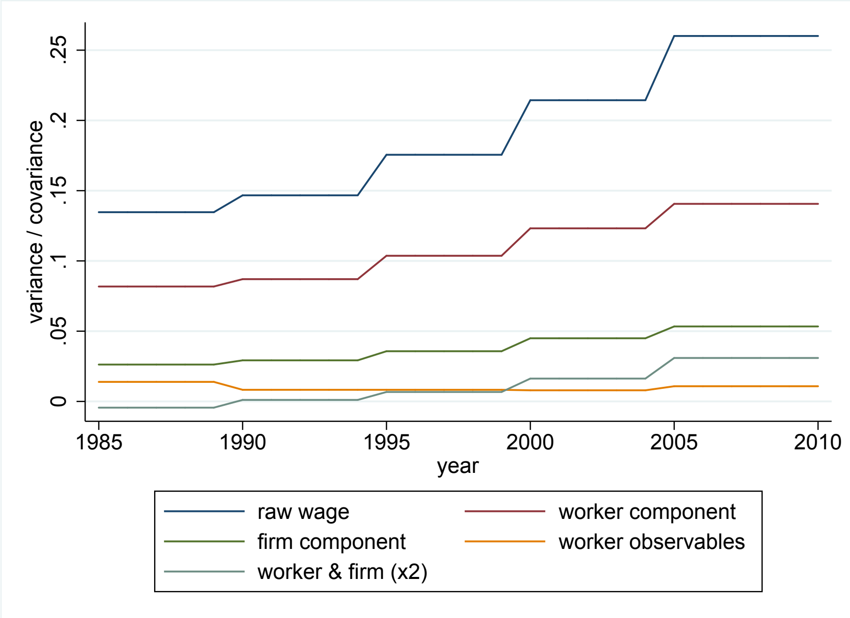
In this subsection, we replicate the results by Card, Heining, and Kline (2013), with some adjustments. For computational reasons, we use a 50% sample instead of the complete sample. Moreover, we change the intervals and use more, yet shorter periods (1985-1990, 1990-1995, 1995-2000, 2000-2005 and 2005-2010), which allow us to account for changes in trade more consistently over time. As expected, our results are very similar to those of Card, Heining, and Kline (2013) (see also table A1 in the appendix).

In figure 1.4, we report the results of the AKM model and the variance decomposition. The decomposition of the variance of log raw wages, $Var(y_{it})$, described in equation 1.2, allows us to assess how much of the increase in overall wage inequality can be explained by changes in the variation of the wage components separately. Because the worker and firm component are fixed effects, they cannot vary over time. To observe changes in these components, we estimate 1.2 separately for 5 overlapping six-year intervals.

$$\begin{aligned} Var(y_{it}) = Var(\alpha_i) + Var(\psi_{\mathbf{J}_{(it)}}) + Var(x'_{it}\beta) + 2Cov(\alpha_i, \psi_{\mathbf{J}_{(it)}}) \\ +2Cov(\psi_{\mathbf{J}_{(it)}}, x'_{it}\beta) + 2Cov(\alpha_i, x'_{it}\beta) + Var(r_{it}). \end{aligned} \tag{1.2}$$

Again, we see that our results are very close to the findings by Card, Heining, and Kline (2013), despite our smaller sample and adjusted intervals. Figure 1.4

Figure 1.4: Variance Decomposition of Wage Inequality by Interval, 1985–2010




Notes: The graph depicts the results of the decomposition of log wages using the AKM method by intervals. The variance of individual log wages (raw wage) can be described as the sum of the variance of the worker fixed effects (worker component), the variance of the firm fixed effects (firm component), the variance of observable worker characteristics, and their covariances. The sample includes full-time working men between 20 and 60 in the manufacturing sector in West Germany between 1985 and 2010.
Source: Own calculations, BeH.

illustrates the increasing dispersion of the person and firm component of wages. The variance of the person effect rises from 0.082 to 0.141 over the observation period, representing 47% of the increase in overall wage inequality. The variance of firm effects increases from 0.026 to 0.053, explaining an additional 22%. The variance of time-varying individual characteristics is much lower and has a decreasing pattern. We also see that the correlation of person and firm effects rises from -0.004 to 0.031. This indicates that higher assortativeness in the assignment of workers to firms contributes another 28% to the rising dispersion of wages.[9]

[9]Postel-Vinay and Robin (2006) argue that as the firm effect is the residual of the person effect (or both are mutual residuals of each other), potential estimation bias in one of the two directly translates into an opposite bias in the other fixed effect. Hence, the correlation between the two is naturally downward biased. This is even more the case as we estimate the AKM model in relatively short intervals, where the average worker only switches the establishment once or twice. Hence, the individual fixed effect is estimated with very high standard errors but consistently, given our very large data set.

## 1.3 Estimation Strategy

To identify the determinants that impact wage inequality in Germany, we estimate the following empirical model:

$$\Delta INEQM_{jt} = \beta_0 + \beta_1 \Delta NETTRADE_{jt} + \beta_2 \Delta RSH_{jt} + D_t + D_j + \varepsilon_{jt}, \qquad (1.3)$$

where $INEQM$ measures the inequality of wages within three-digit industries. The dependent variables are changes in the standard deviation of log wages, in the standard deviation of the firm and the worker component as well as in the covariance of both effects. We run regressions separately for each dependent variable. Although, yearly information on changes in raw wage inequality is available, we prefer to fit the wage data into the same intervals as for the wage components. Since the person and firm effects do not vary within the six-year intervals by construction, all changes are calculated in six-year differences. For example, $\Delta INEQM_{j,2005}$ describes the change in the standard deviation between interval 5 (2005-2010) and interval 4 (2000-2005). $\Delta NETTRADE$ is the change in industries' import exposure, the difference between measured import competition and export opportunities. Equation 1.3 is subject to endogeneity bias, since the net import exposure measure, $\Delta NETTRADE$, is potentially correlated with possible demand shocks of industries. Our primary gravity measure is in fact a measure of relative competitiveness and access to world markets which proxies for net (realized) trade and hence is not instrumented as it attempts to measure the latent driving force of net imports. As a second approach we directly instrument net imports by imports to other advanced economies.
Furthermore, we add an industry measure for technological progress. The routine share intensity ($RSH$) is a proxy for labor substituting technologies. It is explained in further detail below. We also include time dummies ($D_t$) for each interval to account for general trends in the German economy. As we basically use a first-differenced estimator, we abstain from further industry-level controls in our baseline specification, but add two-digit industry dummies ($D_j$) as a robustness exercise.

### 1.3.1 Identifying Trade Exposure

Both demand for labor and demand for imports from the East correspond with unobserved demand-side shocks by German industries. The correlation would typically lead the OLS estimate to understate the true effect of rising competitiveness of the East on German labor market outcomes. To avoid estimation bias, we need to isolate the effect of increased competitiveness and openness of the East from other distorting factors. This problem is commonly solved by using an instrumental variable (IV) approach. ADH make use of China's rising trade interactions as a consequence of their increasing competitiveness and the opening of their markets to world trade. Since these events are exogenous to US demand-side shocks and simultaneously affect other trading partners of China, ADH can apply the increase of Chinese exports to other developed countries as an instrument for Chinese exports to the US.The problem of the IV approach is that a correlation between import growth and demand shocks cannot be completely ruled out if product demand shocks between the developed countries are correlated. ADH circumvent this problem by measuring US imports from China as China's comparative advantage and market access to the US by applying a gravity model. Since this approach has a theoretical foundation and rules out parallel demand shocks in the countries used for IV and the country under examination, we use gravity residuals as our main measure of globalization in this paper.

**Gravity Approach:** Starting with the well-established standard gravity equation, one can assess the relative competitiveness of Germany vis-à-vis the East starting by the following equation 1.4 for trade values:

$$X_{ijk} = \frac{y_{ij} y_{kj}}{Y_{Wj}} (\frac{\tau_{ik}}{P_{ij} P_{kj}})^{1-\sigma}. \tag{1.4}$$

Here, trade of a country $i$ with a partner country $k$ depends on the relative size of the two countries with respect to the world economy $(y)$, the iceberg trade costs $\tau$, and some prize indices $P_i$ and $P_k$ of the two countries. $\sigma$ is the elasticity of substitution between commodities or industries $j$.

As shown in equation 1.5, we exploit the differences between the logs of German and Eastern trade with their respective trading partners. This difference can be interpreted as the relative competitiveness of the East compared to Germany. To control for multilateral trade barriers and distance, country fixed effects are included; and to control for path dependence or industry-specific idiosyncrasies, industry dummies are used. The difference in log trade is then regressed on these dummies. The residuals represent the rise in competitiveness of the East relative to Germany (after taking differences).

$$ln(X_{Ejk}) - ln(X_{Gjk}) = ln(z_{Ej}) - ln(z_{Gj}) - (\sigma_j - 1)[ln(\tau_{Ejk}) - ln(\tau_{Gjk})]. \quad (1.5)$$

A six-year differenced specification allows us to account for the interval structure of the dependent variables and implicitly allows for lagged effects. Formally, the trade shocks are constructed to affect the last period of an interval. They are defined as the sum of the one-year differences from the last period of the earlier interval to the last period of the latter interval:

$$\Delta GRAVITY_{j,t}^{EAST} = \sum_{t=\tau}^{\tau+5}(GRAVITY_{j,t}^{EAST} - GRAVITY_{j,t-1}^{EAST}), \qquad \forall\tau\epsilon\{1985, 1990, ..., 2005\}. \quad (1.6)$$

If trade follows the above-mentioned gravity structure, the gravity residuals account for endogeneity in the direct trade measures. In this case the IV approach is not necessary. By exploiting bilateral trade between many countries, the gravity approach uses more information and compares the rise in competitiveness of China and Eastern Europe with Germany, accounting for multilateral resistance.

**IV Approach:** We also use the conventional IV approach as robustness checks:

$$\Delta ImE_{j,t}^{D\leftarrow EAST} = \sum_{t=\tau}^{\tau+5} \frac{ImE_{j,t}^{D\leftarrow EAST} - ImE_{j,t-1}^{D\leftarrow EAST}}{ImE_{j,t-1}^{D\leftarrow WORLD}}, \qquad \forall\tau\epsilon\{1985, 1990, ..., 2005\}, \quad (1.7)$$

$$\Delta ExE_{j,t}^{D\rightarrow EAST} = \sum_{t=\tau}^{\tau+5} \frac{ExE_{j,t}^{D\rightarrow EAST} - ExE_{j,t-1}^{D\rightarrow EAST}}{ExE_{j,t-1}^{D\rightarrow WORLD}}, \qquad \forall\tau\epsilon\{1985, 1990, ..., 2005\}. \quad (1.8)$$

where $ImE_{j,t}^{D\leftarrow EAST}$ are the imports from the East and $ImE_{j,t-1}^{D\leftarrow WORLD}$ are the imports from the rest of the world to Germany of industry $j$ and in year $t$. An industry's export exposure is derived analogously. The instruments are defined for the same set of countries used in DFS.[10] The regressor we use in the estimations is net imports of German industries with respect to the East:

[10]These are Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom.

$$\Delta NetIm_{j,t}^{D\leftarrow EAST} = \Delta ImE_{j,t}^{D\leftarrow EAST} - \Delta ExE_{j,t}^{D\rightarrow EAST} \tag{1.9}$$

In the first stage, we regress the instrument countries' import measure on the German import measure.

### 1.3.2 Measuring Technological Change

In order to disentangle the effects of trade from those of technological change, we add the exposure to computerization for each industry as a control variable. Ongoing computerization has an enormous impact on the economy and each sector has different conditions and possibilities to use new technologies as substitutes for labor. According to the task-based approach (Autor, Levy, and Murnane, 2003), the substitutability of labor by computers and thus labor demand is mainly determined by the degree of routineness. Routine tasks are more easily codifiable and thus more likely be taken over by a machine, robot or computer. Autor, Levy, and Murnane (2003) provide empirical evidence that indeed the routine-intensive tasks of a job are most easily replaced by automatization. As a result, jobs performing those tasks become obsolete in the production process. In contrast, the demand for nonroutine tasks increases since they complement the work of computers. Inspired by Autor, Dorn, and Hanson (2015), we look at the routineness of industries as a measure of their exposure to computerization. Given the possibility of technological substitution, we assume that there is special pressure on wages in industries with a high share of routine jobs.

In order to measure the routineness of an industry, we first calculate the routine task-intensity of each job $l$. For this, we apply the operationalization by Matthes (2016). She uses the BIBB/BAuA Employment Surveys (1979-2012) to determine how intensively various task categories (routine-manual [rm], routine-cognitive [rc], analytical [a], interactive [i], nonroutine-manual [nm]) are typically carried out in occupations. Based on this indicator, we calculate the routine task-intensity (RTI) for each job $l$ following Autor and Dorn (2013):

$$RTI_l = ln(T_{l,1979}^{rm}) + ln(T_{l,1979}^{rc}) - ln(T_{l,1979}^{a}) - ln(T_{l,1979}^{i}) - ln(T_{l,1979}^{nm}). \tag{1.10}$$

Similar to Autor and Dorn (2013), we classify an occupation as routine if it has an RTI above the 66-quantile of the employment-weighted RTI distribution in the initial year 1979. In the next step, we determine the routine employment share (RSH) for each industry:

$$RSH_{jt} = \frac{\sum_{l=1}^{L} emp_{jlt} \cdot m(RTI_l > RTI^{P66})}{\sum_{l=1}^{L} emp_{jlt}}. \tag{1.11}$$

As in Autor and Dorn (2013), $emp_{jlt}$ is the number of employees in occupation $l$, industry $j$ and year $t$. $m(\cdot)$ is an indicator function which is either one if the occupation $l$ is routine-intensive as defined above, or zero if it is not. In this way, RSH reflects an industry's share of employees with routine-intensive jobs.

### 1.3.3 Industry Statistics: Trade, Automation and Wage Inequality

In table 1.1 two-digit sectors are listed and sorted by the change of the log wage inequality (averages of three-digit industries). We also report the changes in our main independent variables, the gravity residuals and routine-share measures. Additionally, we report the total change in employment (of full-time working men) over the whole period. We color the highest terciles in red and the lowest terciles in green (the highest *decrease* for RSH and worker count).

For all two-digit sectors, over the entire sample period from 1990 to 2010, we see an increase in market access and competitiveness of the East. We find by far the highest increase in the office machinery and computers sector, followed by the radio, tv and other communication equipment industry, which is not surprising since China is an exporting nation in these fields. Looking at wage inequality, the highest increase is in the manufacturing of radio, tv and communication equipment. Also the wearing apparel and the office machinery sector is among those with the highest increase in wage inequality. Regarding routine share intensity, we see that most of the sectors experienced a decrease, first and foremost the wearing apparel and automobile industry. However, from the terciles in table 1.1 we see that the broad trends of wage inequality and gravity move in the same direction. The same holds for the routine-measure, with a little less obvious correlation. For a more in-depth analysis of the effect of trade and technological progress on wage inequality and especially on the inequality in the wage components, we apply regression analyses, which will be discussed in the next section.

Table 1.1: Trade, Computerization and Wage Inequality by two-digit Industries

| | $\Delta$ Interval 5 and Interval 2 in % | | | |
|---|---|---|---|---|
| Industry (two-digit) | SD log wage | Av. gravity | RSH | # workers |
| wood | 11.6 | 415.40 | 6.7 | -26.0 |
| furniture, toys | 12.9 | 637.10 | -2.2 | -40.5 |
| paper | 13.1 | 748.40 | 2.6 | -25.1 |
| food | 13.5 | 182.70 | 7.7 | -24.0 |
| basic metals | 14.1 | 401.10 | -2.9 | -37.6 |
| textiles | 16.3 | 623.70 | -3.8 | -61.5 |
| non-metallic minerals | 17.5 | 857.60 | -3.7 | -41.4 |
| machinery | 18.8 | 614.50 | -10.6 | -25.9 |
| chemicals | 19.5 | 559.10 | -0.9 | -36.0 |
| fabricated metals | 19.8 | 993.80 | -13.6 | -27.5 |
| medical equipment | 20.6 | 1232.10 | -18 | -23.6 |
| rubber, plastic | 21.3 | 915.60 | -1.8 | -14.1 |
| electrical machinery | 22.6 | 1418.40 | -17.8 | -23.8 |
| automobile | 22.9 | 893.00 | -26.3 | -14.6 |
| other transport | 23.3 | 654.50 | -12.3 | -19.1 |
| leather | 23.6 | 661.60 | -11.8 | -59.6 |
| publishing | 24.7 | 1329.60 | -4.1 | -30.6 |
| office machinery, computers | 25.4 | 5791.40 | -2.8 | -48.1 |
| wearing apparel | 25.6 | 1018.50 | -31.9 | -62.2 |
| tobacco | 26.4 | 1611.00 | -9.4 | -10.0 |
| radio, tv, comun. equipment | 26.7 | 3148.80 | -12.4 | -14.3 |

Notes: Gravity describes the gravity residual for each industry. It can be interpreted as the relative competitiveness of the East compared to Germany. RSH describes the routine share intensity, i.e. the share of routine occupations in an industry. The standard deviation of log wages and the number of workers are derived from the 50% random sample of all full-time working men between 20 to 60 in the manufacturing sector in West Germany. The changes are differences between these averages of the fifth and the second interval (1990-1995) in percent. The color green (red) represents the lowest (highest) tercile of each variable: the lowest (highest) increase in wage inequality, the lowest (highest) increase in competitiveness, the lowest (highest) decrease of the routine-share and the lowest (highest) decrease of workers employed.
Source: Own calculations, BeH and Comtrade.

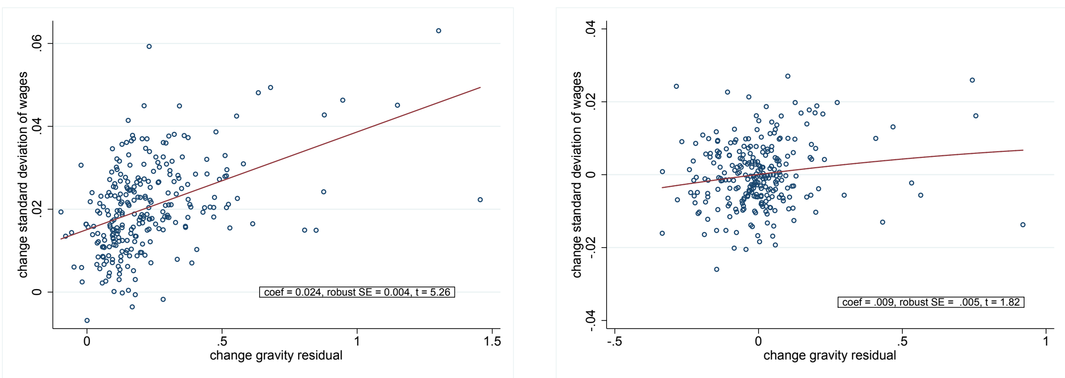
## 1.4 Results

In the following we present our empirical findings on the causal effect of increased competition and openness of the East on the inequality in decomposed wages in Germany. We start with our main results that show that trade affects overall wage inequality via its impact on the distribution of the skill premium of workers and on the sorting of "good" workers to high paying firms. We show that the firm pay premium does not add to the wage inequality via Eastern competition. Section 1.4.2 presents developments within education groups and in section 1.4.3 we look at the decrease in routine jobs and how it interacts with trade. Finally, in section 1.4.4 additionally consider institutional developments, as a third important cause of wage inequality changes. We look at the decline of union coverage by industries and discusses how this may affect the results.

### 1.4.1 The Effect of Trade on Wage Components

Figure 1.5 illustrates the relationship between increasing trade with the East and the dispersion of log wages within industries in Germany. The unconditional relationship depicted in panel A shows that the rise of the East is positively correlated with increasing wage inequality. This relationship remains positive if we control for technological changes, i.e., in routine share intensity, and time, but the size of the coefficient is more than halved.

Figure 1.5: Changes in Import Exposure and in Wage Inequality, 1995–2010




PANEL A: Unconditional PANEL B: Conditional on Observables

Notes: The graphs plot interval changes in the standard deviation of log wages within three-digit manufacturing industries against changes in West German industries' import exposures from the East. We consider changes between six-year intervals from 1995 to 2010. Panel A shows the unconditional correlation. Panel B shows the same correlation if we control for technological changes and time.
Sources: Own calculations, BeH and Comtrade.

**Raw wage inequality:** Table 1.2 contains the regression results from estimating equation 1.3 that we portray in figure 1.5. For now we concentrate on the impact of trade and leave technological changes out. Table 1.2 compares the results for the different trade measures described in section 1.3.1. Columns 1 and 2 include our main specification of trade exposure, i.e., changes in the gravity residuals. Columns 3 and 4 include the results from the IV estimation with net trade and columns 5 and 6 the OLS results with net trade as the independent variable.[11] Models in uneven columns include interval dummies and models in even columns additionally control for two-digit industries. The inclusion of these industry dummies reduce the effects of trade to some extent; however, the main effects remain significant.

In panel A of table 1.2 we regress changes in trade on changes in raw wage inequality. We find that an increase in the net import exposure affects the rise of wage inequality positively. For an average change in the gravity residual of 0.22, the effect of trade accounts for approximately 19% of the increase in the variation in raw wage inequality ($100 * [0.2239 * 0.0175]/0.0204 = 19.21\%$). Columns 3 and 4 include the results for the IV estimation instead of gravity residuals. An average increase in trade exposure of 0.0079 explains about 7% of the rise in overall wage inequality ($100 * [0.0079 * 0.174]/0.0204 = 6.74\%$). The increase in eastern competitiveness measured by the structural gravity parameter explains a much larger share of the increase in wage inequality than the instrumented net import measure. While trade measures include, e.g., higher imports due to cheaper or better intermediate inputs, our gravity variable measures competitiveness and market access and is therefore better suited to capture effects on the labor market.

The effect size is plausible compared to previous studies (see, e.g., Van Reenen, 2011), indicating that the effect of trade explains less than 20% of the increase in wage inequality. Comparing the OLS to the IV estimates, we see an increase in effect size of factor three to four, pointing to a sizable import endogeneity problem in the OLS results.

**Worker Fixed Effect:** The main contribution of the paper is that we focus on the effect of international trade on changes in the distribution of all wage components. We present the results for the individual fixed effects in panel B of table 1.2. Column 1 shows that an increase in the change of the gravity residual by one changes the rise in the standard deviation of the worker wage component by 0.014. Again, considering an average change in the gravity residual of 0.22, trade with the East explains about 18% of the increase of the deviation of the worker fixed effect ($100 * [0.2239 * 0.0141]/0.0179 = 17.64\%$). The effect remains significant even if we control

[11]Note that models 1 and 2 are also estimated by OLS because the gravity approach eliminates the impacts of possible demand side shocks (see discussion in section 1.3).

Table 1.2: Changes in Import Exposure and in Inequality of Wage Components

| | Gravity (1) | Gravity (2) | IV (3) | IV (4) | OLS (5) | OLS (6) |
|---|---|---|---|---|---|---|
| **PANEL A \| Dep. var.: Δ Std. of log wages** | | | | | | |
| Δ gravity | 0.0175*** | 0.00936** | | | | |
| | (0.001) | (0.024) | | | | |
| Δ net imports | | | 0.174** | 0.160** | 0.0617*** | 0.0383 |
| | | | (0.045) | (0.035) | (0.005) | (0.135) |
| R2 | 0.266 | 0.483 | 0.138 | 0.433 | 0.212 | 0.503 |
| **PANEL B \| Dep. var.: Δ Std. of worker fixed effects** | | | | | | |
| Δ gravity | 0.0141*** | 0.00682** | | | | |
| | (0.000) | (0.045) | | | | |
| Δ net imports | | | 0.144** | 0.138* | 0.0283 | 0.0151 |
| | | | (0.026) | (0.050) | (0.247) | (0.596) |
| R2 | 0.0856 | 0.230 | . | 0.153 | 0.0306 | 0.236 |
| **PANEL C \| Dep. var.: Δ Std. of firm fixed effects** | | | | | | |
| Δ gravity | 0.000168 | 0.00290 | | | | |
| | (0.971) | (0.596) | | | | |
| Δ net imports | | | 0.0270 | 0.0255 | 0.0270 | 0.0243 |
| | | | (0.788) | (0.828) | (0.397) | (0.486) |
| R2 | 0.166 | 0.226 | 0.163 | 0.214 | 0.163 | 0.214 |
| **PANEL D \| Dep. var.: Δ Cov. of worker and firm fixed effects** | | | | | | |
| Δ gravity | 0.00247* | 0.00187 | | | | |
| | (0.067) | (0.153) | | | | |
| Δ net imports | | | -0.00801 | -0.00292 | 0.0105 | 0.0106 |
| | | | (0.679) | (0.894) | (0.117) | (0.153) |
| R2 | 0.0520 | 0.215 | 0.0176 | 0.211 | 0.0436 | 0.223 |
| N | 263 | 263 | 262 | 262 | 262 | 262 |
| Interval FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | No | Yes | No | Yes | No | Yes |

Notes: Panel A shows the results of a change in trade on changes in the distribution of log raw wages, while panels B to D show the effect of trade on changes in the distribution of individual and firm fixed effects and on changes in the covariance of both components. The independent variables are either trade measured as gravity residuals, instrumented net imports or net imports estimated with OLS. All models include interval dummies and a constant. In addition, columns 2, 4, and 6 include two-digit industry dummies. $p$-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations, BeH and Comtrade.

for broader industry effects (model 2) or if we use IV (columns 3 and 4).
The positive coefficient of gravity on inequality in the person fixed effect can be explained by two developments. On the one hand, it could reflect an increase of the

skill premium (intensive margin). On the other hand, it can reflect a decrease in the relative demand for medium-skilled workers (extensive margin). This interpretation requires a more in-depth view on changes in the skill-composition of industries. Table A3 in the appendix shows that the number of low- and medium-skilled workers decreases in all industries, whereas the number of high-skilled workers increases. Thus, considering the extensive margin, low- and medium-skilled workers lose their jobs. Newly hired workers apparently do not replace those workers, but rather fit into the "new" labor market that is more polarized regarding the returns to skill.

Workers with a close to average person fixed effect asymmetrically select out of the manufacturing sector and are not replaced, rather the skill distribution is altered under low-wage competition. These results are consistent with the findings by Dauth, Findeisen, and Südekum (2016), who show that workers are pushed out of industries that are highly exposed to imports from the East.

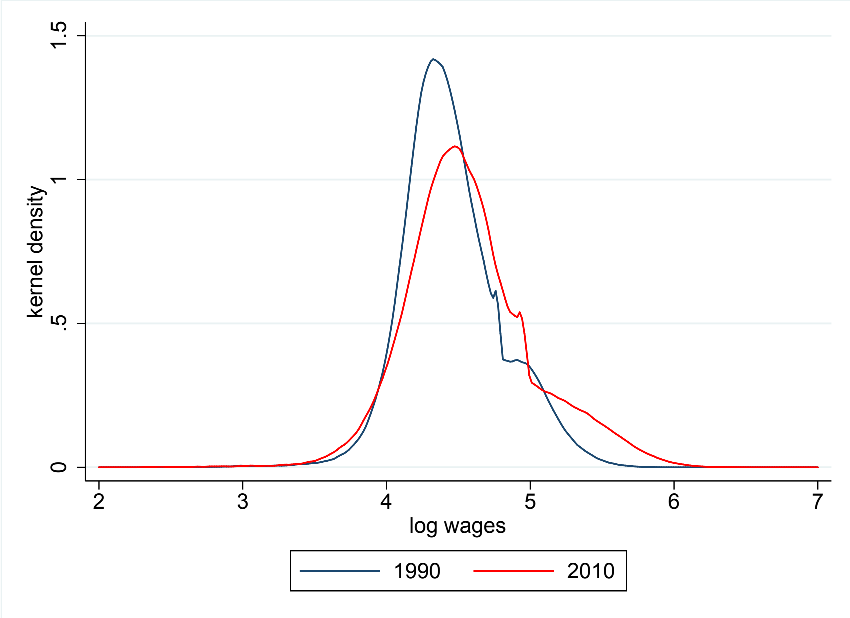
Figure 1.6 visualizes the polarization of wages in the manufacturing sector. The wage distribution in 2010 is wider compared with 1990, with more mass at both ends and considerably less mass in the middle. This means that the size reduction of industries is relatively strong in the middle of the wage distribution. Germany has experienced a strong increase in formal education but relatively small changes in (real) average wages. That is, a worker today has a lower position in the wage distribution than workers in the past with similar formal education. Although formally low-skilled workers left manufacturing, we see polarization in the wage distribution.

To sum up, we observe a reduction in low- and medium-educated workers (see also figure A1), but at the same time more mass in the low income part of the distribution (compare figure 1.6). This process has been ongoing for a longer period already, particularly concerning workers with no training in the manufacturing industry. The increase in formal education does not explain recent changes in wage inequality.

**Firm Fixed Effect and Covariance:** For the firm-specific wage component in panel C of table 1.2 we do not find any significant effect of trade.[12] This finding contradicts recent contributions in trade theory and empirics, e.g., models of rent-

[12]For our analysis on the impact of trade on wage inequality, we measure inequality by the standard deviation of wage components within three-digit industries. In the data we have firm sizes between one and 50,000 workers. In an unweighted measurement both types of firms would count the same and the effect on inequality would be diluted. However, entry and exit of firms is determined by trade, leading to a reallocation of workers that would not be visible in the unweighted measurement. This reallocation is again dependent on the firm effect. Hence, we compute the distribution of the firm-specific wage component by weighting it by the number of full-time male workers in the firm.

Figure 1.6: Distribution of Log Wages, 1990–2010




Notes: The graph depicts the distribution of log wages in interval 2 (1990-1995) and interval 5 (2005-2010) of full-time working men between 20 and 60 in the sample of West German manufacturing industries that we use in our analysis.
Sources: Own calculations, BeH.

sharing in the trade context (e.g., Egger and Kreickemeier, 2009). [13] Finally, panel D of table 1.2 depicts the results for the covariance of the person and firm effects. The effect of our gravity measure is significant and economically large, indicating that increased import pressure from the East leads to more assortative matching in the manufacturing sector in Germany.[14]

Generally, our results are in line with those of other studies looking at the effects of trade on the German labor market. DFS find a negative impact of trade integration with the East in form of job losses in regions that are marked by import-competing sectors. However, given their focus on regional labor markets, they do not find evidence for an effect of rising import exposure on wages within the region. In their recent working paper, Dauth, Findeisen, and Südekum (2016) show that import competition leads to lower earnings within job spells and leads employees to leave

[13] As we do not observe export status or export size of individual firms, we cannot rule out that trade affects rent-sharing and efficiency wages at the firm level (see, e.g., Amiti and Davis, 2011; Frias, Kaplan, and Verhoogen, 2009).

[14] We provide another robustness exercise in table A5, where we look at sub-samples of industries manufacturing production and high-tech goods in comparison to consumer goods.

exposed industries. Also, Dustmann, Fitzenberger, Schönberg, and Spitz-Oener (2014) find an increase in wage inequality in tradable manufacturing sectors, where wages of the lower percentile decrease whereas the median and 85-percentile rise.[15]

### 1.4.2 Inequality within Education Groups

To understand the mechanisms behind wage polarization, we look at raw wage inequality and inequality in the wage components within industries and within conventional skill groups in table A2. Here, we group all workers without any formal training (low-skilled), with vocational training (medium-skilled), or with a college or university degree (high-skilled). For this exercise, we assume that these skill groups are somewhat rigid and, e.g., workers without any training usually do not replace workers with vocational training. Vocational training is traditionally very important in Germany. A large majority of workers receives this kind of training. While generally there is a strong increase in university enrolment in the last decades, the workforce composition is naturally changing slower and its largest group are workers with a vocational degree.

We find that import pressure affects within skill-group inequality, but only for the group of medium-skilled workers. That holds for the dispersion of raw wages as well as for the worker wage component. Again, we do not find any significant effect on the firm premium, which confirms our results in table 1.2. There is no effect on the wage dispersion within the group of high- and low-skilled employees.[16]

The trade effect on assortative matching is also significant for medium-skill workers, either because manufacturing firms with higher matching better survive competition, or because their job loss is less severe on average.

The fact that the effects of trade are only significant within the group of medium-skilled workers speaks in favor of the story that some jobs in the middle of the wage distribution are cut and not replaced accordingly. Table A3 shows that the employment of vocationally trained individuals decreases heavily in the manufacturing sector, supporting an offshoring story of those jobs. The remaining workers are either specialists whose work cannot be offshored and who are better paid, or workers that have to accept a rather low wage or a lower wage increase because of the im-

[15] Dustmann, Fitzenberger, Schönberg, and Spitz-Oener (2014) define the tradable manufacturing sector according to high export volumes. Moreover, they find the strongest increase in wage inequality in the tradable service sector, which we do not consider in this paper.

[16] Note that a large fraction of high-skilled workers is subject to top coding. Hence, the effect of the college premium as a driver of inequality is likely larger.

port pressure. This argument is in line with Dauth, Findeisen, and Südekum (2016) who analyze the individual consequences of trade and find that people working in industries with a high import exposure are more likely to lose their job. Moreover, they find that if workers stay within the same firm or industry, they experience a negative effect on cumulative earnings.[17]

Table A3 also shows that there are substantial changes in the workforce for the group of people without vocational training and those with a university degree. However, no effect of trade is found within any of these groups. These results might also indicate that competition from the East does not change the wage policy of firms to a large extent. Import penetration rather leads to a decrease in the demand for certain occupations and also affects between-skill-group redistributions such as the skill premium.[18]

To sum up, we find that if an industry faces increasing competition from the East, this will positively affect wage inequality within the industry. A closer look reveals, not firm-specific wage premiums drive wage inequality. In fact, trade drives overall wage inequality mainly through its impact on the inequality of the worker-specific wage component and through increased assortative matching. Our results are in line with findings of other authors, like Schank, Schnabel, and Wagner (2007), who find that most of the firm wage premium is driven by observable and unobservable worker characteristics. Higher assortative matching is in line with the survival of relatively more complex production lines under low-wage competition.

### 1.4.3 Trade and Technological Change

Turning to table 1.3, we replicate the results of table 1.2 but extend the regression by adding a measure for technological change ($\Delta RSH$). The main results of table 1.2 remain unchanged. If we control for technological change, the sign of the import competition coefficient is still in line with our expectations, while the size of the coefficient decreases up to 50% compared with the values in table 1.2. In panel A of table 1.3 we see that an increase in the share of routine-intensive jobs within an industry reduces raw wage inequality, which conversely means that technologi-

[17] Dauth, Findeisen, and Südekum (2016) show that high increases in the import exposure lead employees to leave the industry, especially towards the service sector where they earn less. This mobility pattern however is out of the scope of this paper, where we look at within-industry effects.

[18] Note that the AKM model does not control for occupations, heterogeneity between occupations is included in the individual fixed effect (as long as the individual does not change the occupation).

cal change increases wage inequality. The interpretation is straightforward: If an industry experienced a large decline in routine-intensive occupations in the preceding interval, the industry is assumed "trending" in automation and this pushes the increase in wage inequality. In our sample, the average decrease in an industry's share of routine occupations is -0.0084, explaining about 15% of the increase in wage inequality ($100 * [-0.0084 * (-0.362)]/0.0204 = 14.91\%$) (see panel A and column 3 in table 1.3).[19] Panel B of table 1.3 shows that a higher decrease in an industry's RSH leads to a significantly higher increase in the standard deviation of the worker wage component, explaining about 11% of the rise in inequality of the worker fixed effect ($100 * [-0.0084 * (-0.236)]/0.0179] = 11.01\%$). Moreover, we find a negative and significant effect of RSH on inequality in the firm pay component and no effect of technological change on assortative matching.

Because we measure technological progress as an an industry's decrease in the share of routine occupations, it might be correlated with the trade variables to some degree. The reason is that routine jobs can typically not only be readily replaced by machines, but are also easily offshorable to labor abundant countries (Blinder, 2009). As the trade coefficients stay significant when we additionally control for RSH, the correlation of the two measures keeps within limits.[20]

[19] Using the IV approach in model 4 of table 1.3, we find a comparable effect size for computerization.

[20] If we estimate equation 1.3 only with RSH but without any variable for trade, technological change explains about 17% of the increase in raw wage inequality and 13% of the increase in worker-specific wage inequality.

Table 1.3: Changes in Import Exposure, in Technology and in Inequality of Wage Components

| | Gravity (1) | IV (2) | Gravity (3) | IV (4) | OLS (5) |
|---|---|---|---|---|---|
| **PANEL A \| Dep. var.: Δ Std. of log raw wages** | | | | | |
| Δ gravity | 0.0175*** | | 0.00897* | | |
| | (0.001) | | (0.069) | | |
| Δ net imports | | 0.174** | | 0.0784 | 0.0459** |
| | | (0.045) | | (0.369) | (0.028) |
| Δ RSH | | | -0.362*** | -0.388*** | -0.185*** |
| | | | (0.000) | (0.000) | (0.000) |
| R2 | 0.266 | 0.138 | 0.233 | 0.175 | 0.323 |
| **PANEL B \| Dep. var.: Δ Std. of worker fixed effects** | | | | | |
| Δ gravity | 0.0141*** | | 0.00858** | | |
| | (0.000) | | (0.036) | | |
| Δ net imports | | 0.144** | | 0.0795 | 0.0177 |
| | | (0.026) | | (0.244) | (0.481) |
| Δ RSH | | | -0.236** | -0.260** | -0.125*** |
| | | | (0.011) | (0.010) | (0.001) |
| R2 | 0.0856 | . | 0.0621 | . | 0.0901 |
| **PANEL C \| Dep. var.: Δ Std. of firm fixed effects** | | | | | |
| Δ gravity | 0.000168 | | -0.00531 | | |
| | (0.971) | | (0.375) | | |
| Δ net imports | | 0.0270 | | -0.0223 | 0.0218 |
| | | (0.788) | | (0.843) | (0.501) |
| Δ RSH | | | -0.233** | -0.200 | -0.0620 |
| | | | (0.044) | (0.115) | (0.106) |
| R2 | 0.166 | 0.163 | 0.124 | 0.124 | 0.171 |
| **PANEL D \| Dep. var.: Δ Cov. of worker and firm fixed effects** | | | | | |
| Δ gravity | 0.00247* | | 0.00205 | | |
| | (0.067) | | (0.174) | | |
| Δ net imports | | -0.00801 | | -0.0167 | 0.00991 |
| | | (0.679) | | (0.485) | (0.159) |
| Δ RSH | | | -0.0176 | -0.0351 | -0.00700 |
| | | | (0.516) | (0.297) | (0.585) |
| R2 | 0.0520 | 0.0176 | 0.0452 | . | 0.0457 |
| N | 263 | 262 | 263 | 262 | 262 |

Notes: Panel A shows the results of a change in trade and technology (measured as the change in an industry's routine-share intensity) on changes in the distribution of log raw wages, while panels B to D show the effect of trade on changes in the distribution of individual and firm fixed effects and on the covariance of both effects. Trade is either measured as gravity residuals, instrumented net imports or net imports estimated with OLS. All models include interval dummies and a constant. *p*-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations, IEB and Comtrade.

### 1.4.4 Trade and Union Coverage

Another factor that is typically assumed to have an impact on wage inequality are changes in labor market institutions. Unions are an important institution because they bargain with employer's federations about wages and non-monetary benefits. Dustmann, Fitzenberger, Schönberg, and Spitz-Oener (2014) show that the share of employees covered by a union agreement has strongly declined in Germany. In consequence, the wage-setting process is more decentralized, away from the industry towards the firm level, and thus more heterogenous within industries. Moreover, Dustmann, Ludsteck, and Schönberg (2009) find that 28% of the increase in lower-tail income inequality can be explained by a decline in unionization rates. They explain that in Germany the share of workers covered by union agreements is the decisive measure to estimate the impact of unions. The reason is that in Germany collective bargaining results apply to all workers in a firm that recognizes a union and does not require the individual worker to be a union member.

If we assume that the decline of unions is exogenous, we would observe decreasing unemployment and larger wage inequality (if we abstract from the general decrease of manufacturing jobs). This is because low-paid workers benefit disproportionately from union bargaining, leading to a narrower range especially at the lower end of the wage distribution. In addition to direct effects of union coverage on wage inequality, unions can be seen as a factor determining international competitiveness of an industry or firm. An industry's ability to adjust to trade shocks can be restricted in the intensive (wage) margin through bargaining agreements. Unions can also lower their wage demand if they primarily want to prevent employment losses because of trade (see, e.g., Egger and Etzel 2012 and Felbermayr, Hauptmann, and Schmerer 2014 for more information on the relationship between trade and unions. Abstracting from the exogeneity assumption of unions, it is possible that the decline in unionization is a reaction to competitive pressure in the first place, so that firms can easier adjust to trade.

In this section we present some evidence on the correlation between changes in international trade, deunionization and the inequality in wage components. The co-movement of these factors hints at a reinforcing character of trade and deunionization. To derive the union coverage rate for two-digit industries, we use information of the IAB Establishment Panel and construct a union coverage share for industry level bargaining.[21] We then check whether the results of our main specification change if we differentiate between industries with a high or low decrease in the union coverage rate. In a way, this procedure gives us the possibility to consider the influence of labor market institutions, too. Column 1 of table 1.4 shows that the effect of trade on raw wage inequality is strong in industries with a high decrease in the union coverage rate. The interaction effect shows that the impact in industries with a lower decrease in unionization is significantly smaller and roughly halved, at least for raw wage inequality. The effect of increasing import competition on inequality of the worker wage component is significantly positive for the group of industries with a high decline in union coverage (column 3). The effect does not substantially differ for industries with a low decline. The same holds for the impact on changes in assortative matching (column 5). Again, the establishment pay premium remains unaffected within both groups (column 4).

Table 1.4: Import Exposure, Inequality of Wage Components and Deunionization

| | Δ Std. wage (1) | Δ Std. wage (2) | Δ Std. worker FE (3) | Δ Std. firm FE (4) | Δ Cov. FE (5) |
|---|---|---|---|---|---|
| Δ gravity | 0.0175*** | 0.0259*** | 0.0196*** | 0.000467 | 0.00242* |
| low union dec. | | 0.00132 | 0.000730 | -0.000796 | 0.000155 |
| (Δ gravity * low union dec.) | | -0.0135* | -0.00868 | -0.000498 | 0.0000804 |
| R2 | 0.266 | 0.287 | 0.0963 | 0.167 | 0.0528 |
| N | 263 | 263 | 263 | 263 | 263 |

Notes: In columns 1 and 2, the dependent variable is the change in the standard deviation of log raw wages. In columns 3 to 5, the dependent variables are the change in the standard deviation of the worker fixed effect, the firm fixed effect and the change in the covariance of both effects, respectively. The baseline gravity results are included in column 1. In columns 2 to 5, we interact the changes in gravity measure of trade with a dummy that is one if the decrease in the union coverage rate in a two-digit industry is below the median. All models include dummies for intervals and a constant. $p$-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations, BeH, Comtrade and IAB Establishment Panel.

## 1.5 Conclusion

This paper provides evidence *how* international trade influences the wage distribution within industries. We pay particular attention to the impact of import competition with low-wage countries on changes in the wage components, i.e. worker- and firm-specific pay premiums and assortative matching. In this way, our paper

[21] Firms can also implement firm-wide contracts. We do not include such house agreements in our measure of deunionization, because the effect would be part of the establishment-specific pay premium. It would certainly coincide with the firm effect.

contributes to a better understanding of how labor markets adjust to globalization processes.

Our main finding is that the reinforcing effect of trade on overall wage inequality mainly works through increased inequality in the worker latent skill component. The rise in competitiveness of China and Eastern Europe has a significant impact on the increase in the deviation of the individual wage component. We find this effect to be significant both within the group of vocationally trained workers, and between them and university educated workers. Both the group of low- and medium-skilled manufacturing workers is declining, while the high-skilled workforce increases in almost all industries. Thus, our results provide evidence that international trade increases the inequality of the worker wage premium through both a rising skill premium of qualified workers and by changing the composition of the workforce in a way that wages are more polarized. We do not find any evidence that international trade affects the firm pay premium. Moreover, we find a relationship between rising assortative matching and increased competitiveness of the East. This is in line with the interpretation that more complex production lines or plants (as in the O-ring production technology in Kremer, 1993) are more likely to survive low-wage competition. Note that assortative matching is likely underestimated by the decomposition method of AKM (see e.g., Postel-Vinay and Robin, 2006). Consequently, the effect we found should be interpreted as a lower bound. Generally, the German data seem to meet the relatively strong exogenous mobility assumption of the AKM approach quite well (see Card, Heining, and Kline, 2013). They are therefore particular suitable for our analysis.

A limitation of this study is that we are restricted to industry-level trade data. Other papers, like the work by Frias, Kaplan, and Verhoogen (2009), focus on the export status of firms and thus use detailed firm-level information. Having no firm-level information on trade exposure, we cannot rule out an effect of trade in this respect. We emphasize the channel of import competition as an important driver of wage inequality, while competitiveness in exporting has an offsetting effect. Additionally, we find the effect of technological change, measured by the decline in routine-intensive jobs in a given industry, to be almost equally important. In total, we are able to explain about a quarter of the recent increase in wage inequality in the German manufacturing sector.

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# Appendix A: Results of the AKM Model

Table A1 reports the results of the AKM model. The high $R^2$, increasing from 87% to 92%, and low residual wage components indicate a high explanatory power of the AKM model. Our results are very close to the findings by Card, Heining, and Kline (2013), although we use a smaller sample and different time intervals.

Table A1: Summary Statistics of the AKM Effects

| | | | |
|---|---|---|---|
| **Interval 1: 1985-1990** | | | |
| Observations | 33,632,369 | Corr. pers.& firm effect | -0.048 |
| Std. log (daily wage) | 0.367 | Corr. pers. effect & Xb | 0.066 |
| Std. person effects | 0.286 | Corr. firm effect & Xb | 0.068 |
| Std. firm effects | 0.162 | RMSE of AKM residual | 0.139 |
| Std. Xb | 0.118 | Adjusted R-squared | 0.873 |
| **Interval 2: 1990-1995** | | | |
| Observations | 35,845,173 | Corr. pers. & firm effect | 0.011 |
| Std. log (daily wage) | 0.383 | Corr. pers. effect & Xb | 0.140 |
| Std. person effects | 0.295 | Corr. firm effect & Xb | 0.087 |
| Std. firm effects | 0.171 | RMSE of AKM residual | 0.141 |
| Std. Xb | 0.091 | Adjusted R-squared | 0.878 |
| **Interval 3: 1995-2000** | | | |
| Observations | 33,813,314 | Corr. pers. & firm effect | 0.055 |
| Std. log (daily wage) | 0.419 | Corr. pers. effect & Xb | 0.109 |
| Std. person effects | 0.322 | Corr. firm effect & Xb | 0.097 |
| Std. firm effects | 0.189 | RMSE of AKM residual | 0.147 |
| Std. Xb | 0.091 | Adjusted R-squared | 0.892 |
| **Interval 4: 2000-2005** | | | |
| Observations | 32,605,834 | Corr. pers. & firm effect | 0.109 |
| Std. log (daily wage) | 0.463 | Corr. pers. effect & Xb | 0.094 |
| Std. person effects | 0.351 | Corr. firm effect & Xb | 0.122 |
| Std. firm effects | 0.212 | RMSE of AKM residual | 0.152 |
| Std. Xb | 0.089 | Adjusted R-squared | 0.909 |
| **Interval 5: 2005-2010** | | | |
| Observations | 31,291,419 | Corr. pers. & firm effect | 0.178 |
| Std. log (daily wage) | 0.510 | Corr. pers. effect & Xb | 0.073 |
| Std. person effects | 0.375 | Corr. firm effect & Xb | 0.132 |
| Std. firm effects | 0.231 | RMSE of AKM residual | 0.157 |
| Std. Xb | 0.104 | Adjusted R-squared | 0.921 |

Notes: The table follows Table III in Card, Heining, and Kline (2013) for slightly different intervals and for a 50% sample of the BeH including full-time working men between 20 and 60 in the manufacturing sector in West Germany between 1985 and 2010. Xb includes interaction terms of year dummies with education dummies as well as the interaction of quadratic and cubic terms in age with education dummies. Source: Own calculations, BeH.

# Appendix B: Interpretation of Gravity

To derive our gravity measure of trade[22], we start from the basic gravity equation that describes the trade values of industry j between country i and k. It depends on the size of the respective industries in both countries, relative to size of the world industry. It negatively depends on the iceberg transport cost $\tau$ and positively on the respective price indexes in nominal values.

$$X_{ijk} = \frac{y_{ij} y_{kj}}{Y_{Wj}} \left(\frac{\tau_{ik}}{P_{ij} P_{kj}}\right)^{1-\sigma_j}. \tag{1.12}$$

We look at trade between countries G (Germany) and E (the East). We take the natural logs of equation 1.12. World and destination industry sizes vanish by taking differences. We receive relative exports:

$$ln(X_{Ejk}) - ln(X_{Gjk}) = ln\left(\frac{y_{Ej}}{P_{Ej}^{1-\sigma_j}}\right) - ln\left(\frac{y_{Gj}}{P_{Gj}^{1-\sigma_j}}\right) - (\sigma_j - 1)[ln(\tau_{Ejk}) - ln(\tau_{Gjk})]. \tag{1.13}$$

We reduce equation 1.13:

$$ln(X_{Ejk}) - ln(X_{Gjk}) = ln(z_{Ej}) - ln(z_{Gj}) - (\sigma_j - 1)[ln(\tau_{Ejk}) - ln(\tau_{Gjk})]. \tag{1.14}$$

This gives us the relative trade with a third country k for Germany and the East explained by relative real industry sized $z$ or export capabilities and as function of the relative access cost to these markets for both countries. To extract the relative competitiveness we now estimate the following equation for years t:

$$ln(X_{Ejkt}) - ln(X_{Gjkt}) = \alpha_j + \alpha_k + \epsilon_{jkt} \tag{1.15}$$

We estimate the log difference in exports to a third country by industry and third country fixed effects. Substituting equation (1.14) for the term on the left hand side yields:

[22] For a detailed description see Autor, Dorn, and Hanson (2013).

$$ln(z_{Ej}) - ln(z_{Gj}) - (\sigma_j - 1)[ln(\tau_{Ejk}) - ln(\tau_{Gjk})] = \alpha_j + \alpha_k + \epsilon_{jkt} \tag{1.16}$$

Solving for the error term, the gravity residuals are as follows:

$$\epsilon_{jkt} = ln(z_{Ej}) - ln(z_{Gj}) - (\sigma_j - 1)[ln(\tau_{Ejk}) - ln(\tau_{Gjk})] - \alpha_j - \alpha_k \tag{1.17}$$

and reshaping:

$$\epsilon_{jkt} = \left[ln\left(\frac{z_{Ej}}{z_{Gj}}\right) - \alpha_j\right] - \left[(\sigma_j - 1) \cdot ln\left(\frac{\tau_{Ejk}}{\tau_{Gjk}}\right) - \alpha_k\right] \tag{1.18}$$

We end up with two terms, first the relative export capabilities, demeaned by the average of all industries and second the relative cost to exporting demeaned by the average cost difference for that country. Note that the second term is negative if the East has worse market access than Germany and then enters positively to the first term. Finally, we take 6-year differences of these residuals to capture the change in relative market access and export capabilities for our interval periods.

# Appendix C: Within Skill Groups

Table A2 summarizes the results if we estimate our regression model within conventional skill groups. We group all workers with no training, with vocational training and those with a college or university degree.

Table A2: Changes in Import Exposure and in Inequality of Wage Components within Education Groups

| | No vocational training | | | | Vocational training | | | | College/university degree | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Gravity | Gravity | IV | IV | Gravity | Gravity | IV | IV | Gravity | Gravity | IV | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| **PANEL A \| Dep. var.: Δ Std. of log wages** | | | | | | | | | | | | |
| Δ gravity | 0.0174 | 0.00139 | | | 0.0285** | 0.0285** | | | 0.00117 | 0.0191 | | |
| | (0.333) | (0.939) | | | (0.026) | (0.028) | | | (0.956) | (0.406) | | |
| Δ net imports | | | -0.254 | -0.361 | | | 0.364 | 0.116 | | | 0.0612 | 0.347 |
| | | | (0.444) | (0.287) | | | (0.132) | (0.665) | | | (0.783) | (0.182) |
| R2 | 0.201 | 0.304 | 0.168 | 0.276 | 0.146 | 0.238 | 0.0680 | 0.220 | 0.0602 | 0.167 | 0.0497 | 0.115 |
| **PANEL B \| Dep. var.: Δ Std. of worker fixed effects** | | | | | | | | | | | | |
| Δ gravity | 0.0157 | -0.00595 | | | 0.0267** | 0.0208* | | | 0.000799 | 0.0236 | | |
| | (0.336) | (0.738) | | | (0.026) | (0.086) | | | (0.968) | (0.246) | | |
| Δ net imports | | | -0.311 | -0.434 | | | 0.414* | 0.0815 | | | -0.117 | -0.106 |
| | | | (0.318) | (0.175) | | | (0.089) | (0.777) | | | (0.609) | (0.731) |
| R2 | 0.232 | 0.332 | 0.202 | 0.302 | 0.318 | 0.394 | 0.242 | 0.385 | 0.0128 | 0.174 | 0.0191 | 0.172 |
| **PANEL C \| Dep. var.: Δ Std. of firm fixed effects** | | | | | | | | | | | | |
| Δ gravity | 0.000168 | 0.00290 | | | 0.000168 | 0.00290 | | | 0.00195 | 0.00593 | | |
| | (0.971) | (0.596) | | | (0.971) | (0.596) | | | (0.747) | (0.373) | | |
| Δ net imports | | | 0.0270 | 0.0255 | | | 0.0270 | 0.0255 | | | 0.0184 | 0.170 |
| | | | (0.788) | (0.828) | | | (0.788) | (0.828) | | | (0.867) | (0.258) |
| R2 | 0.166 | 0.226 | 0.163 | 0.214 | 0.166 | 0.226 | 0.163 | 0.214 | 0.0817 | 0.211 | 0.0788 | 0.169 |
| **PANEL D \| Dep. var.: Δ Cov. of worker and firm fixed effects** | | | | | | | | | | | | |
| Δ gravity | 0.00265 | 0.00195 | | | 0.00359** | 0.00275* | | | -0.0000943 | 0.000404 | | |
| | (0.227) | (0.411) | | | (0.013) | (0.063) | | | (0.974) | (0.909) | | |
| Δ net imports | | | -0.00876 | -0.000338 | | | 0.00998 | 0.00694 | | | 0.0378 | 0.0535 |
| | | | (0.809) | (0.993) | | | (0.615) | (0.766) | | | (0.415) | (0.375) |
| R2 | 0.00949 | 0.114 | . | 0.113 | 0.0861 | 0.187 | 0.0676 | 0.194 | 0.00559 | 0.0423 | . | . |
| N | 263 | 263 | 262 | 262 | 263 | 263 | 262 | 262 | 263 | 263 | 262 | 262 |
| Interval FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |

Notes: Panel A shows the results of a change in trade on the change in the distribution of log raw wages. In panels B to D the dependent variables are the change in the standard deviation of the worker fixed effect, the firm fixed effect and the change in the covariance of both effects, respectively. The independent variables for trade are either measured as gravity results or instrumented net trade. All models include interval dummies and a constant. In addition even columns include two-digit industry dummies. $p$-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations, BeH and Comtrade.

# Appendix D: Workforce Changes

Table A3 shows the workforce changes during our observational period. The manufacturing industry lost a substantial part of its workforce in the 1990s and 2000s. While the textile industry lost more than two thirds of its workforce, the automobile industry only lost about 20%. Besides the general decline in the manufacturing workforce, we find an increase of college educated workers in almost all industries. Hence, we see the general trend of tertiarization (the general workforce of Germany increased during that period) as well as the rise in the education level of the German workforce.

Table A3: Workforce Changes by Industries and between Skill Groups in %, 1990–2010

| Industry (two-digit) | All<br>(1) | No voc. training<br>(2) | Voc. training<br>(3) | College / Univ.<br>(4) |
|---|---|---|---|---|
| wearing apparel | -69.1 | -77.4 | -70.9 | 36.6 |
| textiles | -69.8 | -82.5 | -64.3 | -18.1 |
| leather | -60.8 | -78.5 | -56.5 | 54.5 |
| office machinery, comp. | -54.5 | -68.1 | -61.5 | -38.2 |
| non-metallic minerals | -44.6 | -72.0 | -33.8 | 11.5 |
| basic metals | -40.7 | -65.5 | -28.5 | 10.7 |
| furniture, toys | -45.7 | -66.1 | -43.8 | 57.1 |
| publishing | -40.3 | -55.9 | -45.4 | 70.9 |
| chemicals | -39.1 | -71.2 | -36.4 | 5.4 |
| tobacco | -10.0 | -63.0 | -6.5 | 131.7 |
| food | -27.7 | -42.7 | -26.9 | 45.2 |
| wood | -32.4 | -61.4 | -22.9 | 85.1 |
| paper | -29.6 | -61.6 | -16.1 | 23.4 |
| medical equipment | -24.4 | -53.2 | -31.9 | 28.3 |
| electrical machinery | -25.2 | -61.0 | -27.7 | 21.1 |
| machinery | -24.8 | -62.3 | -25.8 | 55.0 |
| other transport | -16.7 | -59.7 | -20.8 | 35.1 |
| automobile | -20.2 | -74.6 | -11.0 | 116.9 |
| radio, tv, comun. equip. | -21.1 | -61.5 | -32.4 | 53.1 |
| fabricated metals | -22.5 | -51.7 | -17.4 | 73.7 |
| rubber, plastic | -21.2 | -52.5 | -11.1 | 59.5 |
| **Mean** | -35.3 | -63.9 | -32.9 | 43.7 |

Notes: The table depicts changes in the number of workers (full-time men between 20 and 60 in West Germany) between the years 1990 and 2010 in two-digit manufacturing industries. E.g., the wearing apparel industry lost 69.1% of its workforce. Columns 2 to 4 depict the workforce changes by different skill groups.
Source: Own calculations, BeH.

Looking at table A3 one could assume that the increasing dispersion is solely driven by between-education-group effects of the workforce. In addition to table A3, table A4 shows the within-industry changes in the worker fixed effect distribution. The dispersion of the individual wage component increases for all workers within their education group in all industries. Thus, the between-education-group effects of wages cannot explain all of the dispersion in overall wages and in the worker fixed effect.

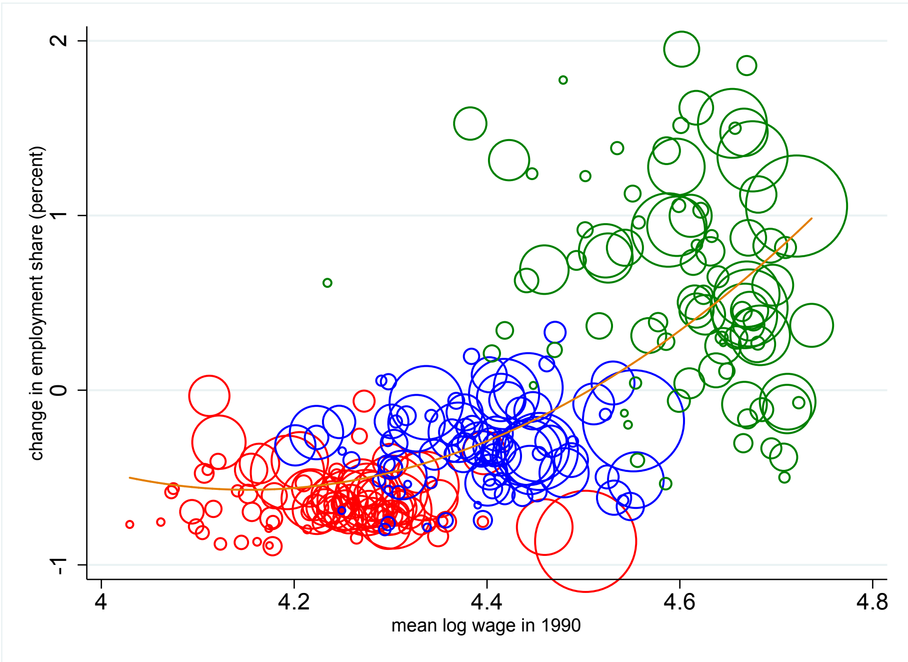
Table A4: Within Skill-Group Changes in the Worker Wage Component in %, 1990–2010

| Industry (two-digit) | No voc. training (1) | Voc. training (2) | College / Univ. (3) |
|---|---|---|---|
| wearing apparel | 21.97 | 18.85 | 11.42 |
| textiles | 9.38 | 5.86 | 14.35 |
| leather | 25.99 | 17.92 | 25.78 |
| office machinery, comp. | 33.99 | 34.58 | 73.62 |
| non-metallic minerals | 12.26 | 9.30 | 27.13 |
| basic metals | 12.64 | 1.09 | 30.99 |
| furniture, toys | 14.84 | 12.08 | 20.63 |
| publishing | 40.80 | 25.44 | 33.69 |
| chemicals | 23.00 | 9.13 | 48.63 |
| tobacco | 46.64 | 19.11 | 55.88 |
| food | 8.23 | 9.61 | 32.38 |
| wood | 12.98 | 7.39 | 20.80 |
| paper | 3.03 | 1.89 | 36.38 |
| medical equipment | 31.90 | 12.44 | 40.43 |
| electrical machinery | 35.67 | 8.49 | 42.04 |
| machinery | 30.36 | 6.13 | 26.37 |
| other transport | 89.34 | 17.12 | 38.54 |
| automobile | 86.63 | 21.32 | 79.93 |
| radio, tv, comun. equip. | 66.83 | 18.03 | 39.09 |
| fabricated metals | 19.03 | 6.62 | 24.40 |
| rubber, plastic | 20.13 | 5.87 | 31.44 |
| **Mean** | 30.75 | 12.77 | 35.90 |

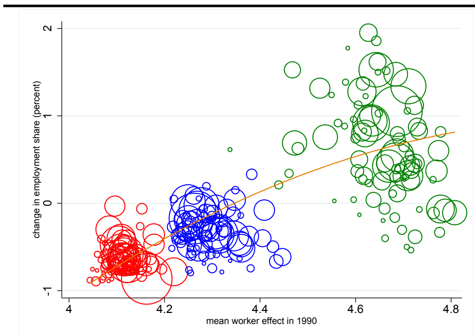
Notes: This table shows changes in the dispersion of the worker fixed effct within skill groups and industries, e.g., the variance of the worker wage component in wearing apparel has increased by 21.97% in the period between 1990 and 2010.
Source: Own calculations, BeH.

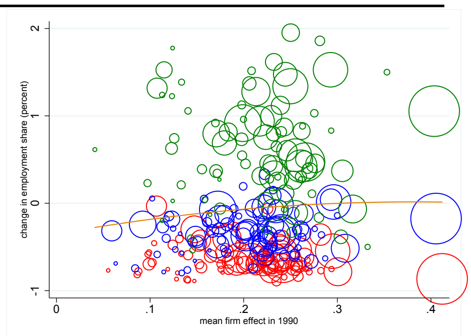
We also see the changes of the employment shares of different skill groups in figure A1. We find a general increase in college-educated workers and moderate to strong declines in non-college-educated workers. This pattern alone cannot explain the polarization of wages found in figure 1.6, although the increase in wages at the right of the distribution is partly attributable to the rise in high-skilled workers. These findings, emphasize the necessity to look at wage inequality within skill groups. Note that around 80% of workers are in the medium-skilled category.

Figure A1: Changes in Industry-Skill Group Employment




PANEL A: Raw Wages




PANEL B: Person Fixed Effect    PANEL C: Firm Fixed Effect

Notes: The y-axis depicts changes in employment shares of industry-skill-groups from 1990 to 2010. On the x-axis these industry-skill-groups are ranked according to their position in the distribution of mean log wages (panel A), mean worker fixed effects (panel B) and mean firm fixed effects (panel C) in 1990. The skill groups are no training (red), vocational training (blue), and college or university degree (green). Circle sizes represent overall industry sizes.
Sources: Own calculations, BeH.

# Appendix E: Product Classes

In table A5 our main trade variable, the gravity residual, is interacted with three different product classes. The product classes are consumer, intermediate and high-tech products. According to those categories, the industries are classified as follows: Consumer industries are industries, which, according to the German input-output table of the Federal Statistical Office of Germany, sell most of their products to final consumers. Intermediate industries sell their products to other industries, e.g., materials. High-tech industries have high shares of R&D without a clear profile of producing intermediate or final products. With the results presented in table A5, we want to check the plausibility of our previous results. We expect that industries producing low-tech consumer goods are very prone to low-wage competition, as the tasks required in their production processes are more likely to be done overseas. The results are in line with our expectations, the effects for consumer products are the largest and those for intermediate products are significantly smaller in size. Interestingly, the assortative matching effect, though insignificant, is largest for high-tech industries and completely irrelevant and even negative for intermediate industries.

Table A5: Product Classes

| | Δ Std. log wages | Δ Std. worker FE | Δ Std. firm FE | Δ Cov. worker/firm FE |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Δ gravity | 0.0250*** | 0.0203*** | -0.00643 | 0.00153 |
| | (0.000) | (0.000) | (0.226) | (0.226) |
| Δ gravity | -0.0177** | -0.0103* | 0.00612 | -0.00166 |
| * production | (0.017) | (0.085) | (0.377) | (0.274) |
| Δ gravity | -0.00997 | -0.00897 | 0.0166* | 0.00318 |
| * high-tech | (0.171) | (0.201) | (0.066) | (0.141) |
| R2 | 0.348 | 0.113 | 0.178 | 0.114 |
| N | 263 | 263 | 263 | 263 |

Notes: The table shows the baseline gravity measure for trade interacted with three different industry groups: Consumption goods (reference category), production goods and high-tech goods. The dependent variables are changes in the distribution of log wage inequality, in the individual and firm fixed effects and in the covariance of both effects, respectively. All models include a constant and dummies for intervals. $p$-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations, BeH and Comtrade.

# Chapter 2

# There and Back Again: A Simple Theory of Planned Return Migration

*Co-authored with Jens Wrona*

## 2.1 Introduction

Theories of temporary migration can be classified into two broadly defined categories, depending on whether the migrant's return decision is either optimally planned or an unanticipated but necessary choice. Planned return migration as integral part of an optimally designed life-cycle migration scheme thereby typically has the migrant in the role of an arbitrageur, who capitalises on institutional difference, which play out differently over the migrant's life cycle. Prominent examples include student migration (cf. Dustmann, 2001; Dustmann and Weiss, 2007; Dustmann, Fadlon, and Weiss, 2011) and the temporary migration of guest workers (cf. Ethier, 1985; Djajic and Milbourne, 1988; Djajic, 1989, 2010, 2013; Dustmann and Kirchkamp, 2002; Mesnard, 2004; Brücker and Schröder, 2012), which are both driven by strong institutional asymmetries (e.g. low costs of human capital accumulation abroad versus high returns to education at home). In the absence of such strong institutional differences unanticipated return migration typically is modelled as the revision of an erroneous initial migration decision in response to a random income/taste shock (cf. Borjas and Bratsberg, 1996; De la Roca, 2017).

In this paper we propose a simple signalling mechanism as a new theoretical explanation for planned return migration in the absence of regional asymmetries. Workers in our model differ in terms of their privately known skills, which are the sole input into a production process, that requires teamwork, and that is characterised by strong complementaries, as in Kremer (1993).[1] Due to the information asymmetry the otherwise optimal positive assortative matching of workers is no longer an option. Employers therefore resort to a second-best matching strategy, that combines only workers, which in expectation have the same skill. Since mismatch is an inherent feature of such a hiring regime, there is an incentive for high-skilled workers to avoid potentially "bad" matches with less skilled co-workers by signalling their true but otherwise unobserved skill through selection into costly temporary or permanent migration. Firms take into account workers' migration histories as an easy-to-verify signal, and form more efficient and better paid job matches, which renders migration attractive even without gains from arbitrage.

If the costs of permanent migration exceed the costs of a temporary stay, only the most high-skilled workers select into permanent migration as the high-cost signal,

[1]Examples of strategic complementaries in the migration literature include Hendricks (2001), Giannetti (2001), Dequiedt and Zenou (2013), as well as Kreickemeier and Wrona (2017).

which is compatible with a positive selection into initial migration and an *ex ante* negative selection into return migration. Migration flows thereby are not directed – as it is not the destination but the mobility as such that promises higher (expected) wages for migrants.

To motivate our theoretical analysis we explore the pattern of and the selection into regional return migration in Germany and establish two stylised facts, which we mean to explain by our theory of planned return migration between symmetric regions: At first, we shown that there is a considerable amount of two-way migration between fairly similar regions in Germany. Initial migration and later migration flows are remarkably balanced in the sense that we often observe migrants of the same type moving into exactly opposite directions. In a second step, we then follow De la Roca (2017), and provide some additional evidence in favour of an *ex ante* negative selection into planned returned migration based on workers' pre-migration wages, which are a comprehensive summary measure capturing all observable and unobservable income determinants (cf. Hunt, 2004). As in De la Roca (2017) we thereby exploit a rich administrative data set to follow individuals over their work lives. While both of these findings are well in line with our theory of planned return migration between symmetric regions, they are rather difficult to reconcile with standard theories of planned return migration between asymmetric regions or unanticipated return migration between *ex ante* symmetric regions.

Modelling planned return migration as a form of arbitrage between asymmetric regions typically implies welfare gains for the arbitrageurs (i.e. temporary migrants). Focusing on a setting without regional asymmetries, we would not expect these kind of welfare gains to matter, and indeed the welfare effects in our model contradict conventional wisdom in so far as all workers (including the migrants) tend to be worse off in an *laissez-faire* equilibrium with temporary and permanent migration than in an equilibrium without migration. Instrumental for the aggregate welfare loss is a negative migration externality, which leads to excessive temporary and permanent migration in the presence of wasteful migration costs.

The negative external effect of migration in our model is a direct consequence of the suboptimal matching of workers in the presence of asymmetric information. Due to the production in teams of two the shared payoff to each team member necessarily is a function of the respective co-worker's expected skill. Migration alters the composition and quality of the co-orker pool, which immediately feeds back not only into the wages of the critical (return) migrant but also into the wages of all workers, whose co-workers are hired from the thus affected group of workers. The critical (return) migrant rationally ignores the negative external effects on other workers' wages. As a consequence we observe excessive temporary and permanent migration, that is associated with wasteful periodical costs. Aggregate production gains, which emerge from a more efficient matching of workers within firms, thereby are completely consumed away by the periodical costs of excessive temporary and permanent migration, which renders the *laissez-faire* equilibrium socially inefficient. Of course this does not mean that all migration, temporary or permanent, is socially harmful per se. Employing an omniscient social planner we find that – if the periodical migration cost are not too high – the socially optimal equilibrium may feature temporary *and* permanent migration, both – of course – at a smaller scale than in the *laissez-faire* equilibrium. The social-planer solution thereby – as we show – can be implemented by a carefully chosen combination of taxes and subsidies, that aim for lower initial mobility and increased return activity.[2]

In order to demonstrate the robustness of temporary and permanent migration as signalling devices we show in an extension to our baseline model that temporary and permanent migration can also be combined with other signals. While there is some crowding out if the cost of migration/signalling are too high, we also find that the most high-skilled workers will always combine multiple signals in order to differentiate themselves from their lower skilled counterparts.

The positive selection into internal or regional migration within single countries is a well established empirical fact (see Greenwood, 1997, for a review of the literature).[3] Using NLYS data from the United States Borjas, Bronars, and Trejo (1992) show that more educated workers are more likely to migrate regardless of their state of origin. Focussing on migration between West-German federal states Hunt (2004) finds that migrants are more skilled than stayers. More recently, De la Roca (2017) has uses administrative data from Spain following individuals over their working lives to show that migrants to big cities are positively selected with regard to their education and their pre-migration income. The initial positive selection into migra-

[2]Benhabib and Jovanovic (2012) determine the globally optimal degree of (temporary and permanent) international migration. Djajic and Michael (2013), Djajic, Michael, and Vinogradova (2012), and Djajic (2013) study optimal policy instruments in the context of (temporary) guest-worker migration.

[3]Focussing on internal migration in Germany, Bauernschuster, Falck, Heblich, Suedekum, and Lameli (2014) argue that educated and risk-loving people are more mobile over longer distances because they are less afraid of crossing cultural boundaries and of moving to regions that are culturally different.

tion thereby typically gets reinforced by the fact that return migrants tend to be negatively selected in comparison to the initial set of movers (cf. DaVanzo, 1983; Kennan and Walker, 2011; De la Roca, 2017).[4]

In order to explain the negative *ex ante* selection of workers into return migration between similar regions, we extend the static two-way migration model by Kreickemeier and Wrona (2017) to allow for temporary *and* permanent migration. We thereby develop a new purely graphical representation of Kreickemeier and Wrona's (2017) central matching result in a labour market with complementary skills à la Kremer (1993) and asymmetric information in the spirit of Spence (1973).[5]

Stark (1995b) and Hendricks (2001) both study the selection into (international) return migration when migrants are matched under asymmetric information. In order to generate a negative *ex post* selection into return migration Stark (1995b) assumes that employers learn the true skills of migrants over time (see also Katz and Stark, 1987; Stark, 1995a). Once information symmetry is restored all migrants are paid the marginal product of labour (instead of an average wage). Low-skilled workers, which in the absence of averaging would not have to migrated, then have an incentive to return home. In an extension to Hendricks's (2001) baseline model migrants can use costly return migration to signal their true but otherwise unobservable skills, which leads to a positive *ex ante* selection into return migration.

Focussing on inter-city migration in Spain De la Roca (2017) combines institutional differences between large and small cities with uncertainty about *ex post* outcomes to generate a negative *ex ante* and *ex post* selection into asymmetric return migration from large to small cities. See also Borjas and Bratsberg (1996) for a theoretical model, that combines the same two features (asymmetries versus uncertainty) to explain the outmigration of foreign born in the United States.

Our paper is structured as follows: Building up on the stylised facts on regional return migration in Germany from Sections 2.2, we develop in Section 2.3 a simple

[4]Studies on international return migration typically focus on a single country or a small group of countries (see Borjas and Bratsberg (1996) for the US, Dustmann and Weiss (2007) for the UK, and Aydemir and Robinson (2008) for Canada, as well as Dustmann (2003) for Germany). Co, Gang, and Yun (2000), de Coulon and Piracha (2005), and Ambrosini, Mayr, Peri, and Radu (2015) report evidence from Hungary, Albania, and Romania, respectively. Gibson and McKenzie (2012) followed high-talented top-performers from five typical "brain drain" countries (Ghana, Micronesia, New Zealand, Papua New Guinea and Tonga). A more detailed review over the respective literature is given in Dustmann and Glitz (2011).

[5]See also the study of von Siemens and Kosfeld (2014), who extend a screening version of Spence's (1973) static job market signalling model to allow for strategic complementaries between workers in the spirit of Kremer (1993)

model of planned return migration between similar regions. Section 2.4 contains the welfare analysis and is used to derive the optimal migration policy mix. In Section 2.5 we extend the model to allow for an alternative signalling device. Section 2.6 concludes.

## 2.2 Stylised Facts on Regional Migration

As highlighted in the introduction, there are two dominating explanations for return migration: On the one hand, there is the notion of planned return migration as part of an optimal life-cycle migration scheme, that is designed to exploit institutional asymmetries across regions and/or countries (e.g. student migration (cf. Dustmann, 2001; Dustmann and Weiss, 2007; Dustmann, Fadlon, and Weiss, 2011) or guest-worker migration (cf. Ethier, 1985; Djajic and Milbourne, 1988; Djajic, 1989, 2010, 2013; Dustmann and Kirchkamp, 2002; Mesnard, 2004; Brücker and Schröder, 2012)). On the other hand, return migration also is explained as the *ex ante* unintended and unanticipated revision of an erroneous initial migration decision (cf. Borjas and Bratsberg, 1996; De la Roca, 2017).

To motivate our theoretical analysis from Section 2.3 we establish in the following two stylised facts on planned return migration between similar regions, which in combination are difficult to reconcile with either of the two aforementioned explanations for regional return migration. In particular, it is shown that inter-regional (return) migration between German regions is remarkably balanced in the sense that we observe a considerable number of initial and return migrants, which move into opposite directions. The existence of two-way return migration clearly is ad odds with an explanation that is derived from regional asymmetries, but is easily rationalised within a random utility framework, in which migrants learn about the true nature of their initial migration choice only upon arrival. In such a setting all initial migrants would have the same expectations regarding their return probabilities, such that we should not expect to find differences in the selection into initial migration, when conditioning on migrants later return decisions. Using initial wages as a proxy for worker's unobservable skills (cf. Hunt, 2004; De la Roca, 2017), we actually find that the positive selection into initial migration is more pronounced for permanent and onward migrants than for return migrants, which we interpret as indirect evidence for planned return migration.

We organise the remainder of Section 2.2 as follows: In Subsection 2.2.1 introduce our data set and provide some descriptive statistics. We proceed in Subsection 2.2.2 by showing that there is a considerable amount of inter-regional two-way migration. In Subsection 2.2.3 we then show that there are differences in selection into initial migration, when conditioning on workers' later return migration decisions.

### 2.2.1 Data and Descriptive Statistics

Our main data source are the Integrated Employment Biographies (IEB) provided by the Institute of Employment Research (IAB) in Nürnberg. We use a 4% random sample of the IEB V12.00.00-2015.09.15., which covers the universe of all workers in the German labour market except for those which are civil servants or self-employed (see also Card, Heining, and Kline (2013) and Oberschachtsiek, Scioch, Christian, and Heining (2009) for a detailed description of the data). The Integrated Employment Biographies link workers' employment history (including unemployment spells) to a detailed set of employer characteristics (including the place of work) from the Establishment-History-Panel (BHP). Our sample covers the time period from 1975 to 2014 (in some specifications we focus on the time period from 1992 to 2014 in order to avoid one-time reunification effects). Using the longest spell in each year we are able to construct a panel that is informative about workers mobility history (approximated by the location of the worker's workplace). Focussing on 402 German NUTS-3 regions ("Kreise") we associate the location of workplaces with the position of the largest city within the respective region. We then conduct our analysis at the level of 96 local labour markets ("Raumordnungsregionen"), which consist of several adjacent NUTS-3 regions that are summarised to commuting zones. Figure B1 from the Appendix illustrates the division of Germany into these 96 local labour markets, which can be classified as: rural, urbanised or metropolitan areas. Following De la Roca (2017) we use workers' employment history to learn about their mobility choices. Since short- and long distance migration seems to be driven by quite different motives (cf. Hunt, 2004), we focus only on long-distance migrants, who have migrated over distances of more than 120 kilometre and who stayed at their new location for at least two consecutive periods.[6] We then can distinguish between three different types of migrants: permanent migrants, return migrants and

[6] We adopt the 120 kilometre threshold from De la Roca (2017). Using information on the place of residence, which is available from the millennium onwards, it is possible to compute workers' exact commuting distances, which rarely exceed De la Roca's (2017) distance threshold. To make sure that our results are not driven by outliers we exclude all workers who migrate more than 10 times (irrespective of their moving distances).

Table 2.1: Descriptive Statistics

| **Descriptive Statistics:** | | | | | | |
|---|---|---|---|---|---|---|
| **Migration Type:** | **Non-migrants** | **Short-distance** | **Permanent** | **Return** | **Onward** | **Total** |
| **Number of Workers:** | 486,850 | 369,574 | 86,874 | 33,792 | 14,188 | 991,278 |
| **Wages:** | | | | | | |
| **Monthly Wage in 2005:** | 2,696.58 EUR | 2,777.74 EUR | 3,250.70 EUR | 3,203.98 EUR | 3,830.26 EUR | 2,827.11 EUR |
| **Top-coded Wages:** | 3.2% | 4.3% | 9.8% | 9.1% | 16.2% | 4.8% |
| **Education:** | | | | | | |
| **no training** | 9.6% | 3.7% | 3.0% | 1.6% | 1.4% | 5.9% |
| **vocational training** | 80.3% | 81.1% | 66.8% | 72.3% | 56.7% | 78.6% |
| **some college** | 1.8% | 3.0% | 3.9% | 4.6% | 4.6% | 2.7% |
| **university** | 8.3% | 12.1% | 26.3% | 21.5% | 37.3% | 12.8% |
| **Employment Status:** | | | | | | |
| **part-time** | 14.2% | 13.6% | 13.7% | 12.3% | 11.3% | 13.8% |
| **public** | | | | | | |
| **unemployed** | 3.3% | 4.8% | 5.2% | 6.0% | 5.4% | 4.3% |
| **in training** | 9.2% | 9.6% | 9.0% | 8.7% | 8.5% | 9.3% |
| **Gender:** | | | | | | |
| **female** | 50.3% | 47.2% | 48.5% | 45.0% | 42.0% | 48.4% |
| **Number of Observations:** | 6,155,812 | 6,660,521 | 1,443,117 | 694,187 | 257,984 | 15,211,621 |

onward migrants. Permanent migrants remain within a 120 kilometre range of their initial migration destination. Return migrants move back to their origin region and subsequently stay within a 120 kilometre range of their return migration destination. Onward migrants move to a third location, which is at least 120 kilometre away from the initial migration destination and also 120 kilometre away from their origin region.

In Table 3.1 we provide some first descriptive statistics for the different migration types in our sample. Our sample consists of 991,278 workers, which are born between 1957 and 1995. Roughly half of the workers never move within our time frame (life time mobility may be higher of course). Another 37.3% of the workers only move within a 120 kilometre range. There are 13.5% long-distance migrants, of which 8.7% are classified as permanent migrants, 3.4% are classified as return migrants, and another 1.4% are classified as onward migrants. Non-migrants and short-distance/term migrants have the lowest wages. Onward migrants have the highest wages among all migrants, and return migrants earn lower wages than permanent migrants, which is in line with the results from Hunt (2004) and De la Roca (2017).[7] A similar ordering is obtained when considering workers' education: Migrants are more educated in general. Among the mobile workers, onward migrants are the most educated, followed by the permanent and the return migrants. The

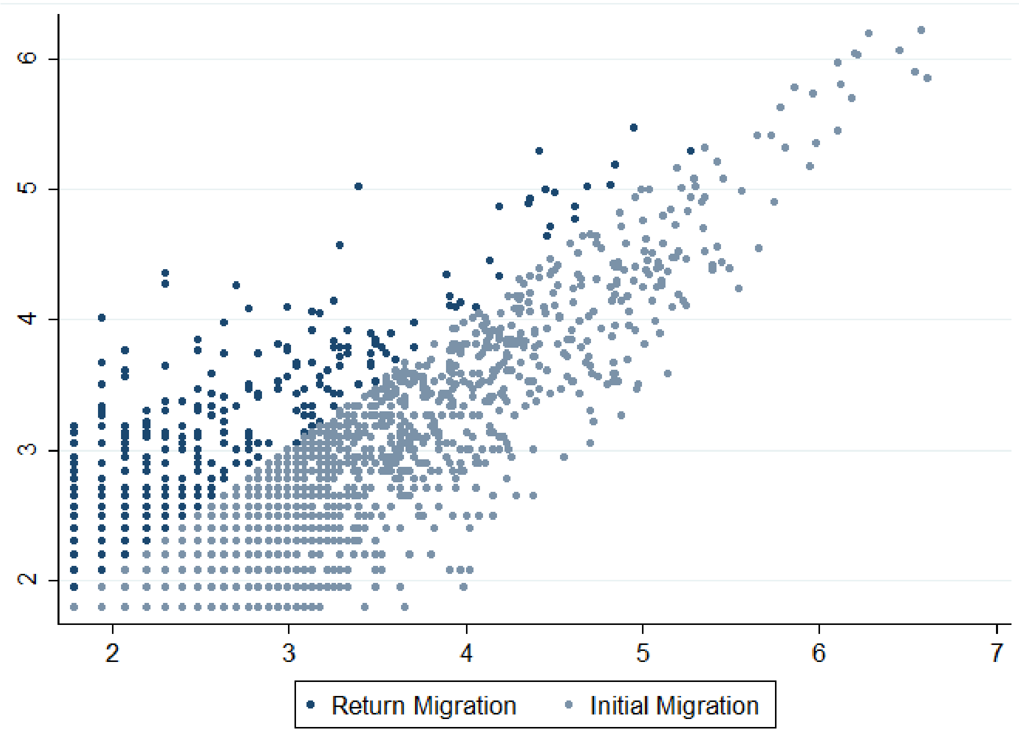
[7] We deal with top-coded income data (roughly 5% of the observations) by applying the imputation procedure recently proposed by Card, Heining, and Kline (2013).

share of unemployed workers is higher among the movers (and in particular among the repeated migrants), indicating that job loss may be a major cause for migration at any stage.

### 2.2.2 Two-way Return Migration

In the following we document the pattern of initial and later return migration between 96 German regions over the time span from 1990 to 2014. As illustrated in Figure 2.1 we find that initial and later return migrants often move into opposite directions. In Figure 2.1 each observation represents a combination of logarithmic

Figure 2.1: Balance in Initial and Return Migration




immigration and emigration flows between a certain pair of regions.[8] Initial migration flows thereby are ordered in such a way that the larger of the two migration flows is measured along the abscissa, whereas return migration flows are ranked such that the larger of the two return migration flows is depicted along the ordinate. As consequence, all initial migration flows appear below the 45°-line, while the return

[8]Following the IAB's data protection guidelines we are only allowed to report flows that consists of more then five migrants.

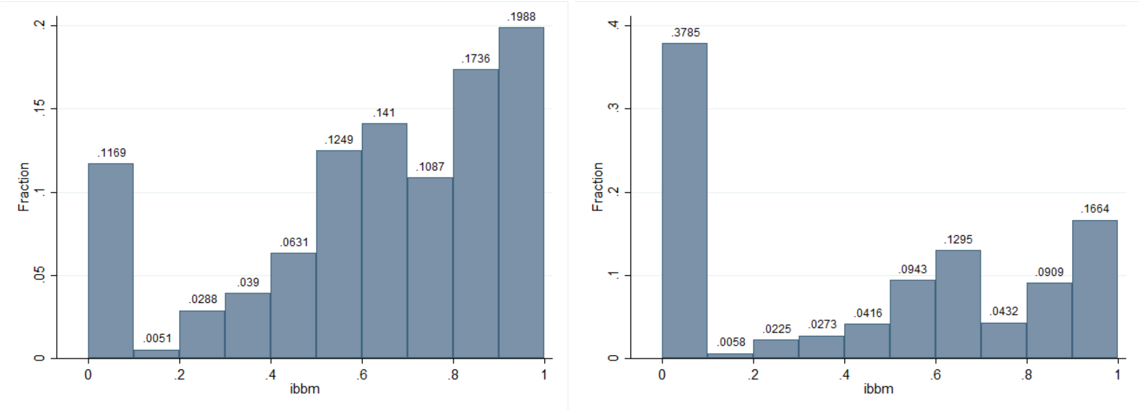
migration flows are reported above the 45°-line. The 45°-line thereby represents a natural benchmark for perfectly balanced (return) migration flows, with observation that are further away from the 45°-line being more unbalanced. According to Figure 2.1 we find initial and later return migration to be rather balanced, with the major difference that there are fewer return migrants than initial migrants.

As a major drawback of Figure 2.1, we cannot observe highly, or even perfectly unbalanced migration flows. In order to quantify the balance in regional return migration we therefore follow Biswas and McHardy (2005) and Kreickemeier and Wrona (2017) and compute the share of bilateral (return) migration between region pair $(x, y)$ that can be characterised as two-way, using an Index of Bilateral Balance in Migration $IBBM_{xy} = 2min\{M_{xy}, M_{yx}\}/(M_{xy} + M_{yx}) \in [0, 1]$, in which $M_{xy} \geq 0$ represents the flow of migrants from region $x$ to region $y$.[9] By construction the index takes a value of one, if migration is perfectly balanced (i.e. $M_{xy} = M_{yx}$) and a value of zero if migration is completely unbalanced (i.e. either $M_{xy} = 0$ or $M_{yx} = 0$). In order to compute the Index of Bilateral Balance in Migration, we require non-zero migration in at least one direction, which is the case for $4,482$ of the potential $96 \times 95 = 9,120$ region pairs.

In Figure 2.2 we depict the distribution of IBBMs for initial and later return migration. In terms of initial migration (see Figure 2.2a) most region pairs are characterised by an IBBM that takes an value that is larger than 0.5, with the most frequent observation being a value in the vicinity of one. For 523 region pairs we find initial migration to be perfectly unbalanced, which may at least partly be explained by the fact that these region pairs are generally characterised by low migration flows (e.g. due to their small population sizes or their large bilateral distance). For return migration a similar pattern arises (see Figure 2.2b), although the share of perfectly unbalanced return migration flows is considerably higher. The high share of perfectly unbalanced return migration flows thereby arises mechanically due to the small-sample properties of the IBBM, which more often takes extreme values because the number of return migrants is much smaller than the total number of (initial) migrants.

[9] The definition of the Index of Bilateral Balance in Migration (IBBM) is directly analogous to the well-known Grubel-Lloyd index (cf. Grubel and G.Lloyd, 1975) measuring the extent of intra-industry trade, that is two-way trade in goods within the same industry (see Brülhart, 2009, for a recent application).

Figure 2.2: Distribution of IBBMs for Initial and Return Migration




(a) IBBMs for Initial Migration (b) IBBMs for Return Migration

### 2.2.3 Selection into Planned Return Migration

Is there supportive evidence for a systematic selection into planned return migration? To answer this question we analyse the selection into different migration modes (permanent, return, onward and no migration) based on individuals' initial migration decisions. When migration is planned to be temporary, we would expect initial migrants to differ depending on their prospects of migrating either temporary or permanently. On the contrary, if return migration results from the revision of an initial migration decision in response to an unanticipated income shock *ex post* to the initial migration decision (as for example in De la Roca, 2017), we would not expect to find differences between initial migrants conditional on their later migration experiences.

In search for systematic differences among initial migrants (conditional on their later return decisions), we follow De la Roca (2017), and run a multinomial logit regression, which allows for four different outcomes: no migration, permanent migration, return migration and onward migration (with no migration as the baseline category). We use lagged logarithmic wages as a comprehensive measure of all observable and unobservable income determinants, and control for an extensive set of time-varying observable individual characteristics (experience, firm tenure, age, and some further employment characteristics) as well as for several constant individual characteristics (education, gender and, home region). To capture a general time trend we include the complete set of year dummies up to the last possible migration year.

In Table (2.2) we report the regression results, comparing non-migrants (baseline

Table 2.2: Selection into Different Types of Migration Based on Initial Wages

| Multinominal Logit for Selection into Different Types of Migration (No, Permanent, Return, Onward) Based on Initial Wages | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Type of Regions:** | All Regions | | | | | | Only Urban | | | | | |
| **East vs. West Germany:** | East & West | | | Only West | | | East & West | | | Only West | | |
| **Migration Type:** | Permanent | Return | Onward | Permanent | Return | Onward | Permanent | Return | Onward | Permanent | Return | Onward |
| **Specification:** | (1) | | | (2) | | | (3) | | | (4) | | |
| **Lagged logarithmic wage** | 1.091*** | 1.071*** | 1.103*** | 1.096*** | 1.061*** | 1.095*** | 1.212*** | 1.113*** | 1.206*** | 1.204*** | 1.119*** | 1.212*** |
| | (13.49) | (6.71) | (5.98) | (13.32) | (5.59) | (5.32) | (15.86) | (6.97) | (7.39) | (14.94) | (7.11) | (7.41) |
| **Education:** | | | | | | | | | | | | |
| vocational training | 1.184*** | 2.315*** | 2.231*** | 1.159*** | 2.185*** | 2.277*** | 0.985 | 2.202*** | 1.755*** | 0.975 | 2.142*** | 1.760*** |
| | (8.52) | (18.90) | (10.26) | (6.84) | (16.86) | (9.40) | (-0.43) | (12.42) | (5.06) | (-0.71) | (11.83) | (4.94) |
| some college | 1.917*** | 4.021*** | 4.797*** | 2.054*** | 4.079*** | 5.356*** | 1.847*** | 3.758*** | 4.019*** | 1.881*** | 3.771*** | 4.056*** |
| | (23.90) | (26.97) | (17.64) | (24.37) | (26.03) | (16.98) | (13.13) | (17.85) | (10.80) | (13.23) | (17.68) | (10.54) |
| university | 3.711*** | 5.635*** | 11.39*** | 4.075*** | 5.831*** | 13.34*** | 3.634*** | 5.523*** | 10.03*** | 3.746*** | 5.536*** | 10.43*** |
| | (63.18) | (37.86) | (30.77) | (62.70) | (37.08) | (29.37) | (36.39) | (26.34) | (20.59) | (36.45) | (26.07) | (20.34) |
| **Employment Status:** | | | | | | | | | | | | |
| part-time | 0.811*** | 0.802*** | 0.876*** | 0.792*** | 0.750*** | 0.851*** | 0.834*** | 0.793*** | 0.968 | 0.828*** | 0.788*** | 0.967 |
| | (-14.62) | (-9.25) | (-3.49) | (-14.59) | (-10.96) | (-3.90) | (-7.08) | (-6.60) | (-0.58) | (-7.11) | (-6.59) | (-0.58) |
| public | 0.736*** | 0.743*** | 0.582*** | 0.739*** | 0.758*** | 0.572*** | 0.693*** | 0.697*** | 0.531*** | 0.704*** | 0.683*** | 0.533*** |
| | (-14.52) | (-8.92) | (-9.15) | (-12.43) | (-7.55) | (-8.19) | (-9.28) | (-7.07) | (-6.48) | (-8.61) | (-7.15) | (-6.20) |
| unemployed | 4.118*** | 3.084*** | 3.699*** | 4.286*** | 3.167*** | 3.807*** | 4.052*** | 2.951*** | 3.874*** | 4.078*** | 2.992*** | 3.929*** |
| | (103.88) | (50.50) | (39.40) | (97.29) | (48.45) | (37.00) | (57.42) | (32.19) | (26.90) | (56.03) | (31.94) | (26.51) |
| training | 1.694*** | 1.422*** | 1.813*** | 1.587*** | 1.379*** | 1.730*** | 1.683*** | 1.335*** | 1.648*** | 1.644*** | 1.299*** | 1.645*** |
| | (35.76) | (15.45) | (17.37) | (29.92) | (13.75) | (15.44) | (18.73) | (8.04) | (8.96) | (17.30) | (7.02) | (8.68) |
| **Experience:** | | | | | | | | | | | | |
| experience | 1.014*** | 1.026*** | 1.019*** | 1.008*** | 1.023*** | 1.014*** | 1.013*** | 1.026*** | 1.017*** | 1.011*** | 1.025*** | 1.016*** |
| | (24.79) | (35.20) | (15.45) | (14.39) | (30.39) | (11.01) | (12.89) | (23.77) | (9.24) | (11.18) | (22.84) | (8.23) |
| tenure | 0.779*** | 0.805*** | 0.741*** | 0.785*** | 0.810*** | 0.743*** | 0.784*** | 0.808*** | 0.749*** | 0.787*** | 0.809*** | 0.751*** |
| | (-120.11) | (-72.98) | (-55.21) | (-104.31) | (-65.69) | (-48.82) | (-63.70) | (-48.48) | (-33.42) | (-60.77) | (-46.78) | (-31.83) |
| **Gender:** | | | | | | | | | | | | |
| female | 1.069*** | 0.930*** | 0.857*** | 1.117*** | 0.995 | 0.925*** | 1.086*** | 0.941*** | 0.879*** | 1.092*** | 0.960** | 0.891*** |
| | (8.40) | (-5.89) | (-7.65) | (12.40) | (-0.37) | (-3.50) | (5.63) | (-3.25) | (-4.05) | (5.84) | (-2.13) | (-3.51) |
| N | 11391995 | | | 9968341 | | | 5247062 | | | 5017193 | | |
| *Pseudo R2* | 0.118 | | | 0.114 | | | 0.111 | | | 0.111 | | |

Notes: All specification show a multinomial logit regression model with dummies for year, age and initial region. The baseline category is non-migration. The urban-to-urban specification shows workers in initially urban regions that move to other urban regions, initially rural workers and movers to rural areas are excluded. If indicated, the sample is reduced to initially west German regions. Robust standard errors are computed. Exponentiated coefficients; $t$-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

category) to the different migrant types (permanent, return, and onward migrants) prior to their initial migration decision. Our preferred Specification (1) covers the complete sample of 96 German regions. In Specification (2) we then focus only on West-German regions, which we also observe prior to the German reunification. In the Specifications (3) and (4) we use a reduced and therefore less heterogeneous sample of 24 urban regions to repeat the exercise.

Throughout, we find that all migrant types are positively selected in terms of their pre-migration income. Apart from the overall effect we find that there are systematic differences among the different groups of migrants. Return migrants are less positively selected than comparable permanent or onward migrants. We interpret this differential selection into initial migration as indirect evidence in favour of planned return migration between regions that are not characterised by strong institutional differences.

Although not the focus of this study, it is noteworthy that our results from Table 2.2 are generally in line with previous findings in the regional migration literature (cf. Hunt, 2004; De la Roca, 2017). In particular, we find that higher educational attainment is positively related to the probability of migrating. The positive selection based on worker's observable skills thereby is more pronounced for return migrants than for permanent migrants, which suggests that there is a difference between the selection based on observable and unobservable skills, as captured by individual pre-migration wages.

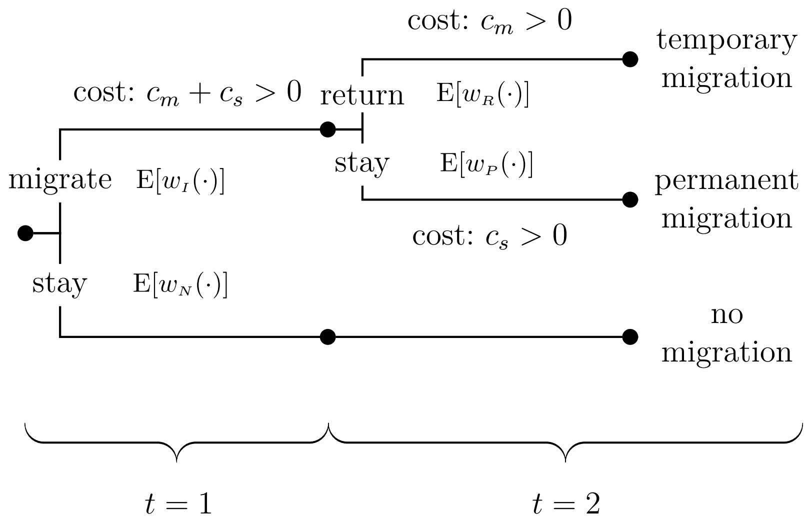
## 2.3 A Simple Model of Planned Return Migration

Having established empirical evidence in favour of planned return migration between similar regions, we now develop a simple model to rationalise this finding. We thereby proceed as follows: In Subsection 2.3.1 we lay out workers' inter-temporal migration decision. Subsection 2.3.2 then describes the hiring process and determines the wages on which workers base their migration decisions. Finally, in Subsection 2.3.3 we jointly derive the selection of workers into initial and return migration.

### 2.3.1 Return Migration Decision

We illustrate individual migration decisions in Figure 2.3. Workers are forward

Figure 2.3: Migration and Return Decisions




looking and base their migration decisions on the expected wages $\mathrm{E}[w_i(\cdot)]$ that they anticipate to earn in response to their mobility choice. Confronted with one-time moving costs $c_m \geq 0$ as well as periodical staying cost $c_s \geq 0$ workers in period one can decide whether to migrate or to stay. Those workers, who initially migrated, then can decide in period two whether to return or to stay permanently. As a consequence, we can distinguish between four different types of workers, to which we refer as non-migrants (indexed by subscript $i = N$), initial migrants (indexed by subscript $i = I$), return migrants (indexed by subscripts $i = R$), and permanent migrants (indexed by subscript $i = P$).

### 2.3.2 Hiring and Wage Setting

We focus on two symmetric regions, each producing a non-storable, homogeneous *numéraire* good, that can be costlessly traded at a normalised price $p \stackrel{!}{=} 1$.[10] Both regions are populated by two overlapping generations of risk-neutral workers, whose privately known skills $s$ are uniformly distributed over the unit interval $s \in [0, 1]$. The production of the homogeneous *numéraire* good is modelled through an "O-ring" production technology (cf. Kremer, 1993), which requires the processing of two tasks $l = 1, 2$, each to be performed by a single worker.[11] Firm-level output then follows as:

$$y = f(s_1, s_2) = 2As_1s_2, \tag{1}$$

with $A > 0$ being a technology parameter and $s_l$ denoting the skill level of the worker performing task $l = 1, 2$. Crucially, we have $\partial f(s_1, s_2)/\partial s_l > 0$ and $\partial^2 f(s_1, s_2)/\partial s_l \partial s_\ell > 0 \ \forall \ l, \ell = 1, 2$ with $l \neq \ell$, such that the technology in Eq. (1) is supermodular and workers enter production as complements (see also Milgrom and Roberts (1990) and Topkis (1998)).

Firms can not observe workers' skills, which are private information. Yet, in an equilibrium, that features some form of migration as described in Figure 2.3, firms can easily identify individual workers according to their (observable) type $i \in \{N, I, R, P\}$. This is the only information firms can base their hiring decision on, and this information is valuable since, as we show below, the average skills within these four sub-groups of workers are different. Taking into account these differences, firms maximise their expected profits by choosing the optimal skill mix of

[10]Given that regions are symmetric, region-specific indices are dropped in order to save on notation.

[11]For anecdotal evidence on the general importance of complementaries in team production see Kremer (1993), who also discusses the eponymous example of a single malfunctioning O-ring causing the 1986 Challenger shuttle disaster. Theoretical applications of Kremer's (1993) O-ring theory include Dalmazzo (2002), Pekkarinen (2002), Fabel (2004), Dalmazzo, Pekkarinen, and Scaramozzino (2007), Jones (2011) as well as Kreickemeier and Wrona (2017).

their employees:

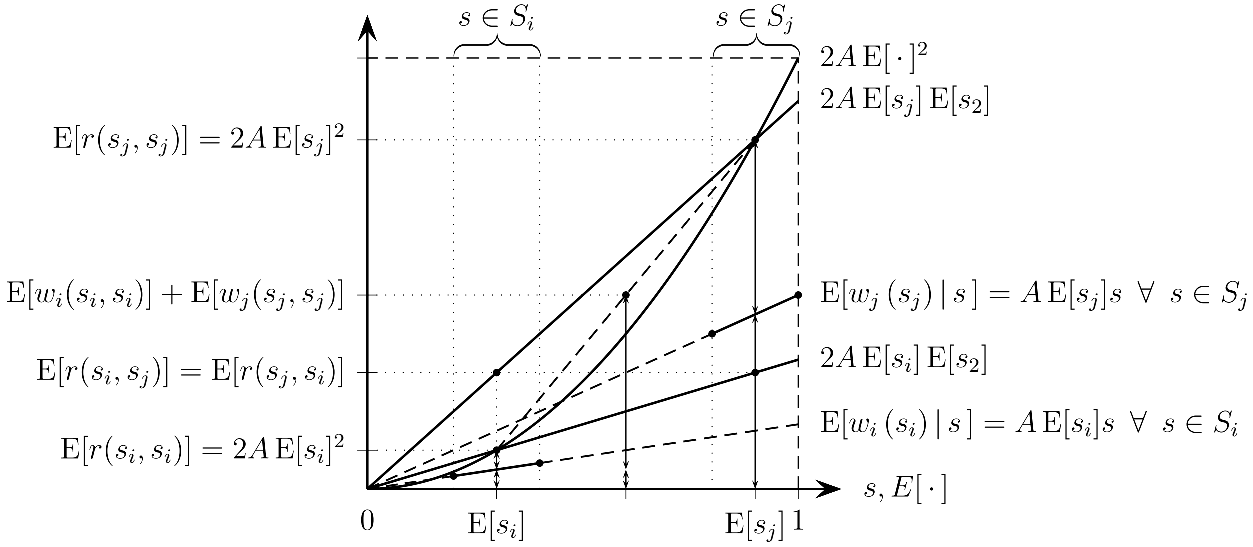
$$\max_{s_1, s_2} \; \mathrm{E}[\pi\,(s_1, s_2)] = 2A\,\mathrm{E}[s_1]\,\mathrm{E}[s_2] - \mathrm{E}[w_1\,(s_1, s_2)] - \mathrm{E}[w_2\,(s_1, s_2)], \qquad (2)$$

with $\mathrm{E}[s_l]$, $l = 1, 2$ referring to the expected skill of the group from which the worker performing task $l$ is recruited, and $\mathrm{E}[w_l(s_l, s_\ell)]$ $\forall$ $l, \ell = 1, 2$ with $l \neq \ell$ being the wage that in expectation has to be paid to this worker.

To rationalise the firm's profit-maximising choice of co-hiring only workers, which in expectation have the same skill, consider the following proof by contradiction. Firms have two basic options of hiring workers: They either hire only workers of the same type, which in expectation have the same skill (i.e. $\mathrm{E}[s_l] = \mathrm{E}[s_i]$ $\forall$ $l = 1, 2$), or they co-hire workers of different types, who differ in terms of their expected skills (i.e. $\mathrm{E}[s_l] = \mathrm{E}[s_i]$ and $\mathrm{E}[s_\ell] = \mathrm{E}[s_j]$ with $l \neq \ell$ and $i \neq j$). In the following it is established that firms, which practice cross-hiring, are outcompeted under perfect competition and free market entry.

Figure 2.4 illustrates a firm's hiring decision for two arbitrary chosen sub-sets of workers ($S_i$ and $S_j$). Suppose firms hires only workers with the same expected skill

Figure 2.4: Hiring Strategies and Wage Formation




(i.e. $\mathrm{E}[s_i]$ or $\mathrm{E}[s_j]$). Expected revenues are then given by the simple quadratic expressions $2A\,\mathrm{E}[s_i]^2$ and $2A\,\mathrm{E}[s_j]^2$, whose values can be read off from the ordinate of Figure 2.4. Wages can not be set according to individual skill, which is private information. We therefore assume that in a zero-profit equilibrium with free market entry each worker is paid exactly half of the firm's revenue, which leads to $\mathrm{E}[r(s_i, s_i)] = 2\,\mathrm{E}[w_i(s_i, s_i)]$ and $\mathrm{E}[r(s_j, s_j)] = 2\,\mathrm{E}[w_j(s_j, s_j)]$ (expected wages payments to each worker are illustrated in Figure 2.4 through the length of the equally sized arrows summing up to $\mathrm{E}[r(s_i, s_i)]$ and $\mathrm{E}[r(s_j, s_j)]$, respectively). Now suppose firms hire workers, who differ in terms of their skills. If the first task is performed by a worker with expected skill $\mathrm{E}[s_i]$, the firm's expected revenue can be expressed as a linear function with slope $2A\,\mathrm{E}[s_i]$, which is increasing in the expected skill $\mathrm{E}[s_2]$ of the worker that is chosen to perform the second task. Evaluating this function at $\mathrm{E}[s_2] = \mathrm{E}[s_j]$ yields $\mathrm{E}[r(s_i, s_j)] = \mathrm{E}[r(s_j, s_i)] = 2A\,\mathrm{E}[s_i]\,\mathrm{E}[s_j]$ as illustrated in Figure 2.4. Finally, to establish that firms, who cross-hire workers from different groups, expect to make losses we acknowledge that in a competitive labour market cross-hiring firms have to offer (at least) $\mathrm{E}[w_i(s_i, s_i)]$ and $\mathrm{E}[w_j(s_j, s_j)]$, summing up to an expected wage bill of $\mathrm{E}[w_i(s_i, s_i)] + \mathrm{E}[w_j(s_j, s_j)]$. As illustrated in Figure 2.4, this expected wage bill can be computed as a simple linear combination:

$$\mathrm{E}[w_i(s_i, s_i)] + \mathrm{E}[w_j(s_j, s_j)] = \tfrac{1}{2}\,\{\mathrm{E}[r(s_i, s_i)] + \mathrm{E}[r(s_j, s_j)]\} = A\,\mathrm{E}[s_i]^2 + A\,\mathrm{E}[s_i]^2,$$

given that $\mathrm{E}[w_i(s_i, s_i)] = \frac{1}{2}\,\mathrm{E}[r(s_i, s_i)] = A\,\mathrm{E}[s_i]^2$ and $\mathrm{E}[w_j(s_j, s_j)] = \frac{1}{2}\,\mathrm{E}[r(s_j, s_j)] = A\,\mathrm{E}[s_i]^2$. Since it is now easily demonstrated that the expected profits of a cross-hiring firm are negative, i.e. $\mathrm{E}[\pi(s_i, s_j)] = \mathrm{E}[r(s_i, s_j)] - \mathrm{E}[w_i(s_i, s_i)] - \mathrm{E}[w_j(s_j, s_j)] = -2A(\mathrm{E}[s_i] - \mathrm{E}[s_j])^2 < 0$ (see also Figure 2.4), we can conclude that workers, who differ in terms of their expected skills, should never be co-hired.

To understand why cross-hiring is a suboptimal strategy we first consider the natural benchmark in which workers' skills are perfectly observable. As demonstrated by Kremer (1993) profits under perfect information are maximised through positive assortative matching, which we illustrate by means of the following simple example: Suppose workers' skills are equally likely to take values of $s = 0$ and $s = 1$. Under random matching there are four equally likely pairings: $(0, 0)$, $(0, 1)$, $(1, 0)$, and $(1, 1)$. Obviously, the parings $(0, 1)$ and $(1, 0)$ are highly inefficient. Unskilled co-workers with $s = 0$ create a bottleneck, which completely invalidates the otherwise valuable input of the skilled workers. As a consequence firm-level production is zero in three out of four instances, which results in an expected revenue of just one fourth. Under positive assortative matching the only remaining pairings are $(0, 0)$ and $(1, 1)$. Firms, that solely hire skilled workers thereby create a revenue of one, and therefore can always afford to outcompete cross-hiring firms by paying higher wages. Now, if skills are private information, firms are forced to match their workers randomly, resulting in an efficiency loss as highlighted above. Any information that correlates with workers' skill therefore is highly valuable as it can be used to refine firms' hiring strategy towards the optimal positive assortative matching. By classifying workers into informative sub-groups, which differ in terms of their expected skill, firms can reduce the likelihood of an inefficient missmatch relative to the first-best hiring strategy of positive assortative matching by combining only workers which in expectation have the same skill.

Given the deliberately simple hiring rule of combining only workers with identical expected skills, we can now turn to the expectations that workers have with regard to their own wages. Consider a worker from group $i$ with skill $s \in S_i$, which is privately known by the worker. Anticipating a co-worker with expected skill $\mathrm{E}[s_i]$ this worker expects to earn a wage:

$$\mathrm{E}[w_i\,(s_i)\,|\,s_i] = A\,\mathrm{E}[s_i]s \;\;\forall\;\; s \in S_i \;\text{ with }\; i \in \{N, I, R, P\}, \tag{3}$$

conditional on knowing his own skill $s$. Given the worker's skill $s$ the expected wage is linearly increasing in group $i$'s expected skill level $\mathrm{E}[s_i]$ (see also Figure 2.4). With this simple notion of workers' wages at hand, the (return) migration decision of a forward-looking worker can now be solved through backward induction following the structure that has been imposed in Figure 2.3.

### 2.3.3 Selection into Return Migration

Following the recursive structure of Figure 2.3 we focus at workers' return decision in period two (implicitly assuming that these workers migrated in period one). We define the expected wage gain that workers give up when returning home in period two as:

$$\Delta_2^w\,(s) \equiv \mathrm{E}[w_P\,(s_P)\,|\,s\,] - \mathrm{E}[w_R\,(s_R)\,|\,s\,]. \tag{4}$$

Thereby, $\mathrm{E}[w_P\,(s_P)\,|\,s\,]$ and $\mathrm{E}[w_R\,(s_R)\,|\,s\,]$ denote the wage that workers (conditional on their skill $s$) expect to earn as permanent and return migrants, respectively. In order to replicate the negative self-selection of workers into return migration, that we have documented in Section 2.2.3, we assume that the periodical cost of staying away from home $c_s$ exceed the one-time moving cost $c_m$, which can be further simplified into $c_s > c > c_m = 0$.

Focussing on positively selected initial migrants, whose skill $s$ lies above the initial migration cutoff $\tilde{s}_m$, we can determine the return cutoff $\tilde{s}_r$, that separates the less skilled return migrants (indexed by subscript $R$) from the relatively more skilled permanent migrants (indexed by subscript $P$). The expected skills of both subgroups thereby follow immediately from the assumed uniform distribution and equal $\mathrm{E}[s_P] = E[\, s \,|\, s \geq \tilde{s}_r] = (\tilde{s}_r + 1)/2 > \mathrm{E}[s_R] = E[\, s \,|\, \tilde{s}_m > s \geq \tilde{s}_m] = (\tilde{s}_m + \tilde{s}_r)/2$. We can now substitute $\mathrm{E}[s_P]$ and $\mathrm{E}[s_R]$ into the expected wage rate from Eq. (3), which in return can be used to replace $\mathrm{E}[w_P\,(s_P) \,|\, s\,]$ and $\mathrm{E}[w_R\,(s_R) \,|\, s\,]$ in Eq. (4). The expected wage gain from permanent migration then equals $\Delta_2^w\,(s) = A(1-\tilde{s}_m)s/2$, which is increasing in individual skill $s$, such that incentives for staying (returning) are highest for those migrants with comparatively high (low) skills. The indifferent return migrant:

$$\tilde{s}_r\,(\tilde{s}_m) = \frac{2\hat{c}}{1-\tilde{s}_m} \tag{5}$$

can therefore be found by equating the wage gain from permanent migration with the corresponding costs, i.e. $\Delta_2^w\,(\tilde{s}_r) \overset{!}{=} c$. Of course permanent migration is more pronounced if the associated costs $\hat{c} \equiv c/A$ are low. However, due to the recursive structure of the migration decision (cf. Figure 2.3) these costs must be weighted by the potential for permanent migration, i.e. the mass of workers $1-\tilde{s}_m$, who decided to migrate in the first period.

To understand the negative selection into return migration it is helpful to revisit the formulation of workers' wages in Eq. (3). As firms prefer to match workers with the same expected skill, there is a monetary benefit from being associated with a group of high-skilled rather than low-skilled co-workers. However, the expected wage gain $\Delta_2^w\,(s)$ from being paired with on average more high-skilled co-workers is non-constant and increases linearly in the respective worker's own skill $s$. Hence, if a worker's status as permanent migrant is both costly and easy to verify, only workers with sufficiently high skills will use permanent migration as an (imperfect) signal to indicate their comparatively high but otherwise unobservable skills. Firms take into account individual migration histories as an easy-to-verify signal, and form more efficient and better-paid matches, which provide workers with an incentive to signal their skills in the first place.

Having established and explained the negative selection into return migration (conditional on positive selection into initial migration), we now complete our model by turning to workers' initial migration decision in period one. Anticipating their later return decision in period two, workers distinguish three possible migration patterns, to which we refer as:

$$
\begin{aligned}
&(a)\ \ 0 < \tilde{s}_m < \tilde{s}_r < 1 \ \ \Rightarrow\ \ \textit{temporary and permanent migration},\\
&(b)\ \ 0 < \tilde{s}_m < \tilde{s}_r = 1 \ \ \Rightarrow\ \ \textit{temporary migration only},\\
&(c)\ \ 0 = \tilde{s}_m = \tilde{s}_r < 1 \ \ \Rightarrow\ \ \textit{no migration}.
\end{aligned}
$$

According to pattern $(a)$ only the best workers with skills $s \in [\tilde{s}_r, 1]$ stay for another period at cost $c > 0$. Workers with lower skills $s \in [\tilde{s}_m, \tilde{s}_r)$ return home in period two. Pattern $(b)$ with $\tilde{s}_r = 1$ implies that everybody, who migrated in period one, returns home in period two. Finally, there also is the trivial pattern $(c)$ with no migration taking place at all.[12]

Knowing that the least skilled initial migrant $\tilde{s}_m$ will never migrate permanently, we derive the expected lifetime wage gain from temporary migration in period one as:

$$\Delta_1^w(s) \equiv \mathrm{E}[w_I(s_I) \,|\, s] + \mathrm{E}[w_R(s_R) \,|\, s] - 2\,\mathrm{E}[w_N(s_N) \,|\, s]. \tag{6}$$

Intuitively, $\Delta_1^w(s)$ depends negatively on the opportunity cost of migrating, which materialise in form of the forfeit income stream $2\,\mathrm{E}[w_N(s_N) \,|\, s]$, that would result from employment as a non-migrant (indexed by subscript $N$) in period one and two. On the plus side, there are the expected wage gains $\mathrm{E}[w_I(s_I) \,|\, s]$ of temporary migrating in period one in addition to $\mathrm{E}[w_R(s_R) \,|\, s]$, which is what the initial migrants expect to earn as returnees in period two. If pattern $(a)$ with $0 < \tilde{s}_m < \tilde{s}_r < 1$ applies, only the best workers with $s \in [\tilde{s}_r, 1]$ stay permanently, while the remaining workers $s \in [\tilde{s}_m, \tilde{s}_r)$, and in particular the indifferent migrant $\tilde{s}_m$, return home to get employed at an expected wage $\mathrm{E}[w_R(s_R) \,|\, s]$. However, if pattern $(b)$ applies, everybody including the indifferent migrant returns home and earns an expected wage rate of $\mathrm{E}[w_P(s_P) \,|\, s]$. Accounting for this difference, we can compute the expected skills of all sub-groups $i \in \{N, I, R, P\}$ as:

$$
\begin{aligned}
&\mathrm{E}[s_P] = (\tilde{s}_r + 1)/2 > \mathrm{E}[s_I] = (\tilde{s}_m + 1)/2 > \mathrm{E}[s_R] = (\tilde{s}_m + \tilde{s}_r)/2 > \mathrm{E}[s_N] = \tilde{s}_m/2 \ \text{ if } (a),\\
&\mathrm{E}[s_I] = \mathrm{E}[s_R] = (\tilde{s}_m + 1)/2 > \mathrm{E}[s_N] = \tilde{s}_m/2 \ \text{ if } (b).
\end{aligned} \tag{7}
$$

[12] In a Technical Supplement, which is available from the authors upon request, we show that an equilibrium with $\tilde{s}_m = \tilde{s}_r$, in which the migration and the return cut-off are the same, does not exist. In such an equilibrium, all workers, who migrated in period one, would stay in period two, which can not be optimal for the initially indifferent migrant $\tilde{s}_m$ as long as costs $c$ are non-decreasing in the duration of staying away from home.

We then substitute the expected skills $\mathrm{E}[s_i]$ from Eq. (7) into the expected wage rates $\mathrm{E}[w_i(s_i) \mid s_i]$ from Eq. (3), which in return can be used to solve the expected lifetime wage gain from temporary migration in Eq. (6) as:

$$\Delta_1^w(s) = \begin{cases} A(1+\tilde{s}_r)\, s/2 & \text{for } (a), \\ As & \text{for } (b). \end{cases} \tag{8}$$

The lifetime wage gain from temporary migration is strictly increasing in the migrant's skill $s$. Provided that there is a negative selection into return migration (i.e. pattern $(a)$ applies), $\Delta_1^w(s)$ also increases in the return cutoff $\tilde{s}_r$. Intuitively, workers are forward looking, and therefore anticipate their later return decision (reflected by the return cut off $\tilde{s}_r$) when forming their initial migration decision. A higher return cut-off $\tilde{s}_r$ increases the expected skills $\mathrm{E}[s_R] = \mathrm{E}[\, s \mid \tilde{s}_m \leq s < \tilde{s}_r] = (\tilde{s}_m + \tilde{s}_r)/2$ within the groups of returnees, which makes temporary migration – *ceteris paribus* – more attractive.

We can use the previously derived return cutoff from Eq. (5) in order to endogenise $\tilde{s}_r$ in Eq. (8). The migration cutoffs:

$$\tilde{s}_m(\hat{c}) = \begin{cases} \dfrac{1+4\hat{c}-\sqrt{1+16\hat{c}^2}}{2} & \text{for} \quad 0 \leq \hat{c} < \dfrac{1}{3} \\ \hat{c} & \text{for} \quad \dfrac{1}{3} \leq \hat{c} < 1, \end{cases} \tag{9}$$

and

$$\tilde{s}_r(\hat{c}) = \begin{cases} \dfrac{4\hat{c}}{1-4\hat{c}+\sqrt{1+16\hat{c}^2}} & \text{for} \quad 0 \leq \hat{c} < \dfrac{1}{3}, \\ 1 & \text{for} \quad \dfrac{1}{3} \leq \hat{c} < 1, \end{cases} \tag{10}$$

can then be solved by equating the expected lifetime income from temporary migration with the associated costs $\Delta_1^w(\tilde{s}_m) \stackrel{!}{=} c$ before substituting the solution for $\tilde{s}_m$ back into $\tilde{s}_r$ from Eq. (5).

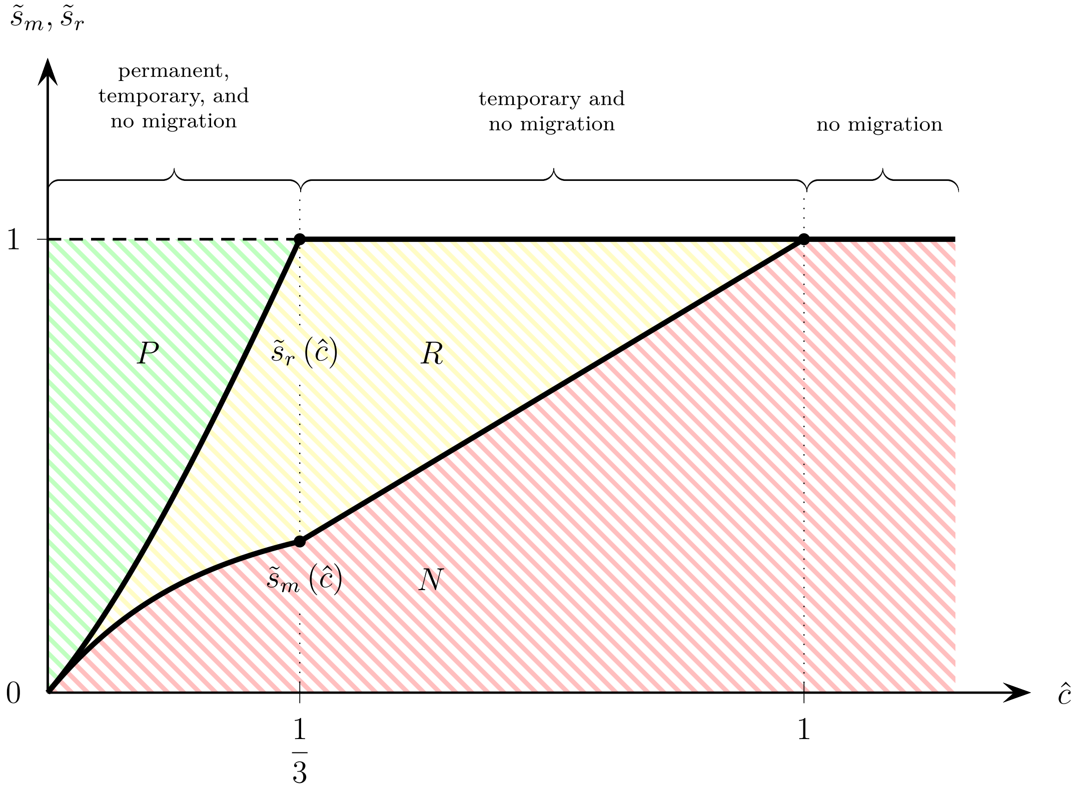
Proposition 1 summarises our selection results, which we illustrate in Figure 2.5:

**Proposition 1.** *For sufficiently low but non-zero cost $\hat{c} \in (0, 1/3)$ high-skilled workers with $s \in [\tilde{s}_r, 1]$ migrate permanently, medium-skilled workers with $s \in [\tilde{s}_m, \tilde{s}_r)$ migrate temporary, and low-skilled workers $s \in [0, \tilde{s}_m)$ do not migrate at all.*

*Proof.* Analysis and formal discussion in the text. □

The positive selection into initial migration as well as the negative selection into

Figure 2.5: Selection into Temporary and Permanent Migration




return migration both follow from the same intuition: costly stays away from home can be used to signal workers' high but otherwise unobservable skills. High-skilled workers with $s \in [\tilde{s}_m, 1]$ thereby use migration in period one as a signal to achieve a separation from their low-skilled counterparts with skills $s \in [0, \tilde{s}_m)$. In the second period medium-skilled workers with skill $s \in [\tilde{s}_m, \tilde{s}_r)$ return home, while the most high-skilled workers with skills $s \in [\tilde{s}_r, 1]$ stay for a second and final period to generate yet again a signal which allows future employers to tell apart the most high-skilled permanent migrants, which can afford to bear the signalling cost $c > 0$ twice, from the medium-skilled returnees, which prefer the weaker signal associated with bearing the cost $c > 0$ only once.

Reassuringly, we find the selection pattern from Proposition 1, that we have illustrated in Figure 2.5, to be well in line with our empirical evidence from Section 2.2. As our model of planned return migration predicts, there is an *ex ante* negative selection into temporary migration. Notably, this result is derived in the absence of any systematic differences between regions. As consequences, initial and later return migration flows are expected to be perfectly balanced between both regions.

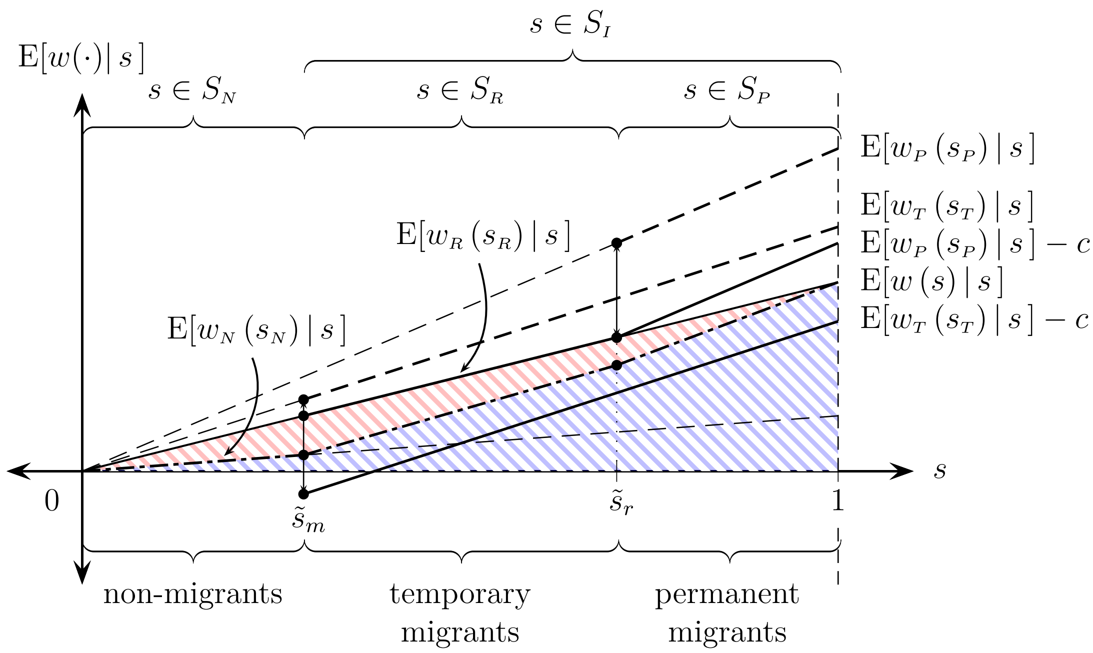
## 2.4 Welfare Implications and Optimal Policy

To characterise the model's wage and welfare results we proceed in three steps: Focussing on an equilibrium with negative selection into return migration, we demonstrate in Subsection 2.4.1 that there is an expected welfare loss relative to an equilibrium without migration. In Subsection 2.4.2 we then introduce an omniscient social planner to show that the laissez faire equilibrium is characterised by sub-optimally high levels of temporary and permanent migration. We conclude by deriving socially optimal migration policies mixes in Subsection 2.4.3.

### 2.4.1 Wages and Welfare

To characterise the individual wage and welfare effects across all four sub-groups $i \in \{N, I, R, P\}$, we focus again on the parameter range $\hat{c} \in (0, 1/3)$ for which the empirically relevant migration pattern $(a)$ with negative selection into return migration applies. Figure 2.6 depicts the expected wage profiles for all four sub-groups (dashed lines), which we compare to the expected wage profile $\mathrm{E}[w(s)|\, s\,] = As/2$ in an equilibrium without any migration (solid line). From the ranking of

Figure 2.6: Individual Wage and Welfare Effects




expected skills in Eq. (7) we can infer that temporary and permanent migrants

are both positively selected with respect to the overall population (i.e. $\mathrm{E}[s_P] > \mathrm{E}[s_I] > \mathrm{E}[\,s\,] = 1/2$), while the sub-group of non-migrants is negatively selected (i.e. $\mathrm{E}[s_N] < \mathrm{E}[\,s\,] = 1/2$). Temporary and permanent migrants therefore have steeper expected wage profiles, which means that both sub-groups enjoy higher wages than in an equilibrium without migration. The sub-group of non-migrants, which has lost its most high-skilled members through migration, is on average less skilled than in an equilibrium without migration, and therefore earns lower wages than in an equilibrium without migration. Since the sub-group of returnees is truncated from below (non-migrants) and above (permanent migrants), there is no clear ranking of the sub-group's expected skill $\mathrm{E}[s_R]$ relative to the expected skill $\mathrm{E}[\,s\,]$ in an equilibrium without migration. In Figure 2.6 we therefore focus on the knife-edge case $\mathrm{E}[s_R] = \mathrm{E}[\,s\,]$, which results under parameter constraint $\hat{c} = 1/4$, separating the the low cost scenario $\hat{c} < 1/4$ with negative selection (i.e. $\mathrm{E}[w_R(s_R)|\,s\,] < \mathrm{E}[w(s)|\,s\,]$) from the high cost scenario $\hat{c} > 1/4$ with positive selection (i.e. $\mathrm{E}[w_R(s_R)|\,s\,] > \mathrm{E}[w(s)|\,s\,]$).
To judge the impact of (return) migration on individual welfare we have to compute workers' expected lifetime income net of the periodical staying costs $c > 0$ (if applicable). The periodical net incomes of initial and permanent migrants in Figure 2.6 are depicted as parallelly downward shifted solid lines, which are drawn below the migrants' expected gross incomes $\mathrm{E}[w_I\,(s_I)\,|\,s\,]$ and $\mathrm{E}[w_P\,(s_P)\,|\,s\,]$, respectively. By averaging across both periods, we obtain workers' expected lifetime welfare, which we depict as dot-dashed line in Figure 2.6. Once the periodical costs of staying away from home are taken into account, we find that not only the non-migrants but also the temporary and the permanent migrants are worse off than in an equilibrium without migration. Proposition 2 generalises this surprising result beyond the illustrative knife-edge case ($\hat{c} = 1/4$), which we have covered in Figure 2.6.

**Proposition 2.** *Workers' expected lifetime welfare in an equilibrium with temporary and permanent migration is weakly lower than in an equilibrium without migration.*

*Proof.* See Appendix A.1 □.

While it is rather obvious that non-migrants suffer from the deterioration in the expected skill of their co-workers, it is less clear why the income-maximising temporary and permanent migrants turn out to be worse off than in an equilibrium without migration. To rationalise this puzzling result it is helpful to recall yet again the formulation of workers' wages in Eq. (3), which positively depend on the expected skill of the respective co-workers $E[s_i]$. The wages of all infra-marginal migrants thus depend on the critical migrant's mobility choice: By entering the group of infra-marginal migrants from below (i.e. with the lowest skill) the marginal migrant drags down the average skill within this group, thereby inflicting wage losses on all infra-marginal migrants. The critical worker rationally ignores this negative external effect on infra-marginal migrants, which results in suboptimally high levels of temporary and permanent migration (see also Subsection 2.4.2) and an expected welfare loss for (almost) all infra-marginal migrants.[13]

As an immediate implication of Proposition 2, according to which workers' expected welfare in a migration equilibrium is (weakly) lower than in an equilibrium without migration, it follows that regions expect aggregate welfare to be smaller than in an equilibrium without migration. To obtain expected welfare at the regional level, we compute at first expected output, which in a zero-profit equilibrium is defined as the sum of workers' expected wages:

$$\mathrm{E}[\,Y\,] = \int\limits_{s\,\in\,S_N} 2\,\mathrm{E}[w_{\scriptscriptstyle N}\,(s_{\scriptscriptstyle N})\,|\,s\,]\,ds + \sum_i \int\limits_{s\,\in\,S_i} \mathrm{E}[w_i\,(s_i)\,|\,s\,]\,ds, \ \ \forall\ i \in \{I, R, P\}. \quad (11)$$

Using the definitions of $\mathrm{E}[w_i\,(s_i)\,|\,s\,]$ and $\mathrm{E}[s_i]$ from Eqs. (3) and (7) in combination with the migration and return cutoffs $\tilde{s}_m$ and $\tilde{s}_r$ from Eqs. (9) and (10) allows us to solve for:

$$\mathrm{E}[Y^{\mathrm{lf}}] = \begin{cases} \dfrac{A}{2} + A\,(1-2\hat{c})\,\hat{c} & \text{for} \quad 0 \le \hat{c} < \dfrac{1}{3}, \\ \dfrac{A}{2} + A\,(1-\hat{c})\,\hat{c} & \text{for} \quad \dfrac{1}{3} \le \hat{c} < 1 \end{cases} \quad (12)$$

where the superscript "lf" has been introduced to distinguish the *laissez faire* equilibrium from the social planner solution (indexed by superscript "sp"), which we will explore in more detail below. Clearly, expected regional output in any migration equilibrium is higher than $A/2$, which is the level of regional output that is expected in an equilibrium without migration. Regional output gains arise because firms use the information on workers' migration history to form more efficient worker matches within the various sub-groups $i \in \{N, I, R, P\}$. To compute expected welfare at the regional level the wasteful periodical staying costs $c > 0$ have to be subtracted from

[13]For the most high-skilled workers with $s = 1$ expected welfare in an equilibrium with and without migration is the same.

the value of expected regional output, which results in:

$$\mathrm{E}[\,W\,] = \mathrm{E}[\,Y\,] - (1 - \tilde{s}_m)c - (1 - \tilde{s}_r)c. \tag{13}$$

Substituting $\tilde{s}_m^{\mathrm{lf}}$ and $\tilde{s}_r^{\mathrm{lf}}$ from Eqs. (9) and (10) then allows us to solve for expected welfare at the regional level:

$$\mathrm{E}[\,W^{\mathrm{lf}}] = \begin{cases} \dfrac{A}{2} - A\,(1 - 2\hat{c})\,\hat{c} & \text{for} \quad 0 \leq \hat{c} < \dfrac{1}{3}, \\ \dfrac{A}{2} - A\,(1 - \hat{c})\,\hat{c} & \text{for} \quad \dfrac{1}{3} \leq \hat{c} < 1, \end{cases} \tag{14}$$

which proves the following Corollary to Proposition 2:

**Corollary 1.** *Expected welfare at the regional level in an equilibrium with temporary and permanent migration is lower than in an equilibrium without migration.*

*Proof.* Analysis and formal discussion in the text. □

Figure 2.6 depicts aggregate welfare in an equilibrium with temporary and permanent migration as the blue area summing up workers' expected income net of the periodical staying cost $c$ with loss in expected welfare relative to an equilibrium without migration being highlighted in red.

The expected welfare loss associated with temporary and permanent migration follows from a negative wage externality, which can be easily explained by means of a simple thought experiment: Suppose initial and permanent migration occur sequentially in decreasing order of migrants' skill. By deciding in favour of migration the respective critical workers inflict losses on all other workers. Non-migrants and return migrants loose because the expected skill within their sub-groups declines if the most high-skilled members of their sub-groups turn into initial or permanent migrants. At the same time, positively selected infra-marginal migrants suffer because the average skill within the sub-groups of initial and permanent migrants gets deteriorated through the entry of the relatively less skilled marginal migrants. The respective critical migrants rationally ignore these social costs, which results in excessive temporary and permanent migration in the *laissez faire* equilibrium. Thereby, the previously identified production gains, that arise from the more efficient matching of workers within their sub-groups, are more than offset by the wasteful migration costs $c > 0$, which are responsible for an expected welfare loss at the regional level.

### 2.4.2 Welfare Maximising Migration

To demonstrate that the *laissez faire* equilibrium features suboptimally high levels of temporary and permanent migration we employ an omniscient social planner, who is constrained through firms' matching technology but otherwise can freely choose the migration and return cutoffs $\tilde{s}_m$ and $\tilde{s}_r$. The social planner thereby ignores individual (return) migration incentives which link $\tilde{s}_m^{\text{lf}}$ and $\tilde{s}_r^{\text{lf}}$ to $\hat{c} > 0$ in the *laissez-faire* equilibrium and maximises instead aggregate welfare in Eq. (13). We summarise the social planner solution in Proposition 3, and depict the socially optimal migration and return cutoffs, $\tilde{s}_m^{\text{sp}}(\hat{c})$ and $\tilde{s}_r^{\text{sp}}(\hat{c})$ together with the implied level of aggregate welfare $W^{\text{sp}}(\hat{c})$ in Figure 2.7.

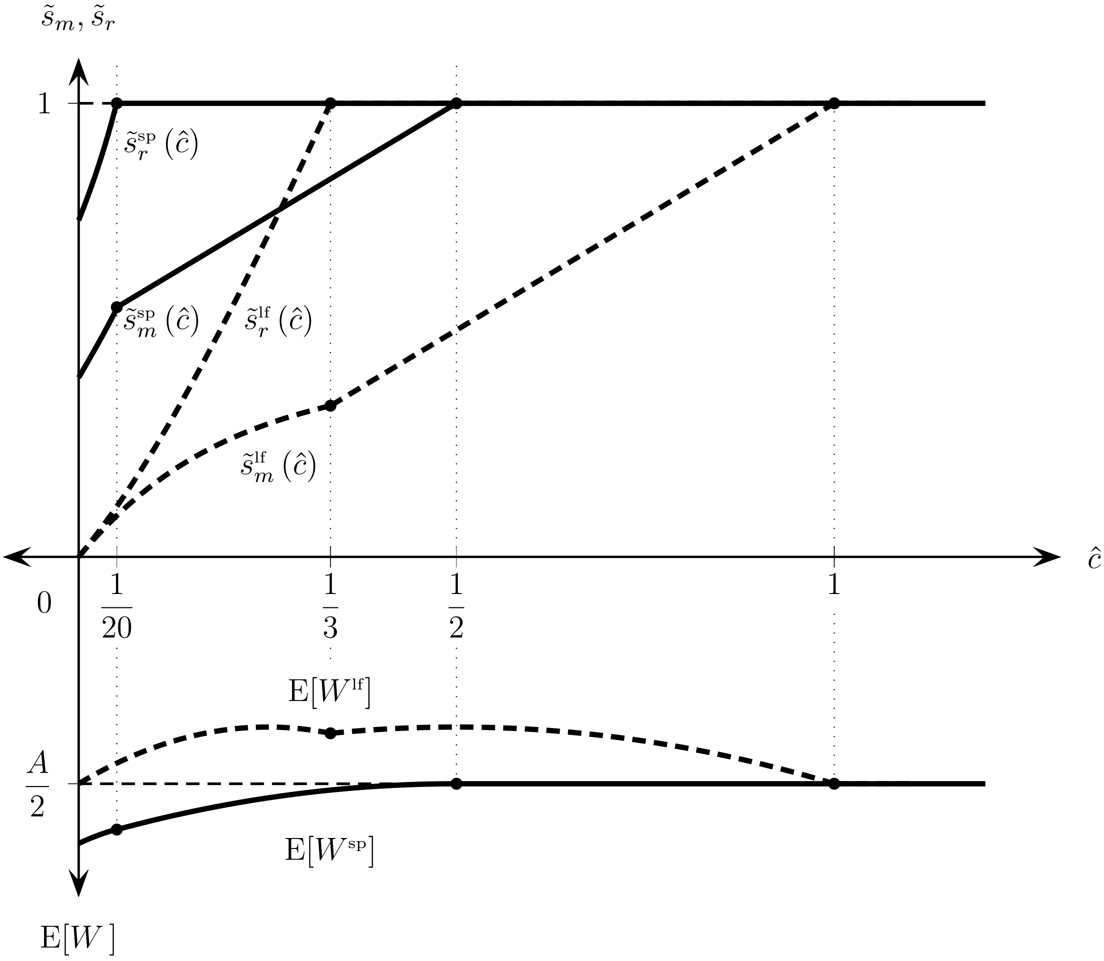
**Proposition 3.** *The laissez faire equilibrium features excessive temporary and permanent migration, which and is characterised by* $\tilde{s}_m^{lf}(\hat{c}) < \tilde{s}_m^{sp}(\hat{c})$ *and* $\tilde{s}_r^{lf}(\hat{c}) < \tilde{s}_r^{sp}(\hat{c})$*.*

*Proof.* See Appendix A.2. □

As evident from Figure 2.7 the socially optimal migration and return cutoffs $\tilde{s}_m^{\text{sp}}(\hat{c})$ and $\tilde{s}_r^{\text{sp}}(\hat{c})$ (solid curves) are strictly larger than their analogues $\tilde{s}_m^{\text{lf}}(\hat{c})$ and $\tilde{s}_r^{\text{lf}}(\hat{c})$ in the *laissez faire* equilibrium (dashed curves). The social planner thereby corrects for the presence of a negative external effect, that the marginal worker's migration decision has on the wages of all non-migrants as well as on the wage of all infra-marginal migrants. Interestingly, it is not in the social planner's interest to always enforces a zero-migration equilibrium. In particular at low costs $\hat{c}$ the aggregate production gains from improved matching exceed the social costs of (repeated) signalling. As a consequence migration pattern ($a$) with negative selection into return migration is implemented for sufficiently low costs $0 < \hat{c} \lesssim 1/20$, while the temporary-migration-only scenario ($b$) with $\tilde{s}_m^{\text{sp}}(\hat{c}) = \frac{1}{2} + \tilde{s}_m^{\text{lf}}(\hat{c})$ is chosen for high – but not prohibitively high – costs $1/20 \lesssim \hat{c} < 1/2$.[14] Intuitively, expected welfare $\mathrm{E}[W^{\text{sp}}]$ in the social planner solution increase in rising levels of temporary and permanent migration as the cost $c$ decline.

[14]Note that from the perspective of an omniscient social planner it is never optimal to implement an equilibrium that only features permanent migration, as the implied separation into a group of high-skilled permanent migrants and a group of low-skilled non-migrants could be more efficiently achieved in an equilibrium that features only temporary migration.

Figure 2.7: Social Planner Solution Versus Laissez Faire Equilibrium




### 2.4.3 Optimal Migration Policies

Is it possible to implement the social planner's solution from Proposition 3 through a carefully chosen migration policy, which separately targets temporary and permanent migrants? To this end we introduce the two policy variables $\tau_m$ and $\tau_r$, which shift the (periodical) costs $\hat{c}_1 = \hat{c} + \hat{\tau}_m$ and $\hat{c}_2 = \hat{c} + \hat{\tau}_r$ with $\hat{\tau}_k \equiv \tau_k / A \ \forall \ k = m, r$, assuming that all surpluses/deficits are redistributed in a lump-sum fashion. To replicate the social planner solution, $\tau_m$ and $\tau_r$ have to be chosen such that

$\tilde{s}_k^{\text{lf}}(\hat{c}_1, \hat{c}_2) = \tilde{s}_k^{\text{sp}}(\hat{c}) \ \forall \ k \in m, r$, where

$$\tilde{s}_m^{\text{lf}}(\hat{c}_1, \hat{c}_2) = \begin{cases} \dfrac{1 + 2\hat{c}_1 + 2\hat{c}_2 - \sqrt{(1 + 2\hat{c}_1 + 2\hat{c}_2)^2 - 8\hat{c}_2}}{2} & \text{for } (a) \quad 0 < \tilde{s}_m^{\text{lf}} < \tilde{s}_r^{\text{lf}} < 1, \\ \hat{c}_1 & \text{for } (b) \quad 0 < \tilde{s}_m^{\text{lf}} < \tilde{s}_r^{\text{lf}} = 1, \end{cases} \tag{9'}$$

and

$$\tilde{s}_r^{\text{lf}}(\hat{c}_1, \hat{c}_2) = \begin{cases} \dfrac{4\hat{c}_2}{1 - 2\hat{c}_1 - 2\hat{c}_2 + \sqrt{(1 + 2\hat{c}_1 + 2\hat{c}_2)^2 - 8\hat{c}_2}} & \text{for } (a) \quad 0 < \tilde{s}_m^{\text{lf}} < \tilde{s}_r^{\text{lf}} < 1, \\ 1 & \text{for } (b) \quad 0 < \tilde{s}_m^{\text{lf}} < \tilde{s}_r^{\text{lf}} = 1. \end{cases} \tag{10'}$$

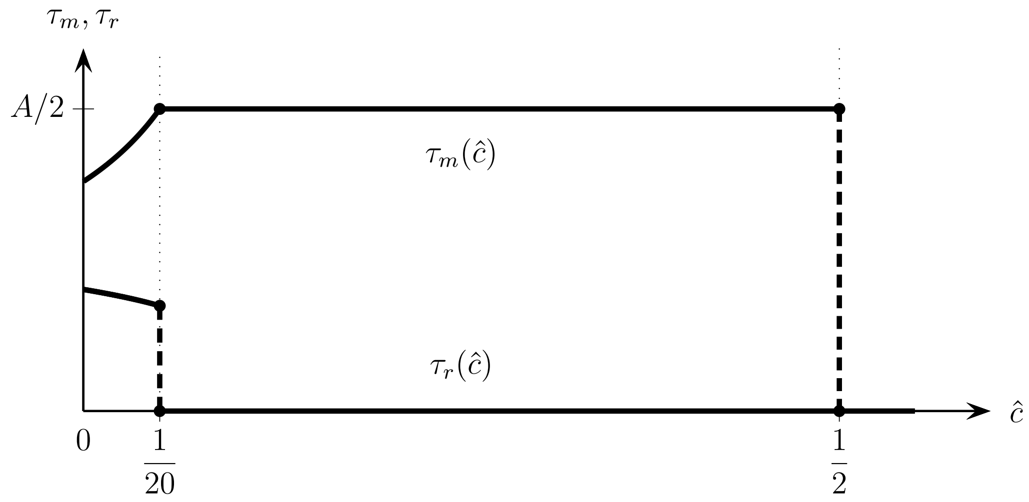
denote the generalised migration and return cutoffs for $c_1 \neq c_2$, which simplify to $\tilde{s}_m^{\text{lf}}(\hat{c})$ in Eq. (9) and $\tilde{s}_m^{\text{lf}}(\hat{c})$ in Eq. (10) for $c_1 = c_2$. We summarise the optimal migration policy in Proposition 4 and illustrate the socially optimal combination of $\tau_m$ and $\tau_r$ (satisfing $\tilde{s}_k^{\text{lf}}(\hat{c}_1, \hat{c}_2) = \tilde{s}_k^{\text{sp}}(\hat{c}) \ \forall \ k \in m, r$) in Figure 2.8.

**Proposition 4.** *The optimal migration policy reduces the number of temporary and permanent migrants by raising the costs of migration either through subsidies to non-migrants and returnees or through taxes on temporary and permanent migrants.*

*Proof.* Analysis and formal discussion in the text. □

For the empirically relevant scenario with negative selection into return migration the optimal policy mix of $\tau_m$ and $\tau_r$ in Figure 2.8 may be understood as arbitrary combinations of subsidies to non-migrants and returnees or taxes levied on temporary and permanent migrants. Thereby it is important to understand that two independent policy instruments are required to separately target the distinct mobility choices of initial and return migrants. Due to the interrelationship between workers' initial migration and initial migrants' later return decision in Eq. (5), each policy instrument simultaneously affects the sub-group of initial migrants and the sub-group of return migrants in their mobility choices. Subsidising only return migration could reduce the number of permanent migrants to the socially optimal level. However, at the same time it would become more attractive for temporary migrants to leave their home region in the first place, which is the reason why a return subsidy always must be complemented by an even stronger subsidy for non-migrants

Figure 2.8: Optimal Migration Policies



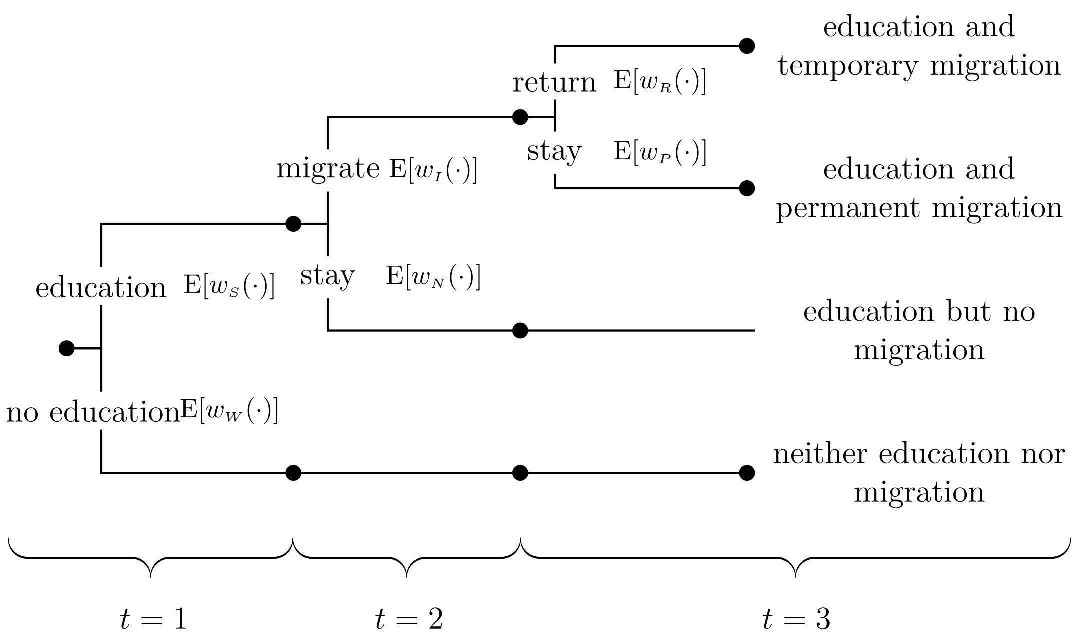

(as illustrated in Figure 2.8).[15]

[15]In a scenario, in which permanent migration (due to sufficiently high costs $c$) no longer is a viable option, a constant subsidy of $\tau_m(\hat{c}) = A/2 > 0$ for non-migrants is sufficient to restore optimality (cf. Kreickemeier and Wrona, 2017).

## 2.5 Alternative Signalling Devices

In this section we show that individuals continue to use temporary and permanent migration as a signal for their otherwise unobservable skills, even when an alternative signalling device (e.g. education as for example in Spence's (1973) seminal signalling model) is available. Adjusting the choice set from Figure 2.3 to allow individuals to first use an alternative signal before turning to temporary or permanent migration as signalling devices leads us to a three-stage decision problem as illustrated in Figure 2.9. In addition to the four migrant types $(N, I, R, P)$ from Subsection 2.3.1,

Figure 2.9: Education, migration and return decisions



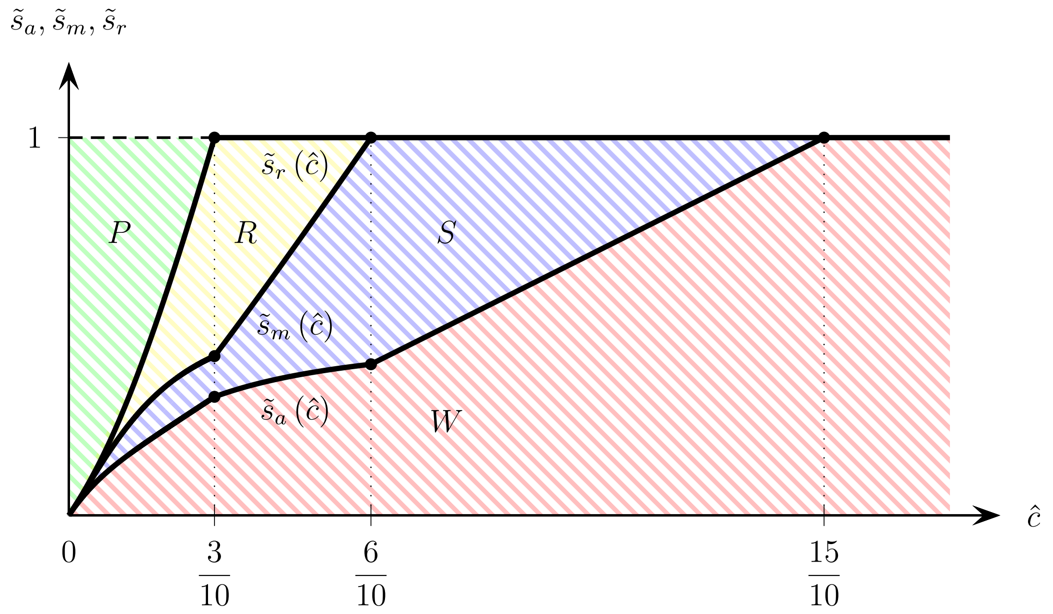

workers can also decide to invest into an alternative signal (indexed by subscript $i = S$) or to proceed without such a signal (indexed by subscript $i = W$). Those workers, who initially signalled then can decide to migrate in the second stage with the option to return in stage three. In order to simplify the analysis we assume the periodical signalling and staying costs to be the same $c > 0$.
Going through the same steps as in Section 2.3.3, we can derive Proposition 5, which summarises the selection results, that also we illustrate in Figure 2.10:

**Proposition 5.** *For sufficiently low but non-zero cost* $0 < \hat{c} \lessapprox 3/10$ *the most high-skilled workers with* $s \in [\tilde{s}_r, 1]$ *combine the alternative signal with permanent* *migration. Less skilled workers with $s \in [\tilde{s}_m, \tilde{s}_r)$ signal and migrate temporary, while workers with $s \in [\tilde{s}_a, \tilde{s}_m)$ invest only into the alternative signal. The least skilled workers with $s \in [0, \tilde{s}_a)$ neither signal nor migrate.*

*Proof.* Delegated to Appendix A.3. □

We illustrate the result from Proposition 5 in Figure 2.10, which depicts the cut-off skill level for the alternative signal $\tilde{s}_a$ (indexed by subscript $a$) and the migration cut-offs $\tilde{s}_m$ and $\tilde{s}_r$. We distinguish between permanent and return migrants by $P$ (in green) and $R$ (in yellow) as well as between workers that only use the alternative signal $S$ (in blue) and those workers, which neither signal nor migrate $W$ (in red).

Figure 2.10: Alternative Signalling Devices




While there is some crowding out of temporary and permanent migration if the cost of signalling are high (i.e. $\hat{c} > 6/10$), we generally find that the most high-skilled workers prefer to combine different signalling strategies to reveal as much as possible of their true but otherwise unobservable skills.

## 2.6 Conclusion

In this paper we have developed a theory of planned return migration between similar regions, in which the selection into initial and later return migration is derived from a straightforward signalling motive. Workers select strategically into costly temporary and permanent migration to generate a proper signal of their high but otherwise unobservable skills. By observing individual migration histories as an easy-to-verify signal firms can form more efficient production teams, which is reflected by an increase in total output.

Surprisingly, we find that not even the migrants expect to benefit from temporary and permanent migration in comparison to an equilibrium without migration. Responsible for the welfare-reducing effect of temporary and permanent migration is a negative wage externality, which emerges due to skill complementaries in team production. The marginal worker rationally ignores the negative external effects that migration has on other workers' wages. As a consequence we observe sub-optimally high-levels of temporary and permanent migration, which are associated with wasteful migration costs, that more than offset the aggregate production gains from a more efficient matching. An optimal migration policy mix aims for reduced but not necessary zero mobility.

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# A Appendix

## A.1 Proof of Proposition 2

We show that in any migration equilibrium the expected lifetime income of each worker, i.e. wages $\mathrm{E}[w_i(s_i)|\, s\,]\,\forall\; i \in \{N, I, R, P\}$ in period one and two net of the migration cost $c$ (if applicable) does not exceed expected lifetime income $\mathrm{E}[w(s)|\, s\,] = As/2$ in a equilibrium without migration.
In the high-cost scenario $(b)$ with $1/3 \leq \hat{c} < 1$ we then have:

$$2\,\mathrm{E}[w(s)|\, s\,] \geq \begin{cases} 2\,\mathrm{E}[w_{\scriptscriptstyle N}(s_{\scriptscriptstyle N})|\, s\,] & \text{if} \quad s < \tilde{s}_m, \\ \mathrm{E}[w_{\scriptscriptstyle I}(s_{\scriptscriptstyle I})|\, s\,] - c + \mathrm{E}[w_{\scriptscriptstyle R}(s_{\scriptscriptstyle R})|\, s\,] & \text{if} \quad s \geq \tilde{s}_m. \end{cases} \tag{B.1}$$

Using the definition of $\mathrm{E}[w_i(s_i)|\, s\,]$ from Eq. (3) in combination with $\mathrm{E}[\,s\,] = 1/2 \geq \mathrm{E}[s_{\scriptscriptstyle N}] = \tilde{s}_m/2$ and $\tilde{s}_m = \hat{c}$ from Eq. (9), we can simplify the first inequality in Eq. (B.1) to $\hat{c} \leq 1$. Substituting $\mathrm{E}[s_{\scriptscriptstyle I}] = \mathrm{E}[s_{\scriptscriptstyle R}] = (\tilde{s}_m + 1)/2 \geq \mathrm{E}[s] = 1/2$ and $\tilde{s}_m = \hat{c}$ from Eq. (9) into the second inequality in Eq. (B.1) allows us to solve for $s \leq 1$, which generally holds true, since $s \in [0, 1]$.
Turning to the low-cost scenario $(a)$ for $0 < \hat{c} \leq 1/3$ we can show that:

$$2\,\mathrm{E}[w(s)|\, s\,] \geq \begin{cases} 2\,\mathrm{E}[w_{\scriptscriptstyle N}(s_{\scriptscriptstyle N})|\, s\,] & \text{if} \quad s < \tilde{s}_m, \\ \mathrm{E}[w_{\scriptscriptstyle I}(s_{\scriptscriptstyle I})|\, s\,] - c + \mathrm{E}[w_{\scriptscriptstyle R}(s_{\scriptscriptstyle R})|\, s\,] & \text{if} \quad s \in [\tilde{s}_m, \tilde{s}_r), \\ \mathrm{E}[w_{\scriptscriptstyle I}(s_{\scriptscriptstyle I})|\, s\,] - c + \mathrm{E}[w_{\scriptscriptstyle P}(s_{\scriptscriptstyle P})|\, s\,] - c & \text{if} \quad s \geq \tilde{s}_r. \end{cases} \tag{B.2}$$

Using $\mathrm{E}[\,s\,] = 1/2 \geq \mathrm{E}[s_{\scriptscriptstyle N}] = \tilde{s}_m^{\mathrm{lf}}/2$ in combination with $\tilde{s}_m = (1 + 4\hat{c} - \sqrt{1 + 16\hat{c}^2})/2$ from Eq. (9), we can simplify the first inequality in Eq. (B.2) into $\hat{c} \geq 0$. The second inequality in Eq. (B.2) can be rewritten as

$$\lambda\,(s) \equiv 1 - \tilde{s}_m - \frac{1 + \tilde{s}_r}{2} + \frac{\hat{c}}{s} \geq 0,$$

where $\mathrm{E}[\,s\,] = 1/2 \leq \mathrm{E}[s_{\scriptscriptstyle I}] = (\tilde{s}_m + 1)/2$ and $\mathrm{E}[s_{\scriptscriptstyle R}] = (\tilde{s}_m + \tilde{s}_r)/2$ have been used to replace $\mathrm{E}[\,s\,]$, $\mathrm{E}[s_{\scriptscriptstyle I}]$, and $\mathrm{E}[s_{\scriptscriptstyle R}]$. Since $\lambda'(s) < 0$, we have $\lambda\,(s) \geq \lambda\,(1)$ and $\lambda(1) \geq 0$ is sufficient for $\lambda(s) \geq 0$. Using $\tilde{s}_m = (1 + 4\hat{c} - \sqrt{1 + 16\hat{c}^2})/2$ from Eq. (9) and $\tilde{s}_r = 4\hat{c}/(1 - 4\hat{c} + \sqrt{1 + 16\hat{c}^2})$ from Eq. (10) we can show that $\lambda(1) \geq 0$ may equivalently be expressed as $\hat{c} \leq 1/3$. Replacing $\mathrm{E}[\,s\,]$, $\mathrm{E}[s_{\scriptscriptstyle I}]$, and $\mathrm{E}[s_{\scriptscriptstyle P}]$ in the third inequality of Eq. (B.2) by $\mathrm{E}[\,s\,] = 1/2 \leq \mathrm{E}[s_{\scriptscriptstyle I}] = (\tilde{s}_m + 1)/2 < \mathrm{E}[s_{\scriptscriptstyle P}] = (\tilde{s}_r + 1)/2$

yields

$$\mu(s) \equiv \frac{4\hat{c}}{s} - \tilde{s}_m - \tilde{s}_r \geq 0.$$

Since $\mu'(s) < 0$, inequality $\mu(1) \geq 0$ is a sufficient condition for $\mu(s) \geq 0$. Using $\tilde{s}_m = (1+4\hat{c}-\sqrt{1+16\hat{c}^2})/2$ from Eq. (9) and $\tilde{s}_r = 4\hat{c}/(1-4\hat{c}+\sqrt{1+16\hat{c}^2})/2$ from Eq. (10) we can show that $\mu(1) = 0$ and, hence, $\mu(s) \geq 0$. □

## A.2 Proof of Proposition 3

In order to derive $\tilde{s}_m^{\text{sp}}$ and $\tilde{s}_r^{\text{sp}}$ as plotted in Figure 2.7, we can use the definition of $\mathrm{E}[s_i]\ \forall\ i \in \{N, I, R, P\}$ from Eq. (7) to rewrite the social planner's objective function as:

$$\mathrm{E}[W(\tilde{s}_m, \tilde{s}_r)] = \begin{cases} A\tilde{s}_m\tilde{s}_r(\tilde{s}_r - \tilde{s}_m)/4 + \sum_k A\left[1 + \tilde{s}_k(1-\tilde{s}_k)\right]/4 - (1-\tilde{s}_k)\,c & \text{for } (a), \\ A\left[1 + \tilde{s}_m(1-\tilde{s}_m)\right]/2 - (1-\tilde{s}_m)\,c & \text{for } (b), \end{cases} \tag{B.3}$$

with $k = m, r$. The corresponding first order conditions then follow as:

$$\frac{\partial\,\mathrm{E}[W(\tilde{s}_m, \tilde{s}_r)]}{\partial \tilde{s}_m} = \frac{A(1 - 2\tilde{s}_m + \tilde{s}_r^2 - 2\tilde{s}_m\tilde{s}_r)}{4} + c \overset{!}{=} 0 \quad \text{for } (a), \tag{B.4}$$

$$\frac{\partial\,\mathrm{E}[W(\tilde{s}_m, \tilde{s}_r)]}{\partial \tilde{s}_r} = \frac{A(1 - 2\tilde{s}_r - \tilde{s}_m^2 + 2\tilde{s}_m\tilde{s}_r)}{4} + c \overset{!}{=} 0 \quad \text{for } (a), \tag{B.5}$$

$$\frac{\partial\,\mathrm{E}[W(\tilde{s}_m, \tilde{s}_r)]}{\partial \tilde{s}_m} = \frac{A(1 - 2\tilde{s}_m)}{2} + c \overset{!}{=} 0 \quad \text{for } (b). \tag{B.6}$$

Since the return margin is fixed to $\tilde{s}_r^{\text{sp}} = 1$ in the high-cost scenario $(b)$, the social planner only has to choose the optimal emigration cutoff $\tilde{s}_m^{\text{sp}}$, and it follows immediately that $\tilde{s}_m^{\text{sp}}(\hat{c}) = \frac{1}{2} + \tilde{s}_m^{\text{lf}}(\hat{c})$, where $\tilde{s}_m^{\text{lf}}(\hat{c})$ is defined as in Eq. (9). For the low-cost case $(a)$ migration cutoff $\tilde{s}_m^{\text{sp}}(\hat{c})$ and return cutoff $\tilde{s}_r^{\text{sp}}(\hat{c})$ follow as the joint solution to Eqs. (B.4) and (B.5). An explicit analytical solution to Eqs. (B.4) and (B.5) exists. However, instead of reporting the lengthy solutions for $\tilde{s}_m^{\text{sp}}(\hat{c})$ and $\tilde{s}_r^{\text{sp}}(\hat{c})$ here, we rather plot them directly as a function of the only exogenous variable $\hat{c}$ in Figure 2.7. Of course we thereby have to distinguish between the low-cost case $(a)$ and the high-cost case $(b)$. In order to identify the cost threshold that separates the high cost case $(b)$ from an equilibrium without migration we use $\tilde{s}_m^{\text{sp}}(\hat{c}) = \frac{1}{2} + \tilde{s}_m^{\text{lf}}(\hat{c}) \overset{!}{=} 1$ in combination with $\tilde{s}_m^{\text{lf}}(\hat{c}) = \hat{c}$ from Eq. (9) to identify a critical value of 1/2. Similarly, when focusing on the low-cost case $(a)$ we find that $\tilde{s}_r^{\text{sp}}(\hat{c}) \overset{!}{=} 1$ implies a critical value of approximately 1/20. □

## A.3 Proof of Proposition 5

For symmetric cost $c > 0$ individual signalling/migration decisions in Figure 2.9 cumulate into four different signalling/migration patterns:

$(a)$ $0 < \tilde{s}_a < \tilde{s}_m < \tilde{s}_r < 1 \;\Rightarrow\;$ *imperfect selection into temporary (permanent) migration*,

$(b)$ $0 < \tilde{s}_a < \tilde{s}_m < \tilde{s}_r = 1 \;\Rightarrow\;$ *imperfect selection into temporary migration only*,

$(c)$ $0 < \tilde{s}_a < \tilde{s}_m = \tilde{s}_r = 1 \;\Rightarrow\;$ *no selection into migration*,

$(d)$ $0 = \tilde{s}_a = \tilde{s}_m = \tilde{s}_r < 1 \;\Rightarrow\;$ *no signalling/migration*,

where $\tilde{s}_a$ denotes the skill cut-off above which individuals select into the alternative signal (indexed by subscript $a$). In the following each of the non-trivial cases $(a)$, $(b)$, and $(c)$ are solved separately.
We begin with scenario $(c)$, in which only the alternative signal is used. The expected lifetime wage gain from signalling then is given by:

$$\Delta_1^w(s) \equiv \mathrm{E}[w_S(s_S) \,|\, s] + 2\,\mathrm{E}[w_N(s_N) \,|\, s] - 3\,\mathrm{E}[w_W(s_W) \,|\, s].$$

Using $\mathrm{E}[w_i(s_i)|\, s_i]$ from Eq. (3) and replacing $\mathrm{E}[s_W] = \tilde{s}_a/2 < \mathrm{E}[s_S] = \mathrm{E}[s_N = (\tilde{s}_a + 1)/2$ in $\Delta_1^w(\tilde{s}_a) \overset{!}{=} c$ allows us to solve for:

$$\tilde{s}_a(\hat{c}) = \frac{2}{3}\hat{c} \quad \text{for } (c).$$

In scenario $(b)$ the most high-skilled workers with $s \geq \tilde{s}_m$ combine their first round signal with subsequent (temporary) migration in order to obtain a more effective overall signal. Solving by backward induction, we begin with the migration decision at stage two. With the expected wage gain being given by:

$$\Delta_2^w(s) \equiv \mathrm{E}[w_I(s_I)|\, s] + \mathrm{E}[w_R(s_R)|\, s] - 2\,\mathrm{E}[w_N(s_N)|\, s],$$

we can use $\Delta_2^w(\tilde{s}_m) \overset{!}{=} c$ in combination with $\mathrm{E}[w_i(s_i)|\, s_i]$ from Eq. (3) and $\mathrm{E}[s_N] = (\tilde{s}_a + \tilde{s}_m)/2 < \mathrm{E}[s_I] = \mathrm{E}[s_R] = (\tilde{s}_m + 1)/2$ in order to solve for:

$$\tilde{s}_m(\tilde{s}_a) = \frac{\hat{c}}{1 - \tilde{s}_a}. \tag{B.7}$$

The expected lifetime wage gain from signalling hence can be computed as:

$$\Delta_1^w(s) \equiv \mathrm{E}[w_S(s_S)\,|\,s] + 2\,\mathrm{E}[w_N(s_N)\,|\,s] - 3\,\mathrm{E}[w_W(s_W)\,|\,s] = A(1+2\tilde{s}_m)\tilde{s}_a/2,$$

where we have used $\mathrm{E}[w_i(s_i)|\,s_i\,]$ from Eq. (3) in combination with $\mathrm{E}[s_W] = \tilde{s}_a/2 < \mathrm{E}[s_N] = (\tilde{s}_a + \tilde{s}_m)/2 < \mathrm{E}[s_S] = (\tilde{s}_a + 1)/2$ in order to establish the above equality. Replacing $\tilde{s}_m$ by $\tilde{s}_m(\tilde{s}_a) = \hat{c}/(1-\tilde{s}_a)$ from Eq. (B.7) in $\Delta_1^w(\tilde{s}_a) \overset{!}{=} c$ finally allows us to solve for:

$$\tilde{s}_a(\hat{c}) = \left(1 + 4\hat{c} - \sqrt{1+16\hat{c}^2}\right)/2 \quad \text{for } (b). \tag{B.8}$$

Substituting $\tilde{s}_a(\hat{c})$ from Eq. (B.8) back into $\tilde{s}_m(\tilde{s}_a) = \hat{c}/(1-\tilde{s}_a)$ from Eq. (B.7) then yields the corresponding migration cutoff:

$$\tilde{s}_m(\hat{c}) = 2\hat{c}/\left(1 + 4\hat{c} - \sqrt{1+16\hat{c}^2}\right) \quad \text{for } (b).$$

Finally, in scenario $(a)$ we have $0 < \tilde{s}_e < \tilde{s}_m < \tilde{s}_r < 1$. We solve by backward induction and start at stage $t = 3$ with the expected wage gain from permanent migration being given by:

$$\Delta_3^w(s) \equiv \mathrm{E}[w_P(s_P)|\,s\,] - \mathrm{E}[w_R(s_R)|\,s\,].$$

Using $\mathrm{E}[w_i(s_i)|\,s_i\,]$ from Eq. (3) in combination with $\mathrm{E}[s_R] = (\tilde{s}_m + \tilde{s}_r)/2 < \mathrm{E}[s_P] = (\tilde{s}_r + 1)/2$ in $\Delta_3^w(\tilde{s}_r) \overset{!}{=} c$ allows us to solve for:

$$\tilde{s}_r(\tilde{s}_m) = \frac{2\hat{c}}{1-\tilde{s}_m}. \tag{B.9}$$

At stage $t = 2$ the expected wage gain from temporary migration is given by:

$$\Delta_2^w(s) \equiv \mathrm{E}[w_I(s_I)|\,s\,] + \mathrm{E}[w_R(s_R)|\,s\,] - 2\,\mathrm{E}[w_N(s_N)|\,s\,].$$

Using $\mathrm{E}[w_i(s_i)|\,s_i\,]$ from Eq. (3) in combination with $\mathrm{E}[s_N] = (\tilde{s}_a + \tilde{s}_m)/2 < \mathrm{E}[s_R] = (\tilde{s}_m + \tilde{s}_r)/2 < \mathrm{E}[s_I] = (\tilde{s}_m + 1)/2$ and $\tilde{s}_r(\tilde{s}_m) = 2\hat{c}/(1-\tilde{s}_m)$ from Eq. (B.9) in $\Delta_2^w(\tilde{s}_m) \overset{!}{=} c$ allows us to solve for:

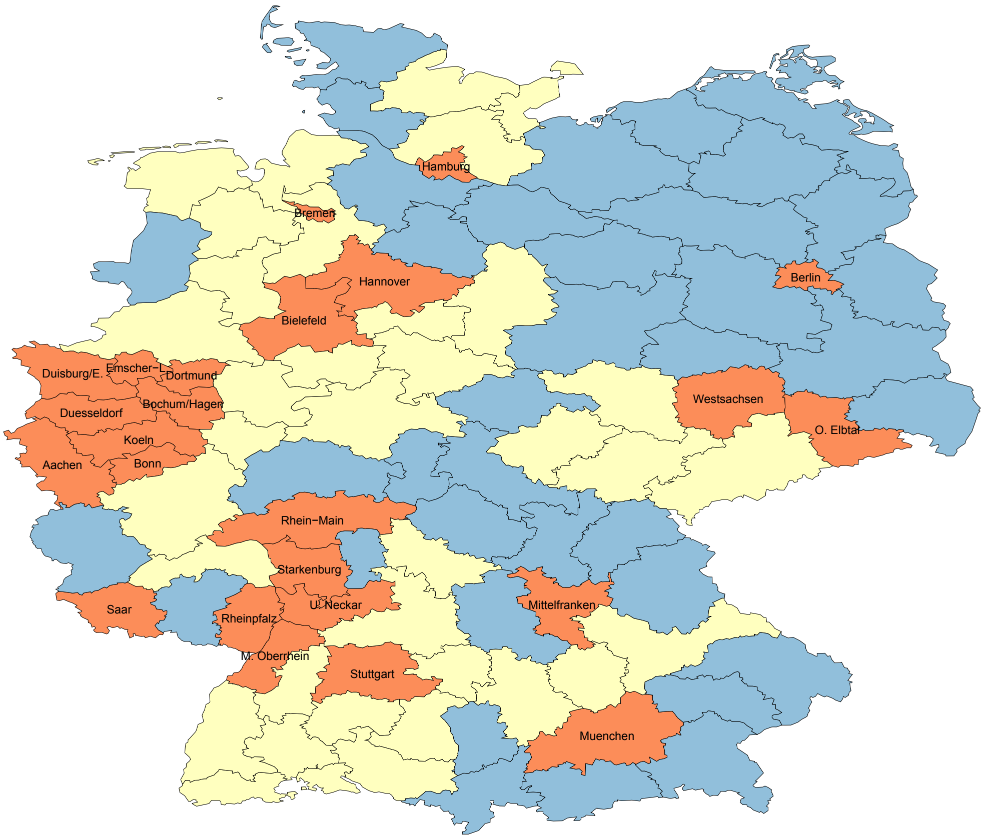
$$\tilde{s}_m = \frac{1 - 2\tilde{s}_a + 4\hat{c} - \sqrt{1 + 16\hat{c}^2 - 4\tilde{s}_a(1-\tilde{s}_a)}}{2(1-2\tilde{s}_a)}. \tag{B.10}$$

Finally, at stage $t = 1$ the expected lifetime wage gain from signalling is given by:

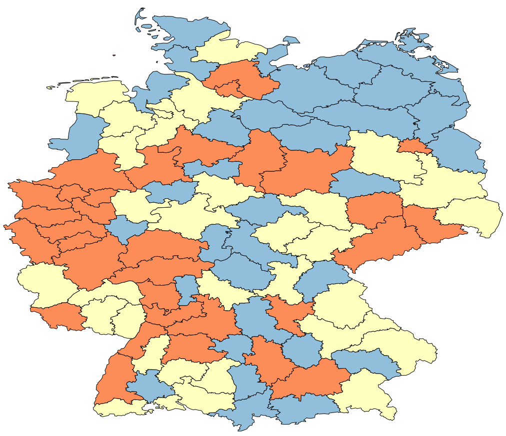
$$\Delta_1^w(s) \equiv \mathrm{E}[w_S(s_S)|\, s\,] + 2\,\mathrm{E}[w_N(s_N)|\, s\,] - 3\,\mathrm{E}[w_W(s_W)|\, s\,].$$

Using $\mathrm{E}[w_i(s_i)|\, s_i\,]$ from Eq. (3) in combination with $\mathrm{E}[s_W] = \tilde{s}_a/2 < \mathrm{E}[s_N] = (\tilde{s}_a + \tilde{s}_m)/2 < \mathrm{E}[s_S] = (\tilde{s}_a + 1)/2$ and $\tilde{s}_m(\tilde{s}_a)$ from Eq. (B.9) in $\Delta_1^w(\tilde{s}_a) \stackrel{!}{=} c$ allows us to solve for $\tilde{s}_a(\hat{c})$ as depicted in Figure 2.10. Substituting $\tilde{s}_a(\hat{c})$ back into the Eq. (B.10) then delivers $\tilde{s}_m(\hat{c})$ as depicted in Figure 2.10. Once obtained, $\tilde{s}_m(\hat{c})$ from Eq. (B.10) can then be used to replace $\tilde{s}_m$ in $\tilde{s}_r(\tilde{s}_m)$ from Eq. (B.9), which finally results in $\tilde{s}_r(\hat{c})$ as depicted in Figure 2.10. $\square$

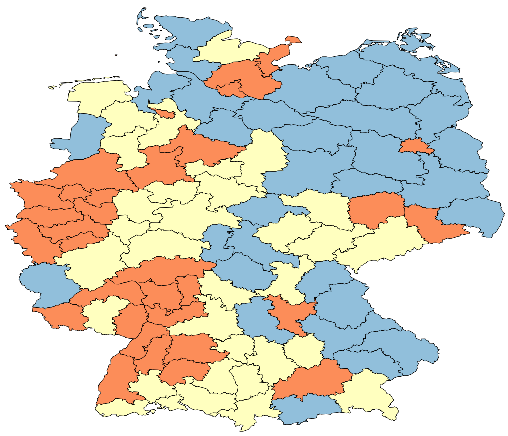
Figure B1: Classification of Regions




Panel A: Raumordnungsregionen (RORs)



Panel B: Population Tercile



Panel C: Pop. Density Tercile

Panel A illustrates the 96 German “Raumordnungsregionen” (RORs), which are classified into 24 metropolitan regions (in orange), 35 urbanised regions (in yellow), and 37 rural region (in blue). For comparison we have plotted 2015 population terciles and the population density terciles in the Panels B and C.
Source: Own calculations, Bundesinstitut für Bau-, Stadt-, und Raumforschung (BBSR).

# Chapter 3

# Self-Selection into Initial and Return Migration based on Unobserved Ability and Firm Quality

*Co-authored with Jens Wrona*

## 3.1 Introduction

It is a well established idea that migrants are, in many ways, positively selected. In particular concerning labor market success, (see, e.g., Chiswick, 1999). International as well as domestic migration is connected to different kinds of costs, such as monetary and personal costs of migration, i.e. to be forced to be separated from our preferred region of living (cf. Sjaastad, 1962). Little is known about selection patterns of workers concerning unobservable or true skill. Apart from broad skill measures such as education and occupation, in large datasets information on skill is usually not available.

With the accessibility of employer-employee data and the possibility to track individual workers it became possible to estimate additive latent worker and firm increments of wages, with the method being a non-structural approach to wage formation (cf. Abowd, Kramarz, and Margolis, 1999; Abowd, Creecy, Kramarz, et al., 2002, henceforth AKM). More recently Card, Heining, and Kline (2013) (henceforth CHK) have applied the method to German data and added a chronological layering making the method more useful for panel applications as well as giving some evidence of additivity.
To explore further the self-selection of workers in migration, particularly to large cities we employ and combine these methods with the migration literature. We estimate a worker component of wages, which covers all monetarisable skill, which is not employer specific and a firm component of wages, which covers the general pay premium a firm offers to all its employees. This measure is correlated to firm size and likely with firm productivity and profitability (cf. Gürtzgen, 2009; Card, Devicienti, and Maida, 2013).
Using discrete duration models, we find a positive selection into initial migration and negative selection into return migration, based on *unobservable* skill.[1] We find that there is a fraction of workers, with the highest skill, which selects into move-on migration.[2] For this group, migration goes along with a significant pay increase for every migration decision. Workers in that category are often lawyers, academics, consultants or other high-skilled individuals. While all migrant types select to higher

[1]In line with studies focussing on selection in observable characteristics (cf. DaVanzo, 1983; Kennan and Walker, 2011).

[2]By move-on migration we mean migration to a third region that is neither close to the initial or to the second region.

paying firms, move-on migrants profit the most, while return migrants profit the least. This may also lead to their decision to return to their home region. We find that return migrants incur a loss in terms of their firm pay premium, when returning to their home region. This can be seen as supportive evidence for the idea that they are willing to incur a cost to end separation from their preferred region.

Reasons for workers to incur costs of migration are higher wage options as well as the possibility to acquire skills in the hosting region (De la Roca, 2017). Migration is used as a signal (Kreickemeier and Wrona, 2017; Knauth and Wrona, 2018) for their ability or willingness to incur costs similar to signaling in models of education. There is a broad consensus that observable skills are an important determinant of workers' wages (see Card, Heining, and Kline, 2013, for estimates on German data), several authors (cf. Card, Heining, and Kline, 2013; Card, Cardoso, and Kline, 2016; Macis and Schivardi, 2016) have recently pointed to the importance of unobservable individual characteristics in explaining the variation in worker's wages. In order to test for established mechanisms with regard to the selection of workers into temporary and permanent migration we follow Macis and Schivardi (2016) in identifying individual-specific wage components that are directly related to workers unobservable skills. Those are based on the structural wage decomposition pioneered by Abowd, Kramarz, and Margolis (1999) and first applied to German data by Card, Heining, and Kline (2013). Using a large panel of administrative data on workers and establishments in West-Germany from 1985 to 2010 that is provided by the German Institute of Employment Research (IAB) in Nuremberg, allows us to follow workers through establishments and regions (counties) across time. We then employ a discrete duration (hazard) model of monthly self-selection as in De la Roca (2017). We provide extensive descriptive evidence on the development of worker and firm components for all worker types pre- and post-move.

In the following section 3.2 we discuss our empirical strategy, in particular the method by Abowd, Kramarz, and Margolis (1999) and Card, Heining, and Kline (2013) to estimate latent heterogeneity, the timing of the hazard model and the construction of our main variables of interest. Section 3.3 describes the data that we use, the restrictions we make to the sample and the classification we employ on migrant types. Section 3.4 shows descriptive statistics for different migrant types in terms of wages and observable characteristics. Section 3.5 shows the main result for selection in to initial and repeat migration.[3] Section 3.6 shows the selection in migration with respect to the firm quality. Section 3.7 concludes.

## 3.2 Empirical Strategy

In our estimation we combine the results of the wage decomposition by Card, Heining, and Kline (2013), with a discrete choice framework of self-selection into migration at different points in time. Compared to wage based measures, the decomposition allows for a better proxy for unobservable skill. In particular we are able to control for a constant firm pay premium, which we will assess separately.

### 3.2.1 Approach by Card, Heining and Kline (2013)

In previous work (cf. De la Roca (2017)) realized incomes have been used as a raw estimate of workers skill, while controlling for other observables or the income rank within certain worker groups. In particular, regional disparities have been emphasized in describing differences in wages and subsequently the mobility of workers. In the following we will disentangle a worker's pay components that are worker specific, in particular his observable and unobservable skill, his industry affiliation, occupation and experience from pay components that are related to plants and hence also incorporate all regional characteristics.
The proportional pay premium of the firm (henceforth firm FE) controls for all non-portable wage components, in particular the location, industry and competitive environment of the firm. We believe the residual individual FE to be a relatively clean measure of individual quality, incorporating all observable measures of skill. It comprises all parts that are equally valuable for all employers.
We follow Card, Heining, and Kline (2013) and estimate the effects fitted into intervals to capture changes over time. We estimate five overlapping intervals of six years, for each interval we estimate the following equation:

$$y_{it} = \alpha_i + \psi_{\mathbf{J}_{(i,t)}} + x'_{it}\beta + r_{it} \tag{1}$$

[3] We will use the term repeat migration, for a second migration episode irrespective of the destination.

with

$$r_{it} = \eta_{i\mathbf{J}(i,t)} + \zeta_{it} + \varepsilon_{i,t}. \tag{2}$$

$y_{it}$ is the log wage in 1985 Euros of person i in year t. $\alpha_i$ is the (interval) time constant individual FE. $\psi_{\mathbf{J}_{(i,t)}}$ is the firm FE, given that individual i works at firm J at time t. $x_{it}$ is experience, approximated with $age$, $age^2$ and $age^3$ interacted with educational attainment.[4] Note that the individual FE captures all direct education effects, the covariates in $x_{it}$ thus only capture education specific experience, as education is constant for all individuals.

In order to identify the effects separately it is necessary to observe different employers for a given employee within an interval. Most ($\sim$ 95%) establishments are connected by job switchers, for the rest of the establishments (and workers) we cannot separately identify the fixed effects and therefore exclude them from the regression.[5]

A majority of workers do not move within the given intervals.[6] Thus, their individual FE is computed as a residual given the firm FE of their employer:

$$\hat{\alpha}_i = 1/T_i \sum_t (y_{it} - \psi_{\mathbf{J}_{(i,t)}} - x'_{it}\hat{\beta}). \tag{3}$$

The error $r_{it}$ consists of the worker-firm specific match component $\eta_{i\mathbf{J}(i,t)}$, that has to be unknown prior to the actual job match. Hence, the decision of matching can not be based upon the match effect. $\zeta_{it}$ is a unit root component, while $\varepsilon_{i,t}$ is white noise. For unbiased estimation it is necessary that non of the error components drive the mobility between firms so that we have random matching given the observables. In particular the matching to all establishments within a given interval have to be independent of the idiosyncratic match effect, which is key to many matching models. Card, Heining, and Kline (2013) provide various tests for the plausibility of the so called exogeneous mobility assumption. They find that the matching effect is relatively small and evenly distributed across firm and worker classes in terms of pay premia. Because most workers are employed in large firms the firm FE will be

[4] Where 20 years are deducted as certain life time outside of the labor force.

[5] See Card, Heining, and Kline (2013) for an extensive description of the method, particularly how to identify the connected set.

[6] Note that in the context of AKM by "move" we mean job switches in general, independent of the spatial dimension.

estimated with relative precision, while the worker FE is only identified from a short panel.

## Further Assumptions

As we do not want our mobility choices across space to interfere with our AKM estimates we compute the person FE as a residual similar to equation (3) for all workers. This residual is a workers wage controlled for a firm fixed effect, which in turn has been controlled for its worker's composition. This will be described in more detail in section 3.2.3.
By this we prohibit the individual workers wage component to depend on future job matches and consist of his wage, net of the firm effect.
We further assume that the firm effect is predominantly determined by job switchers who are not movers. Our mover definition is based on moves, which are long in distance and duration, which will be explained in detail in section 3.3. Most jobs switches take place within regions or between neighboring regions, while far moves are rare events.
If additive structure of worker and firm effect and the assumptions on the error term is violated, migration could be correlated with the firm effect due to firms with migrants investing more in search and obtaining a better fit systematically. This is then resulting in a higher match effect in the error term. As the person effect is computed as a residual this a possible caveat of the interpretation to the AKM effects in this context.
The migration is an event that potentially increases the underlying skill of a worker (learning) or at least the ability to sell his skill at higher prices on the market, potentially due to signaling his commitment.

### 3.2.2 Hazard Model

While the original data come in a daily format we have aggregated them up to the monthly level as this is the true incidence of payment most of the time. Very often new jobs commence at the first of a month and there are hiring spikes at every beginning quarter and year.
As initial and follow up migration happen at varying points in time (or not at all) and we do not observe a full work life we use a discrete duration model tackling the timing for the selection into migration types. In the first stage this is stayer

vs. initial migrant and in the second stage this is permanent migrant (stayer in the second region) vs. return or move-on migrant.
We use a single-exit discrete duration framework as modelled by Jenkins (1995) and De la Roca (2017). The exit is defined as *leaving the region of origin*, given he did not leave before. The hazard rate h(t) depends on year-month observation t as well as time-varying and time constant observable characteristics. We will also use the results of the wage decomposition, the individual as well as the firm component of wages.
The Hazard rate, the relative probability of exit (migration in our case) in every period can be written as follows:

$$h(t) = P[T = t|T \geq t, x(t)] = F[\beta_0(t) + \beta' x(t)]$$

It consists of time dummies and a substantial number of observable characteristics, which are discussed in greater detail in the results section.
The following log-likelihood function consists of the two possible types of spell sequences. Either the worker is a mover with $m_i = 1$ and leaves his initial region at time T, or he does not move in the observational period and the spell sequence is censored ($m_i = 0$). Given he is a mover the likelihood of migration is defined by the likelihood of migration in a given period over the probability he did not move prior to the given period.

$$L(\beta) = \sum_{i=1}^{N} \left[ (1 - m_i) \sum_{t=e_t}^{T_t} log(1 - h_i(t)) + m_i \left( \sum_{t=e_t}^{T_t - 1} log(1 - h_i(t)) + log(h_i(T_i)) \right) \right],$$

which can be re-written as a sequence of binary models and hence estimated as a Logit model with adjusted data structure. In particular the data is cut after the migration occurred:

$$L(\beta) = \sum_{t=1}^{T_t} \left\{ \sum_{i=1}^{N} \mathbf{1}(T_i \geq t \geq e_i)[m_i Y_{ti} \; log(h_i(t)) + (1 - m_i Y_{ti}) log(1 - h_i(t))] \right\}.$$

The same holds true for the second decision to migrate. Given he migrated before he enters into the pool of potential return or repeat migrants, while the baseline option is to stay in the second region until the end of the observational period. For those choices we use a multinomial logit, with two separate exit options.

### 3.2.3 Construction of Main Variables

Our main independent variables are constructed as moving averages of wages and said wage components. For individual i at time t we construct a moving average wage of workers employed with a positive wage at time periods t'. The moving average wage for employed periods ignores the unemployed periods in between. We use a lag of $n = 6$.[7]

$$log(MA^n_{it'}) = log\left(\frac{\sum_{t'}^{n} wage_{i,-t'}}{n}\right)$$

The construction of the variable allows separate analysis of unemployment and wages. For our broad industry categories as well as for the occupation variable we use the latest employed period.
As described above the AKM effect are estimated for six year intervals, taking into account mobility between firms within every interval. As timing is crucial in our hazard design we cannot use the simple worker fixed effect. The use of the worker fixed effect would potentially include effects from future migration success into the current worker fixed effect, depending on the timing of migration within the six year estimation interval. Thus we compute our worker component as a residual of wages, deducting the firm component and other covariates of wages, such as as age and education specific experience:

$$PE_{it} = log(wage_{it}) - (\psi_{\mathbf{J}_{(i,t)}} + x'_{it}\beta)$$

After this step the moving average for the firm and worker wage components is computed similarly to the moving average wage, though taking logs is redundant. Consequently, the firm fixed effect does show little variation over time, only if a worker switches employer or the AKM period changes. We still choose to use the moving average construction for consistency reasons.
Finally, the moving averages are computed separately for all three potential regions a worker can be active in, so that the decisions to return or move on are not affected by first region wages. We will explicitly model this by using the average wages of the first region to explain return and move on decisions.

[7]So, e.g., the moving average of a worker, who was unemployed the last two months, but employed during the previous months, would consist of the average of wages in t-3 to t-9.

## 3.3 Data, Sample Restrictions and Identifying Migrants

For initial estimation we use a 50% sample of all full-time working men in West Germany to estimate the worker and firm fixed effects in our sample with the lowest possible bias as described in section 3.2.3.[8] All workers subject to social security are considered, so part-time work, the unemployed and self-employed workers are ignored in the analysis. Wages above the social security maximum are imputed on a yearly basis as in Borrs and Knauth (2016).

For the main estimation we reduce the sample to the birth cohorts of 1965 to 1970, a cohort of which we observe their earliest entry into the labor force from 18 on up to at least age 40, capturing the relevant years in terms of migration.

In order to get a workable sample we simplify and reduce the potential types of movers. Most importantly, we define the region of entry into the workforce as the first region. We exclude workers who move between districts 9 times or more, aiming at workers whose job is crucially linked to migration such as truck drivers or sales representatives.

We define workers who move more than 120 kilometers from their first region as migrants. In order to be able to assess follow up decisions on migration we keep only workers who stay in their second region for at least 12 months. In order to get a limited number of migration types we exclude workers who move 120 kilometers more than twice. The second migration decision divides the mover group in three types, permanent migrants who move only once, return migrants who move back to their initial extended region and repeat or move on migrants who move to a region, which is at least 120 kilometers away from region one and two.

As we do not observe unemployment/part-time work spells we exclude workers who are missing in the sample for 60 months or more. We also exclude workers that have more than 50% missings within the time span we observe them.

We intentionally reduce the sample to metropolitan areas according to the German *Raumordnungsregionen* (hereafter: "regions"), which comprises rural, urbanized and metropolitan areas. We classify migrants according to their migration patterns in twelve groups, 3x3 migrant groups, as well as 3 stayer groups. We then drop all initially non metropolitan workers as well as all remaining migrant groups who

[8] It is taken from the Betriebshistorikpanel (BeH) of the IAB, comprising employment biografies of workers subject to social security.

migrate to non metro areas for their initial move. Consistently, we drop move on migrants who migrate to non metro areas, so that we compare only metro stayers to different groups of (between) metro migrants. The final step reduces the sample by about 60%. There are 21 metro areas (107 Kreise) in West Germany of 76 areas (325 Kreise) in total (96 including the former GDR, 402 Kreise).
While only comprising 17.73% of the land surface they make up of 47% of the population (est. 2015), and thus are very densely populated.
Concerning the workplace we have district level (German: Kreise, NUTS-3) information, which we will use to compute the bilateral migration distances. For cities (kreisfreie Städte) we use the city center as reference point, while we use the center of the largest settlement for non-city districts (Landkreise).

**Summary of worker types:**

1. Stayers: initially in an urban region, never leave their initial region, move 120 kilometers or less.

2. Initial migrants: initially in an urban region, leave their initial region to another urban region, which is at least 120 kilometers apart, they stay there at least 12 months. In their second region they then reveal their *final* type:

   (a) Permanent migrants: initial migrants who never leave their second region (within 120 kilometers)

   (b) Return migrants: initial migrants, who return to their initial broader region and stay until the last observed period.

   (c) Move-on migrants: initial migrants, who leave their second region, but do not move back to their initial region, instead they move to an urban region, which is at least 120 kilometers apart from region one and two.

Monthly wages above the social security maximum are imputed for our worker cohort. Furthermore, we have information about the workers education, where we use schooling, information on commercial training and university education to define four education groups. We have some information about the occupation of a worker, where we make use of the quality or level of the job as control variables. The 3-digit industry information on the employer level is condensed to four broad industry categories: raw materials and manufacturing, service industry, public employees and others. We can easily compute workers experience and employer tenure for any given month, which is also included in the regressions other covariates include age, time dummies interacted with regional dummies and 1. region averages of above mentioned covariates for the 2. region decisions.

## 3.4 Descriptive Statistics and Stylized Facts

In table 3.1 we show some basic descriptive statistics of all workers in the sample over the observational period. For all mover types we show sums and averages over all regions a worker is employed in, that is two regions for the permanent migrants and three for return and move on migrants. The differences in types will be examined in greater detail in later stages of the paper.

In the column (1) we see workers who are non migrants, that is never move beyond 120 kilometers in the observational period. This class covers 91.5% of the observations. Note that we exclude workers who fulfill some but not all characteristics of a mover, such as moving beyond 120 kilometers but only for a short period of time, so that the remaining stayers are relatively homogeneous.

Their wage is the lowest of all groups, with a low share of censored observations. Their firm effect as well as their person effect, which are net of education specific experience are lowest of all groups. So on average their skill and their average matched firm quality is lowest. Less than 20% are at least college educated.

Permanent migrants, who make up 5.14% of workers have substantially higher wages, firm and person effects. They are less than half as often untrained and half of them has at least some college education. Also in terms of realized occupation rank they outperform stayers. Naturally, to this point it is unclear inhowfar the differences of realized incomes and occupations are driven by post-migration realizations. Potentially, they are positively selected previous to the migration, which is supported by their high education level, which is realized before the entry into the labor market.

The return migrants who make up for 2.65% of all workers in the sample lie in between stayers and permanent migrants in terms of wage and wage components. They also could be negatively selected ex ante, compared to permanent migrants or they could have faced a negative shock in their second region.

Move on migrants who account for 0.70% are by far the highest earning group, with high shares of wages, university education and realized occupations.

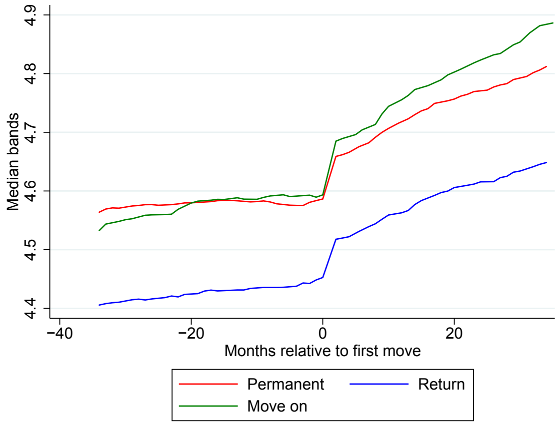
Table 3.1: Descriptive Statistics of Mover Types

| **Descriptive Statistics:** | | | | | |
|---|---|---|---|---|---|
| | | **Mover Types** | | | |
| Migration Type: | **Non-migrants** | **Permanent** | **Return** | **Move-on** | **Avg./Total** |
| **means** | | | | | |
| Daily wage | 80.50 | 97.07 | 90.45 | 103.04 | 81.64 |
| Daily wage (imp.) | 85.04 | 114.96 | 103.63 | 126.19 | 87.13 |
| Firm Effect | 0.18 | 0.21 | 0.19 | 0.22 | 0.18 |
| Person Effect | 4.32 | 4.51 | 4.46 | 4.59 | 4.33 |
| Col. % | | | | | |
| **censored** | | | | | |
| yes | 8.21 | 29.10 | 23.14 | 38.53 | 9.73 |
| **education** | | | | | |
| 1 (no training) | 12.88 | 5.78 | 4.97 | 2.07 | 12.28 |
| 2 (voc. training) | 70.35 | 43.93 | 54.06 | 36.66 | 68.53 |
| 3 (some coll.) | 7.13 | 13.39 | 13.77 | 15.36 | 7.64 |
| 4 (university) | 9.64 | 36.90 | 27.20 | 45.91 | 11.55 |
| **occupation skill** | | | | | |
| 1 (helper) | 4.04 | 2.36 | 2.69 | 1.80 | 3.92 |
| 2 (qualified) | 80.04 | 56.07 | 61.56 | 47.67 | 78.28 |
| 3 (specialist) | 7.19 | 14.68 | 15.14 | 20.65 | 7.82 |
| 4 (expert) | 8.73 | 26.89 | 20.61 | 29.88 | 9.99 |
| **Total** | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| **n** | 195,306 | 10,965 | 5,661 | 1,493 | 213,425 |
| **N** | 42,289,051 | 2,074,687 | 1,138,819 | 273,441 | 45,775,998 |

The table shows simple averages over all types of workers as defined in section 3, which are also used in the regressions later. Different from the regressions we pool over the whole sample period, while the hazard model will be restricted to information prior to the initial moves. Daily wages are given in 2005 euros, firm and person effects as components of log wages.
*Source: Own calculations, BeH.*

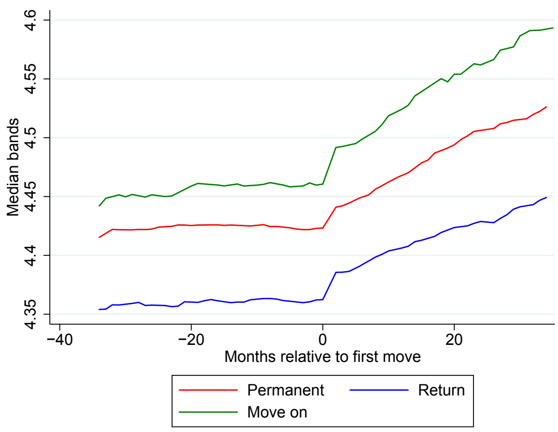
The time dimension is crucial to discriminate between the two potential channels of selection, first ex-ante differences in e.g. innate ability, which can be signaled by costly migration (cf. Knauth and Wrona, 2018) and second a negative shock in the second region, e.g. by job loss or a bad match. In figure 3.1 we show the development of log wage and the individual component of wages (person effect) over time. In panel 3.1a we see the development of the log wage of the median worker, where the log wage is computed as a moving average as described in section 3.2.3. Hence, although job loss is a major determinant of mobility, the graph only shows the moving average of realized matches. Also the moving average *restarts* after the move, such that pre-move salaries do not affect the post-move median worker. This explains the lack of a pre-migration drop in wages which would occur if we would include wage zero for unemployed workers. In this panel 3.1a we see the three mover types, permanent, return and move on migrants. The wages of permanent and move on migrants are very similar pre-move, while move-on migrants outperform permanent migrants after the move. On the right panel 3.1b we normalize the wage such that it is equal for the medians of all three groups in order to compare the relative increase after the move. In terms of wages there is clear ordering of wage increases, with move-on migrants having the highest wage increase, followed by permanent migrants, and return migrants having the lowest but still positive increase for the median worker.

Figure 3.1: Wage Change relative to 1. Move




(a) Log Wages


(b) Relative Log Wages




(c) Person Effects


(d) Relative Person Effects

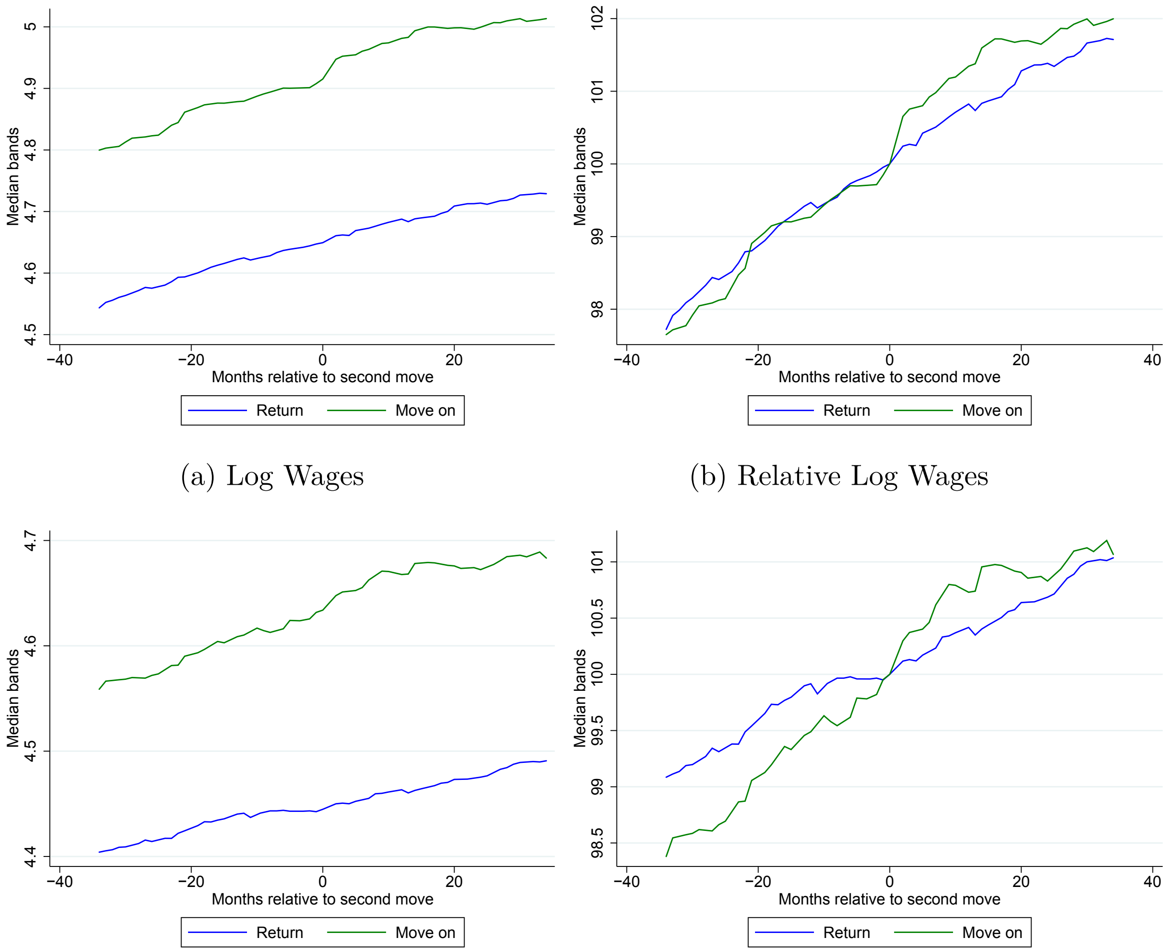
In the above figure the log wage changes and the changes of the individual component of wages are shown relative to the initial move as defined in the main text. All graphs show the respective median worker of the particular mover group. The panels on the left show the absolute values, while the panels on the right show the relative changes, where the month of migration is set to 100. 3 years prior and after the initial move are shown.

A log wage increase by 0.1 is equivalent to an 10.5% increase in wages. In panel 3.1a this corresponds to an approximate increase of 300 Euro a month for the median move-on migrants and little less for the other migrant types, thus a quite substantial

gain.
For our main explanatory variable, the individual component of wages, we see a clear cut ordering previous to the move in panel 3.1c, where move-on migrants are more positively selected with respect to unobservable skill. The relative pattern in panel 3.1d is very similar to the wage results, while return migrants seem to fall behind after some months. Interestingly, the wages and skills are flat before the move, while there seems to be a constant increase still at work three years after their respective moves. We see that the return migrants are negatively selected previous to the move and also have the lowest relative increase over time.
In figure 3.2 we show the changes in the log raw wages and the latent skill component of wage, relative to the second move of workers.
The second decision to migrate can be interpreted as a revision to the initial move, by either returning to the initial region or by moving to a third region. It can also be part of a optimal migration plan in the way that the stay in the second region was initially planned to be temporary (cf. Knauth and Wrona, 2018).
Similar to the initial moves, revisions of them can be based on longstanding under performance in terms of wages or more short-term reactions to job loss. We therefore look at the moving average of realized non-zero wages, thereby excluding job loss from the figure.[9]
For panels 3.2a and 3.2b we see that the wage pre-move is substantially higher for move-on migrants as for return migrants. There is a discontinuity for move-on migrants after their second move, when the median migrant gets a small increase in pay. Although about a third of migrants move after they lose their job (see figure 3.5), decreasing matches or low wages are not typically associated with return or move-on migration. The latent skill or worker fixed effects behaves very similar to the log wages, we see a faster growth of the worker fixed effect previous to the move though.
Naturally, we only can draw comparisons between different mover types given they moved before and are not able to compare the development of wages as compared to permanent migrants in these figures.

[9]See the related figure 3.5 for job loss relative to the second move in the appendix.

Figure 3.2: Wage Change relative to 2. Move




(a) Log Wages

(b) Relative Log Wages

(c) Person Effects

(d) Relative Person Effects

In the above figure the log wage changes and the changes of the individual component of wages are shown relative to the second move, either the return or the move-on move. All graphs show the respective median worker of the particular mover group. The panels on the left show the absolute values, while the panels on the right show the relative changes, where the month of migration is set to 100. 3 years prior and after the second move are shown.

## 3.5 Selection based on Unobserved Ability

We now turn to our regression results looking at each decision to migrate separately, in particular the initial decision and the second decision, given migration has occurred before. In this section we will compare our main explanatory variable the latent monetizable skill, the worker component of wages to observables determinants of migration and conventional raw wage measures. In section 3.5.2 we will then turn to the repeat migration decision.

### 3.5.1 Initial Selection into Migration

In table 3.2 we show the initial selection into migration for common observables, for the moving average wage measure and the moving average measure of unobserved skill.

In columns (1) and (2) we show the various covariates such as education, industries and labor market attachment, tenure and experience and -more importantly- if the individual is unemployed.[10] As can be seen in figure 3.5 up to one third of workers are unemployed previously to the move, additionally workers may anticipate unemployment in the future, due to i.e. an ending contract. This makes unemployment a highly important factor of (initial) migration, coinciding with the high coefficient of the regressions in columns (1) and (2). We can directly interpret the coefficient, such that becoming unemployed increases the hazard of migration by 480%. Having firm tenure of general labor market experience increases the probability to stay, in line with the idea that workers move in their early career stages, even after controlling for age.

Generally, we see higher mobility in the service industry as compared the manufacturing industry, the public sector or other industries. Being employed in the service industry increases the hazard of migration by 80.26% in column (1) compared to the manufacturing industry.

We see that increased formal education increases the probability of migration substantially, in particular for university educated workers. This fact has been documented for Germany and other countries (cf. Hunt, 2004).

We also control for the job quality with our occupation measure, which describes the requirements of jobs and often is used to assess mismatch and under placement of educated workers. In columns (1) we see that individuals with better jobs are more likely to move, which potentially covers else neglected skill as the education coefficients are lower as compared to column (2).

For all specifications we control for year and month, age of the individual, region dummies, as well as region dummies interacted with 5-year periods. These dummies control for region-time specific shocks, such as economic decline or non-labor market reasons to leave a region such as bad infrastructure or public spending.

[10]As we do not directly observe unemployment, we restrict the sample to workers who are employed most of the time, as explained above. We assume that workers who vanish for short periods of time from the sample are unemployed.

Table 3.2: Initial Selection based on Unobserved Ability

| Logit: | (1) Initial | (2) Initial | (3) Initial | (4) Initial | (5) Initial | (6) Initial |
|---|---|---|---|---|---|---|
| Wage based: | | | | | | |
| Moving Average PE (AKM) | | | 1.866*** | 2.042*** | | |
| | | | (23.87) | (28.18) | | |
| Moving Average Wage | | | | | 1.803*** | 1.943*** |
| | | | | | (25.55) | (29.81) |
| Occupation: | | | | | | |
| qualified | 0.928* | | 0.847*** | | 0.836*** | |
| | (-1.83) | | (-3.99) | | (-4.30) | |
| specialist | 1.747*** | | 1.434*** | | 1.400*** | |
| | (12.25) | | (6.33) | | (7.68) | |
| expert | 1.306*** | | 1.060 | | 1.021 | |
| | (6.03) | | (0.19) | | (1.26) | |
| Labor market attachment: | | | | | | |
| experience | 0.899*** | 0.898*** | 0.890*** | 0.888*** | 0.884*** | 0.884*** |
| | (-36.94) | (-37.66) | (-39.29) | (-40.32) | (-40.35) | (-41.46) |
| tenure | 0.961*** | 0.958*** | 0.958*** | 0.956*** | 0.959*** | 0.957*** |
| | (-13.45) | (-14.67) | (-14.32) | (-15.28) | (-13.92) | (-14.76) |
| unemployed | 5.800*** | 5.569*** | 6.142*** | 6.058*** | 6.370*** | 6.324*** |
| | (101.15) | (99.81) | (102.64) | (102.22) | (103.49) | (103.23) |
| Broad industries: | | | | | | |
| service industry | 1.826*** | 1.807*** | 1.825*** | 1.801*** | 1.928*** | 1.916*** |
| | (35.34) | (34.73) | (35.03) | (34.28) | (37.96) | (37.64) |
| public employee | 0.995 | 1.014 | 1.002 | 1.006 | 1.094*** | 1.107*** |
| | (-0.16) | (0.45) | (0.08) | (0.21) | (2.96) | (3.39) |
| elsewhere employed | 1.078 | 1.065 | 1.130 | 1.115 | 1.213 | 1.202 |
| | (0.25) | (0.21) | (0.41) | (0.36) | (0.64) | (0.61) |
| Education: | | | | | | |
| vocational training | 1.517*** | 1.586*** | 1.458*** | 1.479*** | 1.420*** | 1.435*** |
| | (11.77) | (13.12) | (10.48) | (10.95) | (9.74) | (10.09) |
| some college | 2.765*** | 3.097*** | 2.488*** | 2.622*** | 2.362*** | 2.463*** |
| | (25.82) | (29.1) | (22.65) | (24.16) | (21.23) | (22.42) |
| university | 4.190*** | 5.283*** | 3.592*** | 4.006*** | 3.227*** | 3.511*** |
| | (37.48) | (46.49) | (32.45) | (36.63) | (29.09) | (32.08) |
| Year | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Age | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Region | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Region*Interval | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 44974698 | 44974698 | 44701029 | 44701029 | 44701029 | 44701029 |
| Pseudo R2 | 0.120 | 0.118 | 0.121 | 0.120 | 0.122 | 0.120 |

The table shows the hazard model estimated by a simple logit regression. Columns (1)-(2) show standard observables predicting migration. Columns (3)-(4) show the results for our main explanatory variable for unobservable skill. Columns (5)-(6) show the wage based variable. The main variables are computed as moving averages for the last observed months employed as described in the main text.

Exponentiated coefficients; $t$ statistics in parentheses

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

In columns (3) and (4) we add our main explanatory variable constructed as described in section 3.2.3. There is a strong positive selection of workers with respect to our latent skill measure, the coefficients for high-level occupations go down and become insignificant for the highest occupation category. The effect of labor market attachment and broad industry affiliation is not much affected. The education coefficients slightly decrease.
If compared to the conventional raw wage skill measure in columns (5) and (6) we see that the selection is slightly lower for the raw wage measure but the remaining effects are very similar in size.
In this table we have confirmed findings in the literature that workers are positively selected with respect to both observable and unobservable skill measures. We find that our measure shows a stronger correlation with migration than standard raw wage measure. The effect sizes are comparable to other studies (cf. De la Roca, 2017).

### 3.5.2 Selection in Return and Repeat Migration

The fact that there is positive selection to initial migration is a well established fact. More interesting is how the selection plays out for different kinds of migration patterns following the initial migration decision. As we compute the individual or skill component of wages as a residual from the raw log wage, net of the firm component, it includes the part of the wage that is independent of the firms pay policy, corresponding to the current evaluation of his skill and his bargaining power.

Figure 3.1c shows that the individual component further increases after the initial move, emphasizing the two main channels, first migration sets a signal to employers that the worker is mobile and motivated, and second learning is a potential factor, as skills are acquired over time. We see no negative effect of return migration in 3.2c on the individual wage component.
In table 3.3 we now show the two options to either return or move-on to a third region relative to the decision to stay permanent in the second region. The negative selection in the first column of regression (1) shows the negative selection of workers based on their unobserved skill (monetarisable skill), the effect is small though.[11] The likelihood is slightly increased if the wage in the first city was higher compared

[11] The elasticity equals: $(0.834^{-1}-1)/e = 0.073$. So an increase by 10% decreases the probability to return by 0.7%.

to other workers, which is plausible. Compared to the wage measure in regression (2) the effect is slightly smaller. Looking at move-on migration in the second column of the first regression, we see a strong and positive selection of the individual component of wages. This positive selection thus is likely no revision of a negative experience in the second region, particularly as we know from figure 3.1 that move-on migrants profit the most from their initial decision to migrate.

For the other observables we do not see a clear pattern for the decision to return in the home region anymore, i.e. for occupation rank as well as education. Being jobless increases the probability to return home drastically. Workers who where on average longer unemployed in their first region now are more likely to return. Presumably, they were forced to leave and thus are now more likely to return.

Move-on migrants show a positive selection with respect to education for all specifications. Unemployment is also a strong predictor to select into move-on migration. Their selection patterns is quite similar to the selection pattern of the initial migrants in table 3.2.

The overall pattern for unobservable skill confirms selection patterns found in the literature, that migrants are positively selected and returnees are negatively selected. The descriptive figures are in line with commonly assumed channels.

Table 3.3: Return and Move on Selection based on Unobserved Ability

| | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| Multinomial logit: | Return | Move on | Return | Move on | Return | Move on | Return | Move on |
| Wage based: | | | | | | | | |
| Moving Average PE (AKM) | 0.834*** | 1.738*** | | | 0.854*** | 1.854*** | | |
| | (-3.58) | (5.80) | | | (-3.19) | (6.57) | | |
| Moving Average Wage | | | 0.808*** | 1.684*** | | | 0.828*** | 1.785*** |
| | | | (-4.86) | (5.95) | | | (-4.41) | (6.74) |
| Avg. First City Wage | 1.110** | 1.145 | 1.143*** | 1.121 | 1.114** | 1.158* | 1.147*** | 1.129 |
| | (2.37) | (1.68) | (2.97) | (1.40) | (2.46) | (1.80) | (3.05) | (1.49) |
| Occupation: | | | | | | | | |
| qualified | 0.914 | 1.030 | 0.930 | 1.007 | | | | |
| | (-1.07) | (0.13) | (-0.87) | (0.03) | | | | |
| specialist | 1.028 | 1.427 | 1.055 | 1.386 | | | | |
| | (0.31) | (1.50) | (0.60) | (1.38) | | | | |
| expert | 0.969 | 1.154 | 0.996 | 1.112 | | | | |
| | (-0.36) | (0.61) | (-0.04) | (0.45) | | | | |
| Labor market attachment: | | | | | | | | |
| experience | 1.075*** | 0.985 | 1.077*** | 0.983* | 1.075*** | 0.986 | 1.077*** | 0.984 |
| | (14.30) | (-1.47) | (14.53) | (-1.65) | (14.35) | (-1.34) | (14.56) | (-1.54) |
| tenure | 1.078*** | 0.996 | 1.078*** | 0.996 | 1.078*** | 0.996 | 1.078*** | 0.997 |
| | (10.00) | (-0.33) | (9.95) | (-0.28) | (10.00) | (-0.32) | (9.95) | (-0.27) |
| jobless | 9.408*** | 9.784*** | 9.274*** | 9.959*** | 9.414*** | 9.815*** | 9.286*** | 10.02*** |
| | (69.52) | (34.02) | (68.44) | (34.08) | (69.62) | (34.07) | (68.53) | (34.16) |
| Pre-period means: | | | | | | | | |
| avg. in service | 0.978 | 1.050 | 0.981 | 1.056 | 0.972 | 1.035 | 0.975 | 1.043 |
| | (-0.62) | (0.66) | (-0.54) | (0.75) | (-0.78) | (0.48) | (-0.72) | (0.58) |
| avg. in public | 0.812*** | 1.129 | 0.814*** | 1.141 | 0.809*** | 1.119 | 0.812*** | 1.130 |
| | (-3.10) | (1.03) | (-3.06) | (1.12) | (-3.15) | (0.95) | (-3.10) | (1.04) |
| avg. jobless | 1.409*** | 1.713** | 1.492*** | 1.644** | 1.429*** | 1.767** | 1.512*** | 1.686** |
| | (2.83) | (2.34) | (3.28) | (2.15) | (2.95) | (2.47) | (3.39) | (2.26) |
| Broad industry categories: | | | | | | | | |
| service industry | 1.263*** | 1.608*** | 1.244*** | 1.660*** | 1.257*** | 1.579*** | 1.239*** | 1.638*** |
| | (7.05) | (6.83) | (6.55) | (7.28) | (6.90) | (6.57) | (6.44) | (7.08) |
| public employee | 1.129* | 0.869 | 1.097 | 0.930 | 1.128* | 0.855 | 1.099 | 0.922 |
| | (1.88) | (-1.00) | (1.42) | (-0.52) | (1.86) | (-1.11) | (1.45) | (-0.57) |
| elsewhere employed | 1.054 | 3.946 | 1.032 | 4.072 | 1.059 | 3.991 | 1.039 | 4.135 |
| | (0.09) | (1.36) | (0.05) | (1.39) | (0.10) | (1.37) | (0.06) | (1.41) |
| Education: | | | | | | | | |
| vocational training | 1.272*** | 1.841*** | 1.288*** | 1.792*** | 1.281*** | 1.912*** | 1.299*** | 1.853*** |
| | (3.76) | (3.14) | (3.96) | (3.00) | (3.89) | (3.34) | (4.10) | (3.18) |
| some college | 1.258*** | 2.025*** | 1.295*** | 1.928*** | 1.271*** | 2.130*** | 1.309*** | 2.010*** |
| | (3.15) | (3.45) | (3.52) | (3.19) | (3.31) | (3.71) | (3.68) | (3.40) |
| university | 1.205** | 2.321*** | 1.267*** | 2.103*** | 1.227*** | 2.447*** | 1.291*** | 2.176*** |
| | (2.56) | (4.20) | (3.18) | (3.66) | (2.87) | (4.52) | (3.49) | (3.86) |
| Year | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Age | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Years in 2. Region | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 1. Region | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2. Region | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 1641793 | | 1641793 | | 1641793 | | 1641793 | |
| Pseudo R2 | 0.141 | | 0.142 | | 0.141 | | 0.141 | |

The table shows a hazard model estimated by a multinomial logit model to assess selection into return or move-on migration as compared to be permanent migrants (or a stayer after the migration occured). We look at urban-urban migration, conditional urban-urban migration has occurred before. Columns (1) and (3) show the results for our main explanatory variable for unobservable skill. Columns (2)-(4) show the wage based variable. The main variables are computed as moving averages for the last observed months employed as described in the main text. We additionally we control for pre-period averages in terms of wages, broad industries and unemployment.

Exponentiated coefficients; $t$ statistics in parentheses

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## 3.6 Selection based on Firm Quality

While in the previous sections we devoted our attention to estimating a more precise measure of skill from wages, we now turn to the residual of this exercise. We look at the estimated proportional premium a firm pays to all its employees. There is ample evidence connecting firm pay to productivity so that higher paying firms are usually more profitable (cf. Gürtzgen, 2009). While the individual component of wages defines the range of possible wages the individual can obtain, given his skill, the firm premium can be interpreted as defining the realization of his wage.

So an individual working at a low paying firm may wants to switch to a higher paying firm. The worker is potentially willing to move to another region if the firm premium is substantially higher and exceeds the idiosyncratic cost of migration. Unemployed workers, which account for around one third of movers (see figure 3.5), in contrast may have to accept a lower paying firm, compared to previous employers. This which would lead to a decrease in the (average) firm premium and thus an ambiguous prediction in terms of the change in the firm effect.

If the realized firm premium in another region is lower than expected, the worker has the option to either stay in this region, accepting the comparatively low pay, or to return to his initial region and incur the second cost of migration, but potentially benefiting from the end of separation from his preferred region (cf. Knauth and Wrona, 2018).[12]

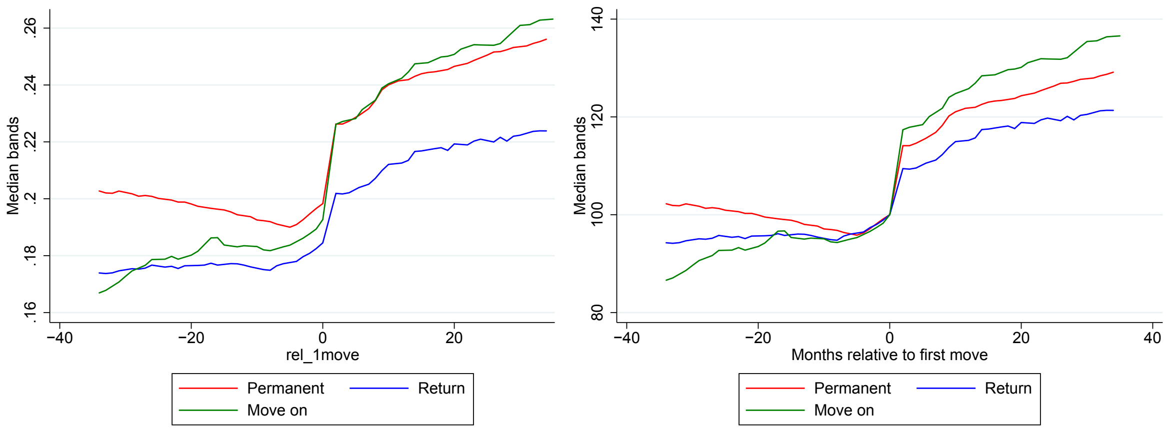
Now in figure 3.3 we descriptively explore the development of wages for all three mover types. From the descriptive statistics in figure 3.1 we know that the average value of the firm premium is around 0.18. In panel 3.3a we show the estimated firm effects over time relative to the first move. The non-mover premium is very similar to the pre-move effects of both repeat move types, while permanent movers are matched to better firms to begin with. For permanent migrants we see a decline in the firm effect previous to the first move. As we exclude job loss from the computation of the moving averages in the whole paper, this decline is either caused by an average decline in pay[13] or voluntary or forced switching to lower paying employers in or close to a workers region. As the the other mover groups stay approximately constant,

[12]In this paper two sorts of potential migration costs are discussed, first the classical costs of moving and second the costs of being separate from e.g., family and friends, which is periodical and ends once the worker returns home.

[13]In the empirical model this can only happen every six years, as firm and worker fixed effects are computed over six year intervals, in order to be identified.

there are potentially other motives behind the initial move (e.g., planned return migration).

Figure 3.3: Firm Effect Change relative to 1. Move




(a) Firm Effects

(b) Rel. Firm Effects

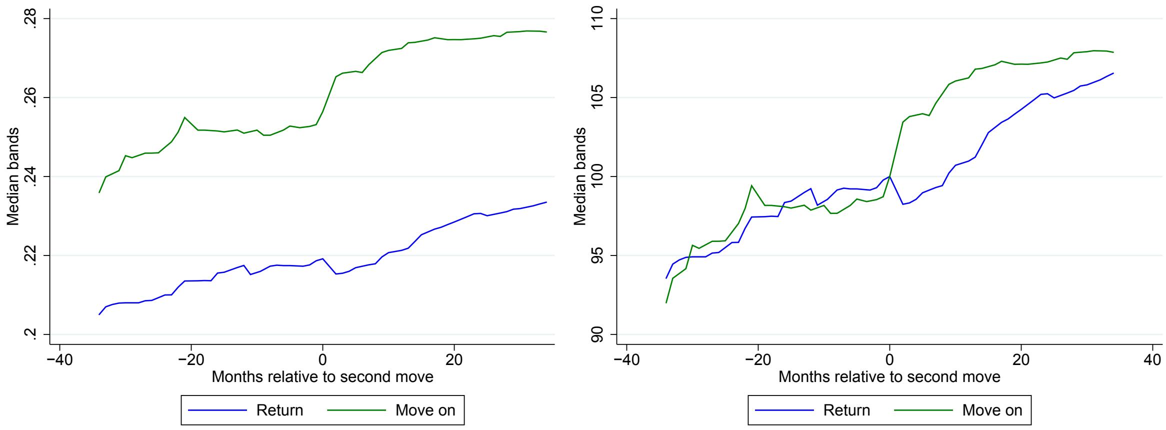
In the above figure the firm pay premium is shown relative to the initial move as defined in the main text. All graphs show the respective median worker of the particular mover group. The panels on the left show the absolute values, while the panels on the right show the relative changes, where the month of migration is set to 100. 3 years prior and after the initial move are shown.

In panel 3.3b the relative increase of the firm effect is depicted. There is a neat ordering which remains consistent over time, where future move-on migrants have to see the highest relative increase in the firm component, above the permanent migrants, who are followed by the later return migrants.

While for the log wages and the person effect the gain from moving was very similar for permanent and (later to be) return migrants, as seen in figures 3.1b and 3.1d. For the firm effect we now see a substantial difference between all three types. In particular return migrants have the lowest increase and the gap widens over time, potentially a reason for their return decision in later periods.

Move-on migrants relatively profit the most and also end up with the highest firm effect overall. As only a small proportion of workers falls into this category and the category is high in university graduates, so that mobility may be an essential part of their occupations.

Figure 3.4: Firm Effect Change relative to 2. Move




(a) Firm Effects (b) Rel. Firm Effects

In the above figure the firm pay premium is shown relative to the second move, the return or move-on move. All graphs show the respective median worker of the particular mover group. The panels on the left show the absolute values, while the panels on the right show the relative changes, where the month of migration is set to 100. 3 years prior and after the initial move are shown.

In figure 3.4 we observe the firm effects around the second decision for the two types of repeat migrants, again in absolute and relative terms. The absolute gap between move-on migrants and return migrants has widened and stabilized over time. Interestingly, the median return migrant experiences a drop in his firm effect after returning. So he is willing to incur a loss in order to return to his supposedly preferred region. On the contrary the move-on migrant, who is similar concerning his previous migration behavior, now observes a wage increase by moving to a third region.

So, although the move-on migrant revises his choice to move to the second region, he is able to further increase his firm match. The behavior and the development of the firm effect of the return migrant is in line with a ”failure” in the second city and a preference for returning close to his initial region. The behavior of the move-on migrant is in line with opportunistic[14] mobility as well as mobility being an integral part of the workers profession.

The above discussion was purely descriptive and unconditional on observables except those discussed in the estimation of the AKM fixed effects.

We now turn and discrete choice logit model, similar to our previous estimation, except that we will focus on the firm pay premium and how it affects decisions for

[14]Such as searching on the job and moving as soon as a higher paying job is found.

Table 3.4: Initial Selection based on Firm Quality

| Logit: | (1) Initial | (2) Initial | (3) Initial | (4) Initial | (5) Initial | (6) Initial |
|---|---|---|---|---|---|---|
| Wage based: | | | | | | |
| Moving Average FE (AKM) | 1.617*** | 1.743*** | 1.606*** | 1.676*** | 0.863*** | 0.827*** |
| | (9.50) | (11.02) | (9.35) | (10.20) | (-2.58) | (-3.33) |
| Moving Average PE (AKM) | | | 1.868*** | 2.034*** | | |
| | | | (23.80) | (27.86) | | |
| Moving Average Wage | | | | | 1.858*** | 2.017*** |
| | | | | | (23.96) | (28.06) |
| Occupation: | | | | | | |
| qualified | 0.920** | | 0.838*** | | 0.834*** | |
| | (-2.00) | | (-4.22) | | (-4.36) | |
| specialist | 1.715*** | | 1.404*** | | 1.392*** | |
| | (11.67) | | (7.23) | | (7.03) | |
| expert | 1.276*** | | 1.033 | | 1.016 | |
| | (5.41) | | (0.70) | | (0.35) | |
| Labor market attachment: | | | | | | |
| exper | 0.896*** | 0.894*** | 0.887*** | 0.885*** | 0.887*** | 0.885*** |
| | (-37.46) | (-38.37) | (-40.15) | (-41.24) | (-40.17) | (-41.22) |
| tenure | 0.961*** | 0.958*** | 0.958*** | 0.956*** | 0.959*** | 0.957*** |
| | (-13.52) | (-14.70) | (-14.35) | (-15.27) | (-13.93) | (-14.77) |
| unemployed | 5.916*** | 5.714*** | 6.261*** | 6.194*** | 6.362*** | 6.315*** |
| | (100.75) | (99.58) | (103.00) | (102.67) | (103.40) | (103.14) |
| Broad Industry Categories: | | | | | | |
| service industry | 1.918*** | 1.911*** | 1.906*** | 1.889*** | 1.907*** | 1.889*** |
| | (36.62) | (36.43) | (36.26) | (35.76) | (36.28) | (35.76) |
| public employee | 1.071** | 1.100*** | 1.077** | 1.086*** | 1.075** | 1.082** |
| | (2.22) | (3.09) | (2.38) | (2.68) | (2.32) | (2.56) |
| elsewhere employed | 1.169 | 1.16 | 1.200 | 1.187 | 1.198 | 1.182 |
| | (0.52) | (0.49) | (0.60) | (0.57) | (0.60) | (0.55) |
| Education: | | | | | | |
| vocational training | 1.518*** | 1.581*** | 1.440*** | 1.458*** | 1.419*** | 1.433*** |
| | (11.63) | (12.85) | (10.14) | (10.55) | (9.73) | (10.04) |
| some college | 2.711*** | 3.006*** | 2.400*** | 2.512*** | 2.365*** | 2.466*** |
| | (24.90) | (27.82) | (21.67) | (22.96) | (21.25) | (22.44) |
| university | 4.046*** | 5.002*** | 3.406*** | 3.746*** | 3.231*** | 3.510*** |
| | (35.74) | (43.57) | (30.81) | (34.35) | (29.11) | (32.06) |
| Year | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Age | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Region | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Region*Interval | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 44701029 | 44701029 | 44701029 | 44701029 | 44701029 | 44701029 |
| Pseudo R2 | 0.120 | 0.118 | 0.122 | 0.120 | 0.122 | 0.121 |

The table shows the hazard model estimated by a simple logit regression similar to table 2. Our main variable of interest is the firm premium of wages. We add the firm pay premium to all specifications in columns (1)-(6). Columns (1)-(2) show standard observables predicting migration. Columns (3)-(4) show the results for our main explanatory variable for unobservable skill as in table 2. Columns (5)-(6) show the wage based variable also as in table 2. The main variables are computed as moving averages for the last observed months employed as described in the main text.
Exponentiated coefficients; $t$ statistics in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

both initial and repeat migration.
In table 3.4 we correlate the firm pay premium with the initial migration decision. As we control for region fixed effects the firm effect can be interpreted relative to the average firm effect within every region. In columns (1) and (2) we only control for the firm premium ignoring the other wage based measures. The effect size in column (2) corresponds to an elasticity of migration of 0.273. So an increase by 10% in the firm pay premium corresponds to a 2.73% increase in the hazard of migration.[15] In columns (3) and (4) we additionally control for our skill measure of the AKM person fixed effect, it only slightly reduces the effect of the premium, speaking in favor of small and positive sorting between ”good” workers to ”good firms”, in the sub-sample of current/future migrants.
Finally, we include our moving average log wage measure, which naturally contains both wage components. It is not surprising that the firm effect strongly decreases as it is positively correlated with the wage by construction. The results in columns (5) and (6) show a negative selection with respect to the firm premium, if holding log wages constant. So given the information contained in the wage the worker is less likely to migrate if he (or believes that he) has a match to a ”good” firm. Thus this conclusion must be handled with caution.
The above results indicate that worker at better paying firms are generally more likely to migrate. Potentially, the firm effect captures very fine grained information on the occupations and the location that lead to a positive selection. The negative selection after controlling for our wage measure hints at the fact that the workers leaves if he has the expectation for a higher firm pay premium.
Table 3.5 shows the selection in to either return or move-on migration relative to the default of staying in the second region in a multinomial regression setting. In the first column of regression (1) we see the relative-risk-ratios to return versus to stay in the second region. A 10% increase in the individual component of wages (PE) leads to a decrease of 0.73% in the probability to return, while a 10% increase in the firm pay premium leads to a substantially stronger decrease of 1.31%. The average wage in the first city increases the probability to return. [16] For the selection

[15]We still control for observables such as occupation level, labor market attachment, broad industry categories, education levels, year and month indicators, current age and region dummies. The effects of the covariates are very similar to the results from 3.2 and are thus not further discussed.

[16]The coefficients for the covariates remain very similar to 3.3 and hence are not discussed in detail here.

Table 3.5: Return and Move on Selection based on Firm Quality

| | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| Multinomial logit: | Return | Move on | Return | Move on | Return | Move on | Return | Move on |
| Wage based: | | | | | | | | |
| Moving Average FE (AKM) | 0.737$^{***}$ | 1.450$^{*}$ | 0.886 | 0.834 | 0.748$^{***}$ | 1.508$^{**}$ | 0.877 | 0.815 |
| | (-3.38) | (1.89) | (-1.17) | (-0.84) | (-3.22) | (2.10) | (-1.27) | (-0.96) |
| Moving Average PE (AKM) | 0.834$^{***}$ | 1.752$^{***}$ | | | 0.856$^{***}$ | 1.866$^{***}$ | | |
| | (-3.59) | (5.86) | | | (-3.13) | (6.61) | | |
| Moving Average Wage | | | 0.831$^{***}$ | 1.739$^{***}$ | | | 0.853$^{***}$ | 1.852$^{***}$ |
| | | | (-3.69) | (5.79) | | | (-3.22) | (6.55) |
| Avg. First City Wage | 1.137$^{***}$ | 1.119 | 1.140$^{***}$ | 1.119 | 1.141$^{***}$ | 1.127 | 1.144$^{***}$ | 1.127 |
| | (2.86) | (1.38) | (2.91) | (1.38) | (2.94) | (1.47) | (2.98) | (1.47) |
| Occupation: | | | | | | | | |
| qualified | 0.930 | 1.012 | 0.932 | 1.009 | | | | |
| | (-0.87) | (0.05) | (-0.85) | (0.04) | | | | |
| specialist | 1.053 | 1.391 | 1.055 | 1.386 | | | | |
| | (0.58) | (1.39) | (0.61) | (1.38) | | | | |
| expert | 0.995 | 1.121 | 0.998 | 1.116 | | | | |
| | (-0.06) | (0.48) | (-0.02) | (0.46) | | | | |
| Labor market attachment: | | | | | | | | |
| experience | 1.077$^{***}$ | 0.983 | 1.077$^{***}$ | 0.983 | 1.077$^{***}$ | 0.984 | 1.077$^{***}$ | 0.984 |
| | (14.55) | (-1.61) | (14.56) | (-1.62) | (14.58) | (-1.50) | (14.59) | (-1.51) |
| tenure | 1.078$^{***}$ | 0.996 | 1.078$^{***}$ | 0.996 | 1.078$^{***}$ | 0.996 | 1.077$^{***}$ | 0.997 |
| | (9.98) | (-0.32) | (9.94) | (-0.29) | (9.98) | (-0.32) | (9.95) | (-0.28) |
| unemployed | 9.298$^{***}$ | 9.895$^{***}$ | 9.270$^{***}$ | 9.950$^{***}$ | 9.306$^{***}$ | 9.942$^{***}$ | 9.281$^{***}$ | 10.01$^{***}$ |
| | (68.75) | (34.05) | (68.42) | (34.06) | (68.83) | (34.11) | (68.51) | (34.13) |
| Pre-period averages: | | | | | | | | |
| average in service | 0.978 | 1.052 | 0.979 | 1.053 | 0.972 | 1.039 | 0.972 | 1.039 |
| | (-0.62) | (0.70) | (-0.61) | (0.71) | (-0.79) | (0.52) | (-0.79) | (0.53) |
| average in public | 0.811$^{***}$ | 1.135 | 0.812$^{***}$ | 1.135 | 0.809$^{***}$ | 1.124 | 0.810$^{***}$ | 1.124 |
| | (-3.12) | (1.08) | (-3.10) | (1.08) | (-3.16) | (1.00) | (-3.15) | (1.00) |
| average unemployed | 1.476$^{***}$ | 1.636$^{**}$ | 1.483$^{***}$ | 1.637$^{**}$ | 1.495$^{***}$ | 1.678$^{**}$ | 1.502$^{***}$ | 1.678$^{**}$ |
| | (3.19) | (2.13) | (3.23) | (2.13) | (3.30) | (2.24) | (3.33) | (2.24) |
| Broad Industry Categories: | | | | | | | | |
| service industry | 1.236$^{***}$ | 1.644$^{***}$ | 1.235$^{***}$ | 1.644$^{***}$ | 1.230$^{***}$ | 1.620$^{***}$ | 1.230$^{***}$ | 1.621$^{***}$ |
| | (6.27) | (7.06) | (6.26) | (7.06) | (6.14) | (6.85) | (6.14) | (6.85) |
| public employee | 1.085 | 0.913 | 1.085 | 0.913 | 1.086 | 0.904 | 1.086 | 0.903 |
| | (1.25) | (-0.63) | (1.24) | (-0.64) | (1.26) | (-0.71) | (1.26) | (-0.71) |
| elsewhere employed | 1.032 | 4.071 | 1.030 | 4.059 | 1.039 | 4.130 | 1.037 | 4.121 |
| | (0.05) | (1.39) | (0.05) | (1.39) | (0.06) | (1.40) | (0.06) | (1.40) |
| Education: | | | | | | | | |
| vocational training | 1.284$^{***}$ | 1.811$^{***}$ | 1.288$^{***}$ | 1.795$^{***}$ | 1.294$^{***}$ | 1.875$^{***}$ | 1.298$^{***}$ | 1.856$^{***}$ |
| | (3.90) | (3.05) | (3.95) | (3.01) | (4.05) | (3.24) | (4.09) | (3.19) |
| some college | 1.282$^{***}$ | 1.968$^{***}$ | 1.292$^{***}$ | 1.926$^{***}$ | 1.297$^{***}$ | 2.058$^{***}$ | 1.306$^{***}$ | 2.006$^{***}$ |
| | (3.40) | (3.30) | (3.49) | (3.19) | (3.57) | (3.53) | (3.65) | (3.40) |
| university | 1.239$^{***}$ | 2.230$^{***}$ | 1.264$^{***}$ | 2.104$^{***}$ | 1.266$^{***}$ | 2.326$^{***}$ | 1.288$^{***}$ | 2.177$^{***}$ |
| | (2.92) | (3.99) | (3.14) | (3.66) | (3.27) | (4.23) | (3.45) | (3.86) |
| Year | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Age | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Years in 2. Region | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 1. Region | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2. Region | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N | 1641793 | | 1641793 | | 1641793 | | 1641793 | |
| Pseudo R2 | 0.142 | | 0.142 | | 0.141 | | 0.141 | |

The table shows a hazard model estimated by a multinomial logit model to assess selection into return or move-on migration as compared to be permanent migrants (or a stayer after the migration occured). We look at urban-urban migration, conditional urban-urban migration has occurred before. We add the firm premium of wages to all four specifications from table 3. Columns (1) and (3) still show the results for our main explanatory variable for unobservable skill. Columns (2)-(4) show the wage based variable. The main variables are computed as moving averages for the last observed months employed as described in the main text. We additionally control for pre-period averages in terms of wages, broad industries and unemployment.

Exponentiated coefficients; $t$ statistics in parentheses

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

in move-on migration the pattern is reversed, although there is positive selection for both the worker component and the firm pay premium, the effect is much stronger for the worker component this time.

Instead of controlling for the person effect we control for the full wage in regression (2). Holding the wage constant the selection into return and move-on migration becomes negative, though insignificant. In particularly, the positive effect on move-on migration vanishes, so that the unintuitive idea that worker leave *due* to a high firm premium is negated. Rather it is likely that a high firm effect leads to a decrease in the probability to return as in regression (1), as a higher wage is attained, while the working at a high paying firm is generally correlated with high mobility occupations. Dropping covariates for job quality slightly increases the size of the coefficients, which is reassuring. Generally, we find that there is more migration from high paying firms, we find that workers migration may act as a reaction to a bad (low paying) firm match.

## 3.7 Conclusion

In this paper we assess the self-selection into migration between high-density regions based 1) on workers unobservable skill and 2) the premium a firm grants its workers over the market price of his skills. For that matter we estimated AKM-type fixed effects and compute monthly moving averages of these effects. In a second step we used detailed information on employment location, pay and duration to estimate a discrete duration model of selection into different migration modes. In the first step selection in to initial migration and in the second step selection from this second location either *home* or to a third region.

We find positive selection in terms of unobservable skill into migration, negative selection for return migration and once more a positive selection into migration into third regions. We find that the selection in to return migration is driven by both, unobservable skill and the quality of the firm a worker is matched to. The effect of the firm match is substantially stronger. These findings support migration theories of learning (cf. De la Roca, 2017) as well as signaling (cf. Knauth and Wrona, 2018).

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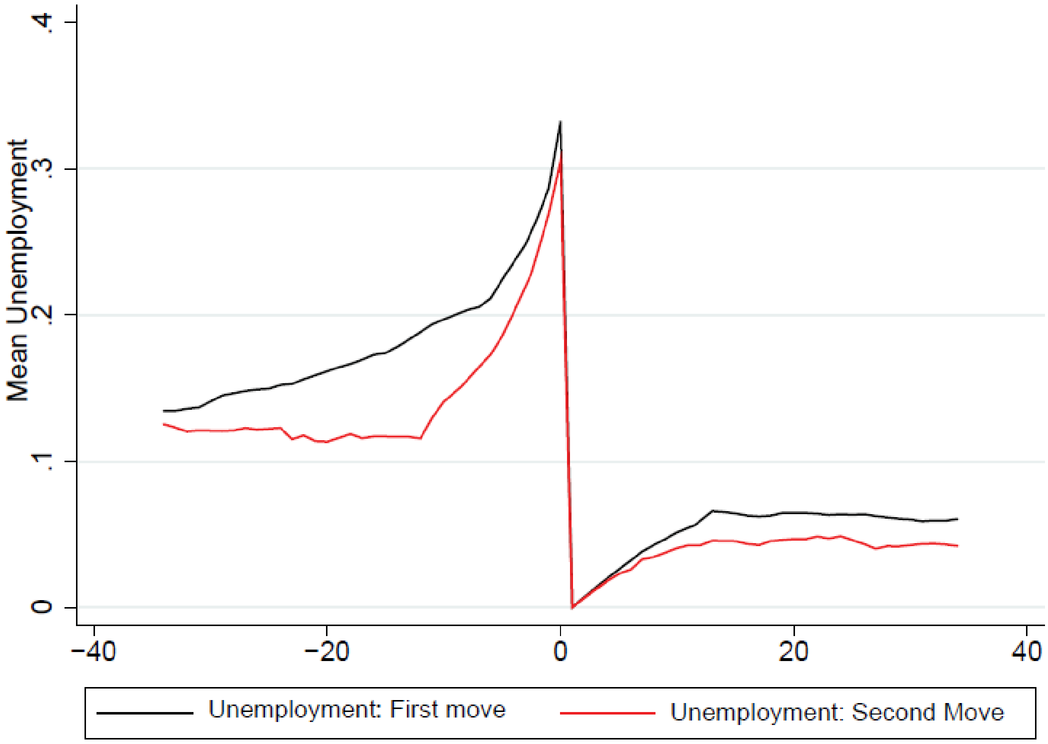
# Appendix

Table 3.6: Descriptive Statistics

| **Descriptive Statistics:** | | | | | |
|---|---|---|---|---|---|
| | | **FE Descriptives** | | | |
| | **Obs.** | **Mean** | **Variance** | **Min.** | **Max.** |
| Stuttgart | 3,920,439 | 0.23 | 0.17 | -1.55 | 1.16 |
| Rheinpfalz | 1,085,743 | 0.22 | 0.17 | -1.44 | 1.49 |
| Unterer Neckar | 1,553,783 | 0.20 | 0.18 | -1.56 | 1.02 |
| München | 3,219,888 | 0.20 | 0.17 | -2.36 | 1.83 |
| Köln | 3,058,369 | 0.20 | 0.17 | -1.38 | 1.99 |
| Rhein-Main | 3,665,133 | 0.19 | 0.16 | -1.58 | 2.03 |
| Starkenburg | 1,225,442 | 0.19 | 0.18 | -1.69 | 1.97 |
| Bochum/Hagen | 2,159,493 | 0.19 | 0.16 | -1.52 | 1.21 |
| Bremen | 703,697 | 0.19 | 0.18 | -1.31 | 1.14 |
| Mittlerer Oberrhein | 1,417,486 | 0.18 | 0.16 | -1.34 | 1.07 |
| Düsseldorf | 4,476,562 | 0.18 | 0.16 | -3.29 | 1.96 |
| Emscher-Lippe | 1,204,377 | 0.18 | 0.15 | -1.30 | 1.60 |
| Hamburg | 2,064,559 | 0.17 | 0.17 | -2.09 | 1.83 |
| Saar | 1,446,460 | 0.17 | 0.17 | -1.27 | 0.99 |
| Duisburg/Essen | 2,721,549 | 0.16 | 0.16 | -1.68 | 2.08 |
| Industrieregion Mittelfranken | 1,822,983 | 0.16 | 0.16 | -1.41 | 1.71 |
| Hannover | 1,615,286 | 0.16 | 0.18 | -1.41 | 2.20 |
| Aachen | 1,480,817 | 0.16 | 0.16 | -1.45 | 1.26 |
| Dortmund | 1,333,710 | 0.15 | 0.15 | -1.45 | 1.14 |
| Bonn | 824,777 | 0.15 | 0.17 | -2.74 | 1.51 |
| Bielefeld | 2,313,475 | 0.15 | 0.15 | -1.35 | 2.78 |

The table gives additional descriptive statistics on the urban regions used in the regressions, and the observations within each region. Furthermore, there are descriptives on the firm fixed effect, particularly means, extremes and variances.
*Source: Own calculations, BeH*

Figure 3.5: Unemployment relative to first and second move




The graphs show the non-employment shares according to our definition before and after the initial (black) and second (red) move. The second move contains return and move-on migrants as defined above. Unemployment is zero by construction one period after the move. Shown are 36 months previous and after the move for the respective median worker.

# Chapter 4

# Latent Heterogeneity and Inequality in German Wage Data

## 4.1 Introduction

We use a 50% random sample of the German workforce to assess sorting patterns in a matched employer-employee framework. We compare different econometric models to estimate two-sided latent heterogeneity of workers and firms using recent methods proposed by Card, Heining, and Kline (2013) and Bonhomme, Lamadon, and Manresa (2017). We discuss and compare the results of the models and compare the assumptions given the results that we find. We decompose the wage components across time with the two methods and compare the trends in wage inequality.
We are the first to employ the BLM method to a large German dataset and discuss our findings of stronger sorting in the light of the recent literature. We apply their short panel method to assess the recent increase in German wage inequality and analyze the role of sorting as compared to other findings as in Card, Heining, and Kline (2013) and Borrs and Knauth (2016). It employs an initial clustering step of the firm effects, reducing the dimensionality of the estimation and allowing for a more complex interactive structure of workers and firms in wage determination.

The methods initially proposed by Abowd, Kramarz, and Margolis (1999) and (Abowd, Creecy, Kramarz, et al., 2002) have been widely used in the literature, e.g. in international trade (cf. Frias, Kaplan, and Verhoogen, 2009; Davidson, Heyman, Matusz, Sjöholm, and Zhu, 2014; Macis and Schivardi, 2016; Baziki, Ginja, and Borota Milicevic, 2016; Borrs and Knauth, 2016), labour (cf. Card, Heining, and Kline, 2013), and urban economics (cf. Dauth, Findeisen, and Südekum, 2017). Their two-sided fixed effects approach decomposes wages into firm and worker components. With this it becomes possible to assess sorting patterns between high wage, presumably high productivity firms and high-wage, high-skill workers. Compared to conventional panel applications, a larger, preferably full-sample of workers is needed to track workers across firms and by this separately identify the fixed effects. Using the full German workforce and fitting the panel into intervals CHK are able show a positive and increasing assortative matching in the labor market. In order to identify the effects, restrictive assumptions have to be made, mostly incompatible with modern search and matching models. In particular, the exogenous mobility assumption prevents match formation to depend on the outcome of the match in terms of wages and hence requires random match formation given worker and firm components and observables. The additive parametric form is also subject to criticism (cf. Eeckhout and Kircher, 2011), it allows only for log-additive complementarities and with this affects the way how, e.g., good workers and good firms interact, in addition to the existing restriction on the idiosyncratic match.

Earlier applications found low or even negative correlations between the two components (cf. Abowd, Kramarz, and Margolis, 1999; Abowd, Creecy, Kramarz, et al., 2002), leading many authors to emphasize problems in the estimation method such as limited mobility or more general the incidental parameter bias. Several authors have discussed the incidental parameter bias inherent in the method (cf. Borovičková and Shimer, 2017; Postel-Vinay and Robin, 2006). Basically, low connectedness of the network, combined with - by construction - a negative correlation of the additive components, particularly leads to a downward bias in the correlation of worker and firm components and thus underestimates the role of sorting in the observed labor market.

Some recent approaches try to address these problems by using within firm rankings of wages (cf. Hagedorn, Law, and Manovskii, 2017) or two-way random effects approaches (cf. Abowd, McKinney, and Schmutte, 2018). The approach by BLM is a hybrid approach with firm group fixed effects, where firms are clustered in advance to essentially reduce the number of fixed effects and to increase mobility between groups and worker correlated random effects. Fewer firm fixed effects lead to a higher precision and to a lower incidental parameter bias. The few observations per worker are more efficiently estimated using random effects, further reducing the scope of the bias. BLM provide different versions of the correlated random effects model, one with discrete worker types forming a mixture model as well as a regression approach based with mean and covariance restrictions without discrete heterogeneity. Furthermore, they introduce an dynamic approach relaxing the strong exogenous mobility assumption. We will focus on the baseline approach with regression based estimation, though.

An initial step of k-means clustering the firms by their wage distribution is shown to have no effect on the further inference (cf. Bonhomme, Lamadon, Manresa, et al., 2017). See (cf. Steinley, 2006) for methods related to the k-means clustering approach and (cf. Cameron and Trivedi, 2005, Ch. 22.8 and Ch. 24.6) for an overview of mixed linear or hierarchical linear models.

We will use the interactive regression based extension of the approach by Abowd, Creecy, Kramarz, et al. (2002) by Bonhomme, Lamadon, and Manresa (2017) to account for a richer pattern of complementarities between workers and firms. It

basically allows for firm class dependent worker types/components of wages and addresses a prominent criticism of the method.
See Bonhomme (2017) for an extensive review of the literature on bipartite networks in general and its application to labor economics.
In the following section 4.2 we describe the German labour market data that we use and the sample restrictions that we employ. We briefly discuss the method by Card, Heining, and Kline (2013) and its interactive extensions as proposed by Bonhomme, Lamadon, and Manresa (2017), in particular concerning the necessary assumptions for identification in the panel data sense. In section 4.3 we describe the k-means clustering approach, discuss the descriptive results and compare them to the Swedish data as used in BLM. In section 4.4 we discuss the results of the variance decomposition in detail for the interval 2002-2004. Then we show a first plot of the estimated components of wage inequality using the BLM method.

## 4.2 Data Description

We use a 50% random sample form the Beschäftigtenhistorik (BeH) of all full-time working men between 20 and 60 years of age in west Germany. Similar to Borrs and Knauth (2016) we impute top coded values with a tobit imputation (see Card, Heining, and Kline, 2013). We have very detailed information on individual characteristics such as birth year, schooling, higher education, occupation, employment status and wages. We know the region of the firm[1] on the NUTS-3 level as well as three digit industries. In combination of worker and firm information we are able to retrieve the size and of firms as well as wage distributions. The observational period ranges form 1985 to 2010.
The dataset is constructed from daily information on the job-spell level. The information is aggregated to the yearly level by choosing the highest paying spell per year. Wages are top-coded and thus imputed with a tobit imputation similar to Card, Heining, and Kline (2013).
Starting from the 50% random sample of all male full-time employed workers, that are working in a firm which is part of the *connected set* as defined by Card, Heining, and Kline (2013), we need some further restrictions. We only take into account

[1] In the whole paper by firm we mean the a local establishment, as the ownership structure across establishments is unknown.

workers, who are constantly employed between 2002 and 2004[2] as well as constantly existing establishments with at least one employee. We exclude the primary sector, as well as some highly regulated or for some other reason problematic sectors including education, health, banks, public administration, construction and private household services. Together with the focus on male workers, we receive a relative high importance of the manufacturing industry compared to the overall economy. It leaves us 2,743,819 workers for the interval 2002-2004. For the application on the development of wage inequality we use overlapping three year intervals from 1986 to 2010, leaving us with twelve intervals.

## 4.3 Econometric Methods of Latent Heterogeneity

In the following we shortly review the methods used to reduce the number of firm fixed effects to be estimated by k-means clustering, while descriptive Statistics on the clusters can be found in section 4.4. We compare the estimation equations in the CHK and BLM approaches and discuss in how far they differ between these methods.

### 4.3.1 k-means Clustering

In a first step we group the firms in ten clusters to reduce the else high dimensionality of the firm dimension as proposed by (Bonhomme, Lamadon, and Manresa, 2017). Heterogeneity is thus assumed to be at the firm class level. The implicit assumption is that firms with very similar wage distributions have a similar wage setting mechanism and that the little number of classes captures a large part of the variance in that respect.

$$\min_{k(1),\dots,k(J),H(1),\dots,H_K} \sum_{j=1}^{J} n_j \int \left(\hat{F}(y) - H_{k(j)}(y)\right)^2 d\mu(y) \tag{1}$$

We minimize the sum of quadratic distances between the hypothetical centers of the clusters and the observed wage distributions of firms. In practice 20 percentiles are used to approximate the wage distributions of firms. We then minimize along those 20 dimensions as in equation (1). Random starting cluster centers are chosen and

[2] As in Borrs and Knauth (2016) we used the highest spell earn in the respective year to determine the yearly observations.

the closest observations are classified accordingly. The algorithm then incrementally shifts the centers until no further improvement of fit can be observed.[3] We follow BLM in choosing 10 classes for our baseline estimates. A key contribution of Bonhomme, Lamadon, Manresa, et al. (2017) is to prove that the clustering algorithm can be used in the first stage to reduce the high dimensionality without affecting the second stage more generally. They assess and discuss the asymptotic properties of the reduction and look into some applications.

### 4.3.2 Method by Card, Heining and Kline (2013)

In the papers by Abowd, Creecy, Kramarz, et al. (2002) and Card, Heining, and Kline (2013) a two-way fixed effects approach, which captures the latent heterogeneity of workers and firms is used. Complementarities in production are restricted due to the log-additive structure, but the model has a high explanatory power as compared to worker-firm match fixed effects.[4]

$$y_{it} = \alpha_i + \psi_{\mathbf{J}_{(i,t)}} + x'_{it}\beta + \varepsilon_{it} \tag{2}$$

$y_{it}$ is the log-wage of an individual i in year t. It is explained by the individual fixed effect $\alpha_i$ and the firm-fixed effect $\psi$, where the subscript $\mathbf{J}_{(i,t)}$ describes whether a match between a worker and a firm occurs during the sample period. As Card, Heining, and Kline (2013) wants to show the change in the importance of these components the sample intervals have been chosen to mediate between the number of possible observations per period and the "quality" of the network, that is the number of observations per worker or the number of links between firms. The covariates include interactions of experience, age and education.

The effects are separately identified between firms where workers switch in between. So for all firms that are part of the network we can identify firm and worker effects. For German data 95% of establishments are identified for all time periods, if using a reasonable length of periods, such as 6 years as in (Borrs and Knauth, 2016).

For most non-movers we have to compute the fixed effect as a mean of the yearly residuals. This means we assume there is no fundamental difference between movers and stayers in wage formation.

[3] We use the kmeansW package in R, as proposed by BLM, which uses the Hartigan-Wong algorithm for optimization.

[4] See Card, Heining, and Kline (2013) for an extensive comparison for German data.

$$\hat{\alpha}_i = 1/T_i \sum_t (y_{it} - \psi_{\mathbf{J}_{(i,t)}} - x'_{it}\hat{\beta}). \tag{3}$$

For unbiased estimation we need $E(\varepsilon_{it}|\alpha_i, \psi_{\mathbf{J}_{(i,t)}}, x_{it}) = 0$ for movers, for stayers we further assume no correlation of the independent variables and the error term for all periods of an interval, following from equation (3). The assumption is extended to the whole interval period for stayers in the standard approach. This means the assumption is somewhat stronger for stayers. It is assumed that the idiosyncratic match does not affect the likelihood of a match to occur. So that workers are matched to firms at random given their observables.

This exogeneous mobility assumption is informally tested with German data by CHK looking at switchers between the firm deciles based on the firm fixed effects and their respective errors, where they find little cause for concern. More recently Abowd, McKinney, and Schmutte (2018) developed a more formal test, looking at whether high future match effects could determine termination of a (previous) match.

Relatively long panels are needed to get multiple observations per worker and a strong connection between firms. Weak links between groups of firms will lead to a loss of efficiency and large measurement error. This reduced scope for repeated observations and assessing change in i.e. wage inequality. There is only little room for complementarities in production, which is not allowed to differ, i.e. across the skill spectrum. The fact that the idiosyncratic match effect it not allowed to predict match formation runs contrary to most modern labor market models of sorting and matching.

### 4.3.3 Method by Bonhomme, Lamadon and Manresa (2017)

The interactive extension of the standard AKM equation in equation (2) allows for different patterns of complementarity for different types of workers and firms as compared to the standard log-additive structure in the baseline AKM approach. $a_t(k_{it})$ is the firm class fixed effect in a simple log earnings regression, replacing the firm fixed effect. The term $b_t(k_{it})\alpha_i$ allows the worker type random effect to depend on the firm class k. $x_{it}$ are potential worker specific but time variant covariates such as experience or tenure.

The exogenous mobility assumption made in the baseline model still has to hold. Conditionally on worker and firm types mobility is exogenous in that it does not depend on the (residual) wage. So that mobility between some pair of firm classes is more or less likely for some worker types.

$$y_{it} = a_t(k_{it}) + b_t(k_{it})\alpha_i + x'_{it}\beta + \varepsilon_{i,t} \tag{4}$$

Given all included variables, worker type, firm type and other covariates the new wage after a move is independent of the previous wage, meaning the error from the regression in $t-1$.
Identification of worker types is reached by restrictions on job movers between any two firm classes, back and forth (see BLM (2017, page 12). It is assumed that the switchers from say class 1 to class 2 differ from switchers in the other direction such that:

$$E_{kk'}(\alpha_i) \neq E_{k'k}(\alpha_i) \tag{5}$$

See BLM (2017) for a formal discussion of identification.
In practice we use a three year interval and check whether workers switch jobs between classes in the second year.
The moment condition is based on that by dividing (4) by $b(k_{it})$ and first differencing out the individual random effect $\alpha_i$ it becomes possible to estimate the coefficients $a_t$ and $b_t$ and the values for the covariates. Using linear IV techniques, particularly using interactions of first and second period firm classes and covariates as instruments the model can be identified. The means of the random effects for each class combination for movers $\mu^m_{kk'} = \mathbb{E}(\alpha_i | k_{i1} = k, k_{i2} = k', m_{i1} = 1)$ can be retrieved as a residual. If the error terms in the two periods are assumed to be uncorrelated, the conditional variance of $\alpha_i$ can be estimated. We are then able to compute the covariance between worker and firm components.
As the firm classes replace the single firms, mobility is allowed to depend on firm classes before and after the move but has to be independent of (residual) past income. Furthermore, there is no serial dependence in the wages y given the firm classes and the mobility indicators
Different from the AKM approach the identification relies on the fact that (5) holds. In the AKM approach the symmetry between movers of different percentiles of effects is used as suggestive evidence of additivity.

The strong assumption of exogenous mobility still has to be made in the static version of the BLM approach. So match formation based on the idiosyncratic match component is not possible. It will be possible to consistently estimate means of all random effects for group combinations of switchers (i.e. workers switching from firm class 3 to class 5), but not the variances without restricting the error structure of the panel, which is needed for computation of i.e. the correlation between worker and firm effects. In a dynamic version of their approach BLM allow for an AR-1 process of errors between job switches, allowing for a limited role for the idiosyncratic match in match formation. They show that this can be nested in formal search and matching models such as Shimer and Smith (2000).

## 4.4 Results

In the following we look at some descriptives statistics of the k-means clustering in order to assess the plausibility of the results and to compare them to the Swedish results by BLM. We discuss the results of the decomposition and compare it to the AKM results over the same period and to the long-panel non-clustered results from Borrs and Knauth (2016) and other decomposition results. Finally, we repeatedly estimate the method for a panel between 1986 and 2010, and discuss the shift in the components of wage inequality.

### 4.4.1 Descriptives Statistics of Firm Clusters

In table 4.1 we provide descriptive statistics for our ten clusters with their respective workers in 2002, similar to table 1 from Bonhomme, Lamadon, and Manresa (2017). The clusters are ordered by the average log wage, as there is no inherent ordering by the k-means algorithm.

We see a substantial variation in between the clusters in terms of log daily wages, corresponding to average monthly earnings of 1429 EURO for the lowest versus 5110 EURO for highest cluster. Comparing the cluster ordering with the average values of the firm and worker fixed effects in 2002 estimated in the interval 2000-2005 in Borrs and Knauth (2016) we see a positive though not perfect correlation for both values as one would expect.

The between firm variance of wages largely consists of the between class variance of wages, indicating that the loss of information is not severe. We have a substantial number of workers and firms within all classes as well as enough movers between all

classes to identify the static model.
We indicate the largest establishment per class, counting only the workers in the sample.
Higher paying firm classes tend to have fewer firms with a larger number of employees. Accordingly the firm size of the median workers also increases with the firm class. Class 8 has the largest firms (by median), as well as by a high margin the largest manufacturing share of workers, suggesting that the large German car manufacturing plants and chemical industries fall under this category. There is a detailed table on the typical/largest industries across the firm classes, supporting this point (see table D2).
We also have strong disparities in the share of university graduates as part of the workforce. While the lowest four groups all have below 10% of workers with at least some college education we have 43.3% and 65.04% in the highest two groups, respectively.
Interestingly we find the highest share of manufacturing workers in the middle to upper part of the firm classes with shares above 60% in classes 6 to 8, partly driven by the German car industry (see table D2).
The between group variance of wages explains 91.16% of variance between establishments. The loss of information induced by clustering is hence small and of comparable size to the Swedish data in BLM.

### 4.4.2 Empirical Comparison of Methods for 2002-2004

The table 4.2 is based on a simple variance decomposition, where the estimated means and variances of the random effects of the switchers and stayers between groups are used.

$$var(y_{it}) = var(\alpha_i) + var(k_{it}) + 2 \cdot cov(\alpha_i, k_{it}) + var(\varepsilon_{it}) \qquad (6)$$

The variance components have been normalized to a percentage of total explained variance.
In table 4.2 the results from the interactive model in panel (a) is compared to the reduced AKM type estimation with $b = 1$ in panel (b), as seen in equation (2). It shows the relative importance of the worker and firm components as well as their covariance, shown as a percentage of total variance. The BLM approach, which

Table 4.1: Descriptive Statistics

| Class: | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Mean/Sum |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Wages** | | | | | | | | | | | |
| Log earnings | 3.82 | 4.13 | 4.28 | 4.38 | 4.43 | 4.50 | 4.62 | 4.72 | 4.87 | 5.09 | 4.53 |
| Monthly earnings in EUR | 1429.51 | 1929.14 | 2230.99 | 2449.22 | 2673.66 | 2803.86 | 3203.86 | 3531.83 | 4139.21 | 5110.67 | 3050.24 |
| Variance of log wage | 0.1069 | 0.0577 | 0.0644 | 0.0449 | 0.1202 | 0.0650 | 0.0997 | 0.0869 | 0.1120 | 0.1042 | 0.0863 |
| Between firm variance | 0.0565 | 0.0070 | 0.0045 | 0.0035 | 0.0052 | 0.0025 | 0.0023 | 0.0022 | 0.0019 | 0.0022 | 0.0059 |
| Pe (AKM; BK (2017)) | 3.99 | 4.12 | 4.18 | 4.21 | 4.29 | 4.27 | 4.36 | 4.41 | 4.55 | 4.73 | 4.33 |
| Fe (AKM; BK (2017)) | -0.09 | 0.08 | 0.15 | 0.22 | 0.19 | 0.28 | 0.30 | 0.36 | 0.35 | 0.37 | 0.25 |
| **Firm & Group Size** | | | | | | | | | | | |
| # workers | 137,819 | 199,185 | 292,384 | 227,640 | 257,592 | 344,168 | 411,543 | 359,341 | 299,377 | 214,770 | 2,743,819 |
| # firms | 49746 | 42320 | 37716 | 27853 | 20143 | 21044 | 18845 | 18108 | 15206 | 16269 | 267,250 |
| Largest sample firm | 544 | 578 | 561 | 1409 | 529 | 5088 | 4330 | 18882 | 13121 | 7729 | 6092.75 |
| Median worker firm size | 4 | 8 | 17 | 28 | 28 | 80 | 91 | 259 | 133 | 112 | 88.43 |
| Avg. firm size | 2.77 | 4.71 | 7.75 | 8.17 | 12.79 | 16.35 | 21.84 | 19.84 | 19.69 | 13.20 | 10.27 |
| **Education in col. %** | | | | | | | | | | | |
| No training | 19.7 | 13.61 | 12.59 | 11.38 | 11 | 11.17 | 7.5 | 5.92 | 4.22 | 2.14 | 9.23 |
| Vocational Training | 74.15 | 80.54 | 80.54 | 81.7 | 75.07 | 78.37 | 72.41 | 71.56 | 53.49 | 32.82 | 70.45 |
| Some College | 4.27 | 3.84 | 4.05 | 3.34 | 6.44 | 3.9 | 6.34 | 6.06 | 9.95 | 11.6 | 6.03 |
| University | 1.88 | 2.01 | 2.82 | 3.58 | 7.48 | 6.56 | 13.76 | 16.45 | 32.35 | 53.44 | 14.29 |
| **Age Group in col. %** | | | | | | | | | | | |
| <30 | 29.96 | 21.75 | 17.88 | 14.10 | 16.50 | 12.16 | 12.55 | 11.67 | 10.61 | 7.92 | 14.42 |
| 30-39 | 31.23 | 35.20 | 35.79 | 36.10 | 35.88 | 35.10 | 36.47 | 35.88 | 38.74 | 39.43 | 36.19 |
| 40-49 | 25.38 | 28.51 | 30.82 | 32.79 | 31.03 | 34.47 | 33.53 | 34.32 | 33.02 | 34.87 | 32.44 |
| $\geq$ 50 | 13.43 | 14.55 | 15.51 | 17.00 | 16.59 | 18.27 | 17.45 | 18.13 | 17.62 | 17.78 | 16.95 |
| **Broad Industries in col. %** | | | | | | | | | | | |
| Manufacturing | 16.72 | 34.63 | 46.88 | 52.54 | 51.8 | 68.03 | 69.21 | 73.12 | 54.78 | 39.58 | 55.14 |
| Services | 79.96 | 62.96 | 50.09 | 42.12 | 45.75 | 27.35 | 27.36 | 24.64 | 39.77 | 56.4 | 41.23 |
| Public | 3.29 | 2.4 | 3.02 | 5.22 | 2.44 | 4.6 | 3.41 | 2.22 | 5.43 | 4 | 3.61 |
| Other | 0.03 | 0.01 | 0.01 | 0.12 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 |

The table contains descriptive statistics, particularly means, medians and sums of worker and firm variables within firm clusters. Furthermore, we have merged some results from the paper by Borrs and Knauth (2016), where a two-way fixed effect is estimated over the interval 2000-2005. The clustering results are based on a k-means algorithm as described in (1). The broad industry categories are complemented by table D2. Wages are imputed, above the social security maximum.
*Source: Own calculations, BeH.*

allows for richer interactions between firms class fixed and worker type correlated random effect, does not improve fit in comparison to the additive version. Comparing our main results in (a) to the Swedish data, we find a remarkably similar pattern. The firm effects are low, we find a high correlation between firm fixed and worker conditional random effect.

The two-sided AKM fixed approach for Germany in (e) by Borrs and Knauth (2016) and (f) by CHK, though for different and necessarily longer time periods, presumably underestimates the role of sorting of high earning types to on average high paying firms.

The two sided fixed effects approach with millions of parameters on both dimensions is prone to incidental parameter or ”low mobility bias”, which would affect the correlation between the two fixed effects. Intuitively, weak links between firms, that is few switchers between firms lead to larger errors in estimation that affect both wage components in the opposite direction. Both the dimension reduction by clustering and the discrete-type random effects avert inefficiency in the estimation in the two-sided fixed effects. The interactive version gives very similar results to the linear specification with $b = 1$. Though the increased possibilities of complementarity seem not to have a large effect on the results, both for Swedish and German data. Finally, it should be noted that the samples differ. While panels (a) to (d) have been similarly restricted, panels (e) and (f) use all industries and much longer panels to increase mobility between firms.

### 4.4.3 Application: Increase in Wage Inequality in Germany

We have estimated the fixed firm and random worker components for our exemplary period of 2002-2004. As we have access to a long panel we construct overlapping intervals to trace short-run changes. In figure 4.1 we see the course of the explained variance over time. It is spit up in the three components of interest, variance of the ten firm class fixed effects, the six worker type random effects and twice the covariance of the two. On the left panel (a) we see the relative importance of these components over time, while we show the overall increase in all components in panel (b).

There is a general increase in relative importance of the firm effect as well as an strong increase of the covariance in the end nineties. The overall importance of the covariance in explaining the wage dispersion in Germany is high compared to the findings of Card, Heining, and Kline (2013) and Borrs and Knauth (2016). This could hint at a higher importance of complementarities as previously thought for German labor market data.

While we see a parallel movement of overall inequality and the worker component, there is a substantial increase of both the firm effect and the covariance, interpretable as a sorting component, since around 1995. It has been argued that this rise can be attributed to more complex production processes, may it be due to internationalization of the production process or skill-biased technological change.

The increase in wage inequality in the United States (cf. Autor, Levy, and Murnane, 2003; Beaudry and Green, 2005), Germany (cf. Spitz-Oener, 2006; Dustmann, Ludsteck, and Schönberg, 2009) and other advanced economies (cf. Goos, Manning, and Salomons, 2009) has been prominently discussed, in particular concerning an increasing polarization of jobs and complementarities between high or low-skilled workers with recent advances in technology most notably the advent of computer

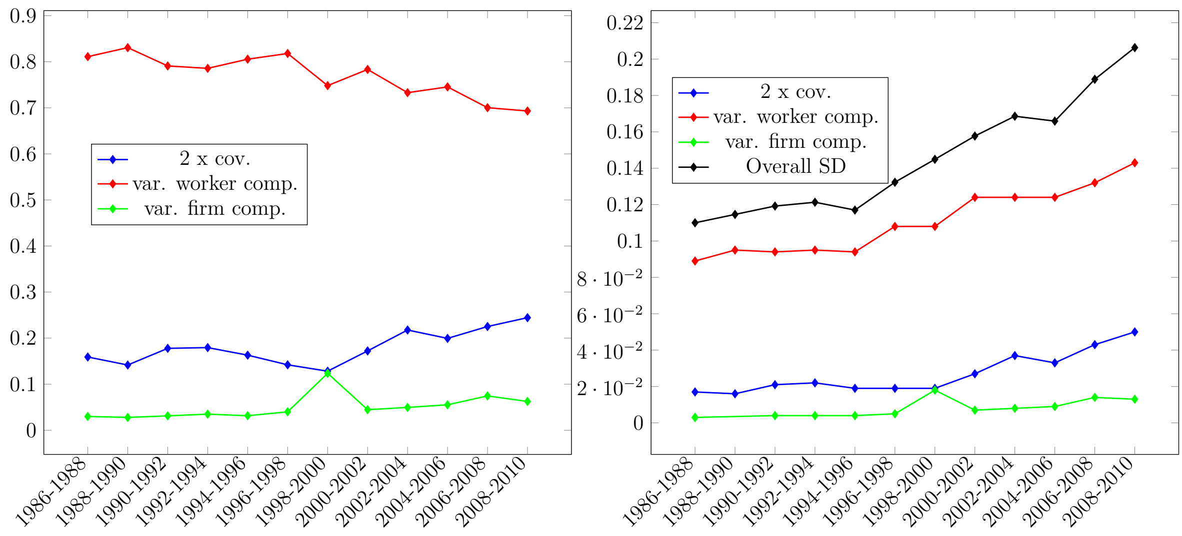
Table 4.2: Variance Decomposition 2002-2004

| $\frac{Var.Firm}{Var}$ | $\frac{Var.Worker}{Var}$ | 2 x Covariance | Correlation | $R^2$ |
|---|---|---|---|---|
| (a) German Data, ('02-'04), interactive (BLM-type) | | | | |
| 0.0507 | 0.7254 | 0.224 | 0.5838 | 0.785 |
| (b) German Data, ('02-'04), linear (AKM-type) | | | | |
| 0.0495 | 0.7329 | 0.2176 | 0.5716 | 0.776 |
| (c) BLM, Swedish Data ('02-'04), interactive | | | | |
| 0.030 | 0.814 | 0.156 | 0.502 | 0.694 |
| (d) BLM, Swedish Data ('02-'04), linear | | | | |
| 0.024 | 0.837 | 0.138 | 0.485 | 0.724 |
| (e) BK ('00-'05), linear | | | | |
| 0.2217 | 0.6076 | 0.08 | 0.109 | 0.9459 |
| (f) CHK ('02-'09), linear | | | | |
| 0.2257 | 0.5438 | 0.1745 | 0.249 | 0.9412 |

Notes: The AKM and BLM results are computed without covariates and show the share of variance explained by the listed components, which then add up to one. For reference we show related results from other studies. In particular the original swedish results. The values for CHK ('02-'09) and BK ('00-'05) are computed with basic covariates which are excluded in the table, hence shares to not add up to one. The difference in values between BK and CHK shows the increase in sorting in the latter half of the interval.
Source: Own calculations, BeH.

technology and automation. More complex production processes may make an increased sorting of the factors of production more profitable.
Particularly between 1995 and 2005 there was a considerable increase in German wage inequality, with several concurrent developments such as a comparatively stagnant economy in Germany, increasing competition from China and Eastern European economies and a decrease in union coverage.
Borrs and Knauth (2016) only find a small role for the correlation between the two

Figure 4.1: Increase in Wage Dispersion




(a) Shares

(b) Absolute Increase

Notes: The graphs depict the changes of variances and covariances of wage components as computed with the static interactive model by BLM. (a) gives the relative shares while (b) shows the absolute increases in dispersion and its components. The sample includes full-time working men between 20 and 60 in West Germany between 1986 and 2010, fully employed during the sub-sample period and not working in an excluded industry (as named above).

Source: Own calculations, BeH.

effects, similar to Card, Heining, and Kline (2013). The first study that, due to using the full German sample, is able to find at least a positive and rising role of positive sorting between their additive fixed effects. Still their effects may be biased downwards due to limited mobility bias.

In applications of the approach by CHK such combining the wage components with instrumented trade shocks as in BK they did not find a clear link between internationalization and increased trade with these Eastern economies and the sorting component of wages, potentially due to an underestimation of this effect. This underlines the scope and importance of an unbiased estimation of sorting patterns.

## 4.5 Conclusion

We apply the simplest model from the recent paper by Bonhomme, Lamadon, and Manresa (2017) to German data. It extends the AKM approach into an interactive regression model, employing a hybrid approach between fixed firm class effects and

correlated random worker effects.
We see a strong advantage in the reduced dimensionality due to their proposed firm clustering in the pre-stage of the estimation. The interactive regression based approach addresses prominent criticism of the baseline AKM approach such as the overly simplistic additivity in the wage components and is even extendable to dynamic framework, with attempts to address the strong exogenous mobility assumption by allowing for serial dependence in the error structure.
We use their method to show that sorting is largely underestimated in previous studies of the German labor market, something potentially relevant for applied studies using the AKM fixed effects. Similar to their finding for a small Swedish dataset we find that the incidental parameter bias is largely responsible for the underestimation of correlation between the wage components. A useful feature is the potential reduction in interval length allowing for more detailed descriptions over time, as well as the possibility to work with smaller samples.
Depending on the application, the clustering approach could be combined with a AKM type fixed effects approach on the second stage.
We replicate and confirm the baseline findings from BLM with very similar reactions of the data for specification manipulations.

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# Appendix

The results of the decomposition in table (D1) are similar to our main findings in table (4.2) in terms of the importance of the wage components. In particular the covariance remains high for different numbers of clusters. Controlling for age and education dummies and their interactions leads to a twofold increase in the importance of the firm components, potentially due to an increase in efficiency in the estimation as there is substantial sorting based on formal education and some sorting based on age (see table 4.1).

Table D2 is complementary to table 4.1 as it shows the most common and the largest industries within the ten clusters we estimated. In the second column we corrected for the size of the industries and listed the top three industries per firm class, which have the highest propensity to have workers in that firm class. On the right side we see the top three industries by sheer size. In the lower classes we see mostly establishments with a lot of low skilled service workers such as hotels and restaurants, retailers and transport services. In the middle of the distribution we find large manufacturing industries, such as metals and machinery

The upper-middle clusters are dominated by the German car, machinery and chemical industries, while the top has many workers from computer and skilled service industries.

”other business activities” is a highly mixed industry, which can be found in the top and the bottom of the clusters. It includes temporary personnel service (”Zeitarbeit”), cleaning services but also law firms, architectural offices and consultancies.

Table D1: Variance Decomposition 2002-2004, Robustness

| $\frac{Var.Firm}{Var}$ | $\frac{Var.Worker}{Var}$ | 2 x Covariance | Correlation | $R^2$ |
|---|---|---|---|---|
| | | (a) 5 clusters, interactive | | |
| 0.0462 | 0.7512 | 0.2026 | 0.5438 | 0.7654 |
| | | (b) 5 clusters, linear | | |
| 0.049 | 0.733 | 0.218 | 0.5749 | 0.7822 |
| | | (c) 10 clusters, interactive | | |
| 0.0494 | 0.7331 | 0.2176 | 0.5715 | 0.7766 |
| | | (d) 10 clusters, linear | | |
| 0.0504 | 0.726 | 0.2236 | 0.584 | 0.7848 |
| | | (e) 15 clusters, interactive | | |
| 0.0522 | 0.7343 | 0.2136 | 0.5453 | 0.7596 |
| | | (f) 15 clusters, linear | | |
| 0.0513 | 0.7218 | 0.2268 | 0.5893 | 0.7856 |
| | | (g) 10 clusters, interactive, net of education and age | | |
| 0.0986 | 0.6819 | 0.2196 | 0.4235 | 0.597 |
| | | (h) 10 clusters, linear, net of education and age | | |
| 0.0865 | 0.646 | 0.2674 | 0.5658 | 0.7091 |

Notes: We compare our baseline results to different specifications with 5, 10 and 15 clusters in the years 2002-2004, for both the linear (AKM-type) and interacted versions. In Panels g) and h) we first run a yearly regression with interacted age and education group dummies on the wage and apply the method on the residual.
Source: Own calculations, BeH.

Table D2: Most Common 2-digit industries across classes in 2002

| Class | Most Common | Largest Share |
|---|---|---|
| 1 | | |
| | hotels and restaurants (55) | other business activities (74) |
| | other business activities (74) | land transport; transport via pipelines (60) |
| | other service activities (93) | Hotels and restaurants (55) |
| 2 | | |
| | hotels and restaurants (55) | retail trade, except of motor vehicles and motorcycles (52) |
| | wood and wood products (20) | Supporting and auxiliary transport activities (63) |
| | Supporting and auxiliary transport activities (63) | wholesale trade and commission trade (51) |
| 3 | | |
| | wood and wood products (20) | wholesale trade and commission trade (51) |
| | textiles (17) | retail trade (52) |
| | furniture; manufacturing n.e.c. (36) | fabricated metal products (28) |
| 4 | | |
| | post and telecommunications (64) | land transport; transport via pipelines (60) |
| | land transport; transport via pipelines (60) | fabricated metal products (28) |
| | Sewage and refuse disposal (90) | machinery and equipment n.e.c. (29) |
| 5 | | |
| | leather and leather products (19) | wholesale trade and commission trade (51) |
| | wearing apparel; dressing and dyeing of fur (18) | machinery and equipment n.e.c. (29) |
| | textiles (17) | fabricated metal products (28) |
| 6 | | |
| | basic metal (27) | basic metal (27) |
| | pulp, paper and paper products (21) | machinery and equipment n.e.c. (29) |
| | Sewage and refuse disposal (90) | fabricated metal products (28) |
| 7 | | |
| | collection, purification and distribution of water (41) | machinery and equipment n.e.c. (29) |
| | air transport (62) | fabricated metal products (28) |
| | machinery and equipment n.e.c. (29) | wholesale trade and commission trade (51) |
| 8 | | |
| | motor vehicles, trailers and semi-trailers (34) | motor vehicles, trailers and semi-trailers (34) |
| | chemicals and chemical products (24) | machinery and equipment n.e.c. (29) |
| | other transport equipment (35) | chemicals and chemical products (24) |
| 9 | | |
| | tobacco products (16) | motor vehicles, trailers and semi-trailers (34) |
| | air transport (62) | other business activities (74) |
| | coke, refined petroleum products (23) | machinery and equipment n.e.c. (29) |
| 10 | | |
| | computer and related activities (72) | other business activities (74) |
| | office machinery and computers (30) | computer and related activities (72) |
| | coke, refined petroleum products (23) | wholesale trade and commission trade (51) |

Notes: The table shows the most common 2-digit industries across the groups resulting from the k-means clustering. We show the top three industries providing most workers per class on the right and the most common industry on the left. By most common we mean, which industry has the highest propensity to have workers in that particular class or which industry would have the largest worker share given all industries have the same size. The industry classification is the German *Wirtschaftszweige* (WZW) of 1993, which is closely related to the NACE Rev. 1.1. industrial classification. Some industry names have been shortened.
Source: Own calculations, BeH.