Discussion Paper No.11-074

Unequal Pay or Unequal Employment? What Drives the Skill-Composition of Labor Flows in Germany?

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Das Wichtigste in Kürze

Die wirtschaftliche Prosperität von Regionen hängt unter anderem von ihrer Fähigkeit ab, ein für Hochqualifizierte attraktiver Standort zu sein. Ein besseres Verständnis der Bestimmungsgründe selektiver Migrationsströme ist daher eine wichtige Voraussetzung für die Gestaltung politischer Maßnahmen zur Verhinderung von Brain-Drain-Phänomenen.

Die bisherige Literatur geht davon aus, dass Individuen die Region wählen, die für ihre Humankapitalausstattung die beste Rendite verspricht. Bei der Wahl zwischen zwei Regionen mit demselben durchschnittlichen Lohnniveau sollte ein Hochqualifizierter daher die Region mit der größeren Bildungsrendite und damit der größeren Lohnungleichheit wählen. Gering Qualifizierte sollten hingegen diese Regionen meiden, da eine höhere Lohnungleichheit für sie geringere Lohneinkommen erwarten lässt. Empirische Studien für die USA konnten die Relevanz eines solchen Selektionsmechanismus wiederholt nachweisen, während dies im deutschen Kontext bisher kaum gelang. Eine mögliche Ursache dafür könnten regionale Lohnrigiditäten als Folge nationaler, auf Branchenebene geführter Lohnverhandlungen sein. In diesem Fall kommen regionale Einkommensunterschiede vermutlich eher über Beschäftigungsunterschiede zustande, so dass ein beschäftigungsbasierter Selektionsmechanismus wirksam werden könnte. Da Beschäftigungschancen tendenziell mit dem Humankapital eines Individuums steigen, sollten gering Qualifizierte wiederum Regionen meiden, die für sie aufgrund einer hohen Beschäftigungsungleichheit mit einem hohen Arbeitslosigkeitsrisiko einhergehen.

In einem um diesen Beschäftigungsmechanismus erweiterten theoretischen Rahmen zeigt das Papier, dass Regionen eine umso qualifiziertere Zuwanderung erfahren, je höher sowohl das regionale Lohn- und Beschäftigungsniveau als auch die Lohn- und Beschäftigungsungleichheit sind. Anschließend werden diese Vorhersagen für Bruttowanderungsströme zwischen 27 Regionen in Deutschland getestet. Dafür wird zunächst die durchschnittliche Humankapitalausstattung eines jeden Stroms über einen Zeitraum von zehn Jahren geschätzt und anschließend auf interregionale Unterschiede in den Parametern der regionalen Lohn- und Beschäftigungsverteilungen regressiert.

Die Ergebnisse bestätigen die Bedeutung eines beschäftigungsbasierten Selektionsmechanismus. Eine Region zieht eine umso qualifiziertere Zuwanderung an, je höher die durchschnittlichen Beschäftigungschancen (je niedriger die Arbeitslosenrate) und je ungleicher die Beschäftigungschancen unter den regionalen Erwerbspersonen verteilt sind. Regionale Lohnunterschiede spielen für die selektive Wanderung in Deutschland hingegen keine Rolle. Im Vergleich zum Standardmodell zeigt sich, dass das erweiterte Modell besser in der Lage ist, den beobachteten Nettoverlust an Humankapital aus Ostdeutschland zu erklären. Im Fall regional wenig flexibler Löhne, wird die räumliche Allokation von Humankapital somit stärker über die Beschäftigungsseite determiniert, ein Ergebnis, dass auch in anderen Ländern von Relevanz sein dürfte. Wirtschaftspolitische Maßnahmen zur Vermeidung eines Brain Drains sollten daher nicht allein auf Lohnkonvergenz zielen, sondern auch Wirkungen ungleicher Beschäftigungschancen berücksichtigen.

Non-technical summary

Regional economic prospects to some extent seem to hinge on the region's human capital endowment and, thus, its ability to attract skilled labour. For any related policy, it is thus important to better understand the determinants of skill-selective migration.

As the main selection mechanism, the existing literature suggests that individuals move to regions that best reward their skills in terms of wages. For this reason, skilled individuals with a choice between two regions that have the same average wage rate should prefer the region with the higher wage inequality, while unskilled individuals should avoid such regions. While this selection mechanism has been empirically confirmed for the US, evidence within the German context is much weaker. We suspect that regional wage rigidities resulting from central wage bargaining prevents a wage-based selection mechanism and, therefore, propose an additional employment-based selection mechanism. The main idea is that income differentials rather than wage differentials determine skill-selective migration. Since the probability of being employed is not equally distributed across the workforce, but tends to increase with the skill level, unskilled individuals should avoid regions with a high employment inequality.

In fact, an extended framework predicts skilled workers to be disproportionately attracted to regions with higher mean wages and employment rates as well as higher regional wage and employment inequalities. We test these predictions for gross labour flows between 27 regions in Germany. For this purpose, we estimate the observable skill level of an average labour migrant for each gross flow across a ten year period. In addition, we estimate the parameters of the regional wage and employment distributions for each region and year. Using both a labour flow fixed effects model as well as a GMM estimator, the findings suggest that regional differentials in the employment distribution turn out to be important. In particular, a region attracts an increasingly skilled inflow of migrants, the higher is its average employment rate (i.e. the lower its unemployment rate). The same is true for an increasing employment inequality. The less equal employment chances are spread across the regional workforce, the more a region attracts an increasingly skilled inflow of migrants. In contrast, regional differentials in the wage distribution exert no significant effect on the skill composition of labour flows in Germany. For this reason, the extended model has a much better predictive power for the observed net skill transfer between, for example, eastern and western Germany, than the standard wage-based model.

Hence, this paper suggests that when wages tend to be rather inflexible at a regional scale, the spatial allocation of human capital may be driven by regionally varying employment chances rather than wages. These findings are relevant beyond Germany whenever regional wage rigidities prevent flexible wage adjustments. Moreover, policies that aim at preventing brain drain phenomena should not focus on fostering wage convergence alone, but need to take into account the effects of regionally varying employment chances as well.

Unequal Pay or Unequal Employment? What Drives the Skill-Composition of Labor Flows in Germany?*

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Abstract

This paper examines the determinants of gross labour flows in a context where modeling the migration decision as a wage-maximizing process may be inadequate due to regional wage rigidities that result from central wage bargaining. In such a context, the framework that has been developed by Borjas et al. (1992) on the selectivity of internal migrants with respect to skills has to be extended to allow migrants to move to regions that best reward their skills in terms of both wages and employment. The extended framework predicts skilled workers to be disproportionately attracted to regions with higher mean wages and employment rates as well as higher regional wage and employment inequalities. Estimates from a labour flow fixed effects model and a GMM estimator show that these predictions hold, but only the effects for mean employment rates and employment inequality are robust and significant. The paper may thus be able to explain why earlier attempts to explain skill selectivity in Europe within a pure wage-based approach failed to replicate the US results.

Keywords: gross migration, selectivity, wage inequality, employment inequality

JEL: R23, J31, J61

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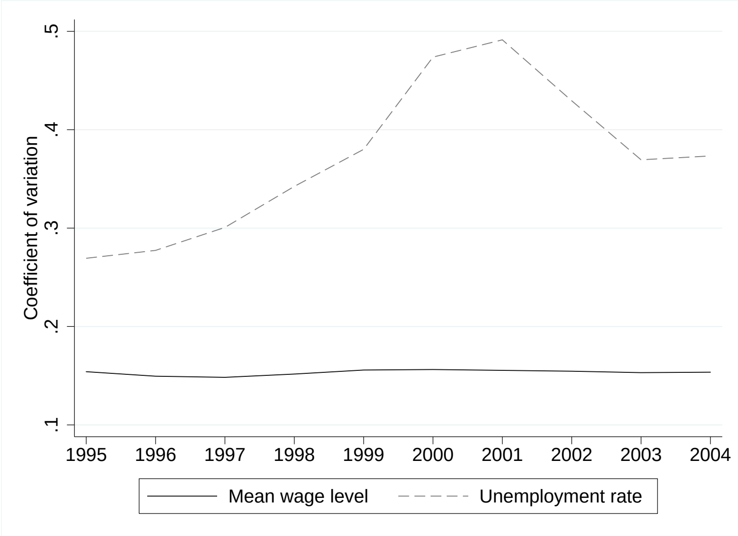
1 Introduction

Interregional migration is mostly viewed as a desired mechanism for mitigating regional income and employment disparities. Yet, skill-selective migration may cause quite the opposite if the local concentration of human capital tends to raise output and wages due to skill complementarities and local skill externalities resulting from the sharing of formal and informal knowledge (Lucas 1988, Romer 1990). Indeed, several empirical studies confirm a positive link between the local human capital endowment and the development of wages and growth (Rauch 1993, Peri 2001). Thus, understanding the determinants of the spatial allocation of human capital may be an important link to better understand the development and persistency of regional disparities.

One major theoretical explanation for the skill composition of internal migration flows has been proposed by Borjas et al. (1992): Skilled workers should be attracted to regions that best reward their abilities by paying high wage returns to their skills. Regions with high returns to skills as reflected in a high wage inequality should thus be more attractive to skilled workers than regions with the same average wage level, but a lower wage inequality. While Borjas et al. (1992) and Hunt and Mueller (2004) demonstrated the relevance of this selection mechanism for internal migration in the US, corresponding evidence in the German context has been surprisingly weak (Arntz 2010, Brücker and Trübswetter 2007).

One underlying reason for a wage-based selection mechanism to fail could be that central wage bargaining in Germany prevents a flexible wage adjustment at the regional level as has been found by Topel (1986) for the US. Consistent with this argument and similar to the results by Niebuhr et al. (2011), Figure 1 shows that the average wage level barely varies across regions and remained nearly unchanged between 1995-2004. In contrast, the unemployment rate is more volatile across regions. Moreover, this volatility increases with deteriorating business cycle conditions until 2001, suggesting that employment levels rather than wages are flexible at a regional scale. This is in line with Mertens (2002) and Linzert (2004) who found that employment rather than wages react to regional labour demand shocks in Germany. Similar results have been found for European regions by Decressin and Fatás (1995) and Abraham (1996). As a consequence, European regions have become increasingly polarized in terms of their unemployment rates (Puga 2002, Faini et al. 1997).

Figure 1: Wage and Unemployment Volatility Across Regions



Note: Regional classification as shown in Figure 2.

In such a context, income differentials that drive migration decisions may result from employment rather than wage differentials.

For this reason, this paper suggests that skill-specific regional employment chances may be a missing link to fully explain skill-selective migration in a context where wages are rather inflexible at a regional scale. In particular, we argue that the risk of unemployment is decreasing in worker ability because unskilled individuals are more likely to be atypically employed (Giesecke 2009) and less likely to be hoarded during economic downturns compared to their skilled counterparts (Nickell and Bell 1995, Morrison 2005). As a consequence, unskilled workers are more likely to become unemployed during an adverse regional shock (Mauro and Spilimbergo 1999), and are more prone to repeated and prolonged unemployment periods (Riddell and Song 2011, Juhn et al. 1991, Wilke 2005). Such findings are in line with a theoretical model developed by Helpmann et al. (2010) that suggests that the unemployment rate is decreasing in worker ability, whereas the average wage is increasing in worker ability. Hence, just as regions with a high wage inequality penalize unskilled workers, regions with a high inequality in employment chances penalize these workers and should attract predominantly skilled workers.

Therefore, this paper contributes to the literature by extending the Borjas framework to allow for a selection mechanism based on both wage and employment differentials. The extended model predicts the average skill level of a migration flow to be a positive function of the wage and employment inequality in the destination as compared to the origin region. Moreover, unlike the Borjas framework, the model suggests that mean wage and employment differentials also induce a positive skill sorting. As a second contribution, we test these predictions for the average skill level of gross labour flows between 27 German regions. For this purpose, we make use of administrative data on all German employees and determine the skill content of each flow with regard to observable skills. We then regress this skill measure on the mean and the dispersion of the regional wage and employment distribution. Instead of only conditioning on the regional unemployment rate as is done by Pissarides and McMaster (1990), Parikh and Leuvensteijn (2003), Etzo (2011) and others, we thus capture not only the average risk of being unemployed, but also allow regions to differ in how this risk is spread among the local workforce. As a third contribution, we are able to exploit the panel dimension of our data in order to condition on average time constant utility differentials between regions (e.g. amenity differentials) that may otherwise bias the estimation results. In order to control for the endogeneity, we also estimate the model with the Difference GMM estimator proposed by Arellano and Bond (1991). The findings confirm the relevance of regional employment differentials for the skill-composition of the labour flows, while regional wage differentials have no robust and significant impact.

The structure of the paper is as follows. Section 2 presents an extended theoretical framework for the self-selection of migrants. Section 3 introduces the data base, while section 4 presents descriptive evidence on the proposed selection mechanism. Section 5 describes the estimation strategy and presents the findings which are then subject to additional robustness checks in section 6. Section 7 concludes.

2 Theoretical Framework

Our theoretical framework builds upon Borjas et al. (1992) who formalize the self-selection of interstate migrants and test their model in the US context. Their framework is linked to the self-selection of workers as described by Roy (1951), and the extension of this approach is linked to the self-selection of immigrants as developed by Borjas (1987). However, while the latter approach focusses on the selection based on unobservable abilities, Borjas et al. (1992) focus on the selectivity of internal migrants with respect to both observable skills and unobservable abilities. For empirical reasons discussed in section 3.1, we focus on observable skills only. The following framework extends their theoretical model by allowing for unemployment. As a consequence, migration decisions do not depend on differentials in regional wage distributions alone but also hinge on the probability of receiving this wage, i.e. the probability of being employed as has already been discussed by Todaro (1969) and Fields (1976). As a consequence, differentials in regional income distributions that reflect both the employment and the wage distribution affect migration decisions and the selectivity of internal migrants.

Consider $j = 1, \ldots, J$ regions that only differ with respect to the income distribution. For ease of exposition, our theoretical framework abstracts from other utility differentials between regions such as regional amenities or disamenities including regional price differentials as well as from migration costs.[1] An income-maximizing individual chooses to live in region j if

$$\pi_j > \underset{i \neq j}{max}[\pi_i] \tag{1}$$

with π_j as the income in region j which is the product of the probability of being employed e_j in region j and the wage w_j paid in this region if employed. Note that employment chances e_j are not only capturing an initial job finding chance in region j, but should be thought of as measuring the expected probability that an individual is employed on any workday given the region-specific chances of finding, keeping and loosing a job.

Now, assume a continuous random variable υ with mean zero that reflects the region-invariant distribution of all skills and abilities. We define high-skilled individuals as those in the upper part of the skill distribution with $\upsilon > 0$ and low-skilled individuals as those in the lower part of the skill distribution with $\upsilon < 0$. We assume that skills and abilities are perfectly transferable between all regions, an assumption we consider justified for internal migration.[2] Following Borjas et al. (1992), the wage distribution can then be decomposed into a part reflecting the mean wage μ_w that is independent of an individual's skills and abilities and a part that measures person-specific

[1] Our empirical approach controls for time-constant regional differentials and, thus, takes account of much of these factors.

[2] While this assumption may be unproblematic within western and eastern Germany, it is less clear whether the assumption can be applied to migration across the former German border. We will thus run some sensitivity analysis in section 6.

deviations from this mean wage that depend on individual i's skills υ_i and the returns to skills paid in region j. The population wage distribution in region j can then be written as

$$w_j = \mu_{w_j} + \sigma_{w_j}\upsilon. \tag{2}$$

Hence, an individual's potential wage is determined by his position in the skill distribution and the region-specific returns to these skills σ_{w_j}. Note that even for the least skilled individual, the wage is still positive, thus implying $\mu_{w_j} > \sigma_{w_j}\upsilon$ to hold for every υ. We further assume an analog decomposition of the population employment distribution which can be written as

$$e_j = \mu_{e_j} + \sigma_{e_j}\upsilon, \tag{3}$$

with μ_{e_j} as the average probability of employment on any workday and υ as defined above. Hence, an individual's employment probability is determined by the average employment probability and the region-specific returns to their skill level in terms of employment σ_{e_j}. The employment dispersion thus measures how the employment chances are spread across the workforce. Since we assume all individuals of the labour force to have positive employment chances, it must also hold that $\mu_{e_j} > \sigma_{e_j}\upsilon$ for any υ.

If we apply the two decompositions in equation (2) and (3), the income in region j can be written as

$$\begin{aligned} \pi_j &= (\mu_{w_j} + \sigma_{w_j}\upsilon) \cdot (\mu_{e_j} + \sigma_{e_j}\upsilon) \\ &= \mu_{w_j}\mu_{e_j} + (\mu_{e_j}\sigma_{w_j} + \mu_{w_j}\sigma_{e_j} + \sigma_{w_j}\sigma_{e_j}\upsilon)\upsilon \\ &:= M_j + R_j(\upsilon) \end{aligned} \tag{4}$$

where the first term M_j corresponds to the income of an average individual with $\upsilon = 0$ in region j, and the second term $R_j(\upsilon)$ reflects all region-specific returns to skills.[3] This second income component is an increasing function of υ and induces a sorting of individuals into regions that best reward their skills. In particular, the utility differential U_{jk} between region j and k depends on the parameters of the wage and employment distribution in both regions and on individual skills. It

[3]Note that, analogous to Borjas et al. (1992), we assume relative prices of all skills to be region-invariant so that we do not have to operate with a multifactor model of ability.

can be written as

$$\begin{aligned} U_{jk} &= \pi_j - \pi_k \\ &= M_j - M_k + R_j(\upsilon) - R_k(\upsilon) \\ &:= \Delta M_{jk} + \Delta R_{jk}(\upsilon). \end{aligned} \quad (5)$$

The partial effect of increasing average employment and wage levels in j can thus be written as

$$\frac{\partial U_{jk}}{\partial \mu_{w_j}} = \mu_{e_j} + \sigma_{e_j}\upsilon \quad \text{and} \quad \frac{\partial U_{jk}}{\partial \mu_{e_j}} = \mu_{w_j} + \sigma_{w_j}\upsilon. \quad (6)$$

Note that these derivations are positive for all individuals irrespective of the skill level since $\mu_{w_j} > \sigma_{w_j}\upsilon$ and $\mu_{e_j} > \sigma_{e_j}\upsilon$ for any skill level υ. However, individuals will be rewarded by an increasing average wage to the extent that the individual is employed in region j. Since skilled individuals are more likely to be employed, they benefit from an increasing mean wage more than their unskilled counterparts. The migration flow from k to j should thus become more skilled on average. The same argument can be applied to an increase in the average employment probability. Since better average employment chances are most beneficial for well paid skilled individuals, the migration flow from k to j should again become more skilled on average. Note that the opposite predictions hold for increases in the average wage and employment level in region k.

Changes in the employment and wage inequality in region j affect the second part of equation (5) only. The partial effects for corresponding changes can be written as

$$\frac{\partial U_{jk}}{\partial \sigma_{w_j}} = (\mu_{e_j} + \sigma_{e_j}\upsilon)\upsilon \quad \text{and} \quad \frac{\partial U_{jk}}{\partial \sigma_{e_j}} = (\mu_{w_j} + \sigma_{w_j}\upsilon)\upsilon. \quad (7)$$

Note that these derivations are positive for individuals with $\upsilon > 0$ and negative for those with $\upsilon < 0$. An increasing wage inequality will thus attract skilled individuals with a positive υ who can expect to benefit from the increasing returns to skills to the extent that they are employed in region j. In contrast, individuals with a below average skill level will experience an income and, thus, utility loss if wage inequality increases. The skill composition of the migration flow from region k to j should consequently become more skilled on average if either wage inequality or employment inequality increases.

Three further issues warrant a short discussion. First of all, we neglect the case that any of the regions is unpopulated. Thus, we assume each region to make a competitive offer to at least some individuals. Hence, for any three regions $j-1, j, j+1$ that are adjacent in terms of their returns to skills with $R_{j-1}(v) < R_j(v) < R_{j+1}(v)$, region j can only exist if the mean income in region j satisfies

$$M_j > \frac{(R_{j+1}(v) - R_j(v))M_{j-1} + (R_j(v) - R_{j-1}(v))M_{j+1}}{R_{j+1}(v) - R_{j-1}(v)}. \tag{8}$$

If mean incomes were the same across all regions, all skilled individuals would prefer the region with the highest return to their skills, whereas individuals lacking these skills would be attracted to regions with the lowest penalty from lacking these skills. Thus, a region that ranks in the middle in terms of the returns to skills can only exist if it offers a competitive mean income level that exceeds the mean income level in at least one of the neighbors. For this reason, the existence condition rules out cases where the relationship between the returns to skills R and the mean income M is flat or even inversely U-Shaped but allows for a monotonously decreasing or increasing as well as for a U-shaped relationship. While this does not differ from the insights in Borjas et al. (1992), the extended model suggests an important derivation. In particular, unlike the simple wage-based framework, the relationship between μ_w and σ_w can be inversely U-shaped as long as the relationship between μ_e and σ_e makes up for it by a U-shaped relationship. The extended model thus implies that a region can compensate a disadvantage in terms of its wage distribution and therefore ensure its existence by a favorable employment distribution and vice versa.

Secondly, it may be helpful to discuss the reasons why we expect flows in opposing directions to exist. This may be the case because there are new cohorts entering the labour market each period among which a certain share is likely to be mismatched to their origin region in terms of their skills. Thus, while the most able individuals will leave their region for regions with a higher returns to their skills, less-skilled individuals may prefer the opposite direction in order to minimize the penalty from lacking skills. Moreover, individuals for whom a particular region once offered the optimal return to their skills need not be optimally matched forever if individuals shift their position in the skills distribution due to training effects or due to the depreciation of skills.

Finally, the model abstracts from a number of potential complications such as regional amenity differentials, price differentials as well as from migration costs. As long as these components are not correlated to the skill level, the key results remain unchanged. However, there are reasons to believe that migration costs decrease in abilities if abilities facilitate the gathering of information and reduce the psychological costs of migration. If this is the case, the key results of the theoretical model remain unchanged only conditional on such costs. Similarly, if individuals differ in how they value certain regional amenities and disamenities depending on their skill level as has been argued by Berry and Glaeser (2005), the key results also remain intact only conditional on regional differentials in amenities and disamenities. Our estimation approach, thus, needs to take account of these complicating factors.

3 Data

We use the employment register data (BeH) of the German Federal Employment Agency, an administrative data set that contains information on the population working in jobs that are subject to social insurance payments, thus excluding civil servants and self-employed individuals. The data allows for reconstructing individual employment histories including periods of employment and periods of unemployment benefit receipt on a daily basis. For each employment period, the data contains individual and firm-level characteristics including the daily gross wage, the educational attainment as well as the micro-census region of the workplace. We are thus able to identify gross labour flows rather than population migration flows between regions by comparing workplaces before and after an interregional job transition. However, as has been noted by Leuvensteijn and Parikh (2002), general migration and labour migration yield similar results in migration models using German data.

The sample is restricted to the time period between 1995-2004 because the labour flows between eastern and western Germany are severely underestimated in the years right after re-unification due to the fact that many individuals did not show up in the data before starting to work in western Germany. From the mid 1990s on, the observed labour flows correspond to migration patterns that are officially reported by the Federal Statistical Office. Furthermore, we focus on men between the age of 16 and 65 because women's lower labour force attachment would aggravate the selectivity of the sample used for the analysis.[4]

[4]We further exclude men attending military or civilian service since they are centrally registered so that the

For all subsequent analyses, we distinguish between 27 aggregated planning districts. These regions lump together 97 German planning districts ('Raumordnungsregionen') that are defined according to commuting ranges and already comprise labour market regions that are relatively self-contained. In order to ensure a sufficient number of job moves between each region for different skill levels, we had to aggregate these planning districts to 27 larger regions. We do so based on an algorithm that minimizes the remaining external commuting linkages subject to merging only up to four adjacent regions, thereby ensuring that the regional division yields relatively equally sized and self-contained labour markets.[5] For each year between 1995 and 2004, we estimate the employment and wage distribution for the 27 regions as well as the size and composition of the 702 gross labour flows between these regions. The following subsections discuss the corresponding details.

3.1 Data on Interregional Labour Flows

For the computation of interregional labour flows, we exploit information on the entire working population, i.e. we use the full employment register data (BeH) that is only available to researchers at the Institute for Employment Research (IAB). For the computation of labour flows, we use yearly cross sections to the cut-off date June 30th and compare the workplace location between two consecutive years. We are thus able to calculate the gross labour flows by identifying the origin and the destination region for all interregional job moves. Note that the identification of an interregional job move necessitates an individual to be employed on June 30th of two consecutive years. While the sample may include individuals who have been unemployed between these two cut-off days, long-term unemployed persons are clearly underrepresented in our data. In total, we observe almost 137 million individuals between 1995 and 2004 of which 3.6 million (2.6%) experience an interregional job move between two consecutive years.

Based on these data, we calculate the average skill level of each gross labour flow. Rather than using the formal education as a skill measure which would allow for distinguishing between few different skill groups only, we calculate an alternative skill measure based on ranking individuals in the predicted wage distribution as has been proposed by Borjas et al. (1992). The underlying idea is

identification of their exact location is not possible, and we neglect apprentices and all employment spells with minor employment since its definition changed in 1999.

[5] Details on the algorithm is available from the authors upon request.

that wages reflect the marginal product of labour and may thus proxy for abilities and skills. More precisely, we estimate individual i's daily gross wage[6] in region j and year t over the time-period 1994-2004 with the following Fixed-Effects (FE) model for all individuals in the sample:

$$log\ w_{ijt} \quad = \quad \beta_0 + \beta_1 REGION_j + \beta_2 YEAR_t + \beta_3 X_{ijt} + \varepsilon_{ijt} \tag{9}$$

where the composite error $\varepsilon_{ijt} = c_i + u_{ijt}$ is decomposed into an individual-specific time-constant unobserved effect c_i and a remaining idiosyncratic error term u_{ijt}. The wage is a function of a vector of dummy variables indicating the workplace location (REGION), a vector of dummy variables indicating the year of the observation (YEAR) and a vector of individual- and time-specific observable skill characteristics (X). These observable skill characteristics include age, age squared, occupation (12 categories), industry (28 categories), educational attainment (7 categories), establishment size, establishment size squared and a dummy for part-time employment. We control for part-time employment, because we do not observe hourly wages, but only daily wages that may differ between fulltime and part-time employees due to different working hours.

We then predict the wages for all workers in the sample based on the vector of observable skill characteristics (X) only. This way our skill measure does not reflect differences in predicted wages due to region- and year-specific factors.[7] We are thus constructing a region- and time-invariant skill distribution. We then measure the skill content S_{kjt} of each labour flow by calculating the average predicted log wage for the N movers of each labour flow:

$$S_{kjt} \quad = \quad \frac{1}{N} \sum_{i=1}^{N} \log \hat{w}_{ikjt}$$

In order to compare movers and stayers we also calculate the average predicted log wage for the stayers in the sending region.

Note that we focus on observable skills only, although one could also calculate the unobserved skills of migrants by estimating the time-constant unobserved effect c_i in equation (9) as proposed by

[6]Unfortunately, around 15% of all wages are top-coded at the contribution limit of the social security. Therefore, we impute the censored wages with an estimation procedure described by Gartner (2005). This procedure adds a randomly drawn error term to the predicted wage level and, thereby, avoids a strong correlation between the error term and the explanatory variables.

[7]Ideally, we would rank individuals in the income distribution. However, we are not able to estimate the income distribution for the full BeH data because the data is reduced to a cross-section that lacks information on the previous employment history. Extending the data to include the full employment history is impossible due to the resulting size of the data.

Table 1: Summary Statistics for Gross Labour Flows and Employees Staying in the Sending Region, 1995-2004

Variable		**Mean**	**SD.**	**Min**	**Max**	**Obs.**
Gross labour flows between $k = 1, \ldots, 27$ sending and $j = 1, \ldots, 26$ receiving regions						
Average number of migrants	overall	506	827	5	11955	$K \times J \times T = 7020$
	between		805	15	8700	$K \times J = 702$
	within		193	-1710	5554	$T = 10$
Average predicted wage ($\frac{1}{N} \sum_{i=1}^{N} \hat{w_{ikjt}}$)	overall	79.4	8.1	49.5	132.3	$K \times J \times T = 7020$
	between		4.9	65.2	94.7	$K \times J = 702$
	within		6.5	50.7	120.5	$T = 10$
Immobile employees in the sending regions $k = 1, \ldots, 27$						
Average number of stayers (in 1000)	overall	494	211	150	1112	$K \times T = 270$
	between		213	170	1050	$K = 27$
	within		24	368	634	$T = 10$
Average predicted wage ($\frac{1}{N} \sum_{i=1}^{N} \hat{w_{ikjt}}$)	overall	67.6	4.9	56.1	82.1	$K \times T = 270$
	between		3.5	62.4	75.5	$K = 27$
	within		3.5	60.3	75.7	$T = 10$

Borjas et al. (1992). However, one problem with this approach is that unobservable skills and their region-specific returns are not really separable. Since motivation and the like are remunerated differently across regions, c_i differs depending on the regions in which an individual is observed. Put differently, one cannot really construct a region-invariant distribution of unobservable skills. For this reason, we decided to stick to observable skills only.

Table 1 reports descriptives on the number of migrants and the average skill level for the 7,020 gross labour flows across the ten year period. On average, 506 migrants with a predicted daily wage of 79.4 euro follow a particular migration path in any year, but the variation across flows and time is large. In order to check whether flows with only few migrants produce outliers that dominate the estimates, we ran sensitivity tests by excluding labour flows with less than 50 migrants (7.96 percent of all flows). The exclusion didn't change the results. Also note that those who experience an interregional move, on average, are positively selected with respect to observable skills compared to immobile employees whose average predicted daily wage of 67.6 euro is shown in the bottom panel of Table 1.

3.2 Regional Wage and Employment Distributions

In order to test the theoretical predictions presented in Section 2, we need to estimate the means and standard deviations of the wage and employment distribution for each region and year.

For the construction of the regional wage distribution, we predict the wages of the regional workforce that result from separate region- and year-specific OLS-regressions of equation (9). By estimating this model separately across years and regions, we allow for varying returns to observable skill characteristics across years and regions. We use the same covariates as in equation (9) since we want to measure the regional differences in the returns to the characteristics that also reflect the skill measure that we use for the labour flows. We then calculate the mean and the standard deviation of the predicted wage distribution for each year and region.[8]

For the regional employment distribution, it is not immediately clear which measure to choose. One might think about using the probability of receiving a job in a particular region, i.e. the job-finding chances. However, for the expected income, what counts is the number of days that someone can expect to be employed in a particular region given the risk of loosing a job, being long-term-unemployed and finding employment again. For this reason, we decided to look at the number of days a worker is employed during a year. We do so based on a two percent random sample of the employment register data since we need full spell information on periods of employment and unemployment.[9] As with wages, we then construct the predicted employment distribution of the regional workforce. However, since the number of days employed during a year comes with mass points at 0 and 365 employed days, we need to take account of this unusual distribution by modeling the different cases separately. For this, let $I_{ijt} = 0, 1, 2$ denote an individual-specific indicator function that depends on the number of days d_{ijt} that an individual i is employed during

[8] The selection of skilled individuals into labour markets that best reward their skills as is predicted by the theoretical framework may give rise to an upward bias in the returns to skills as has been shown by Dahl (2002). For this reason, Dahl used bias-corrected returns to skills in an estimation of skill-selective migration. Despite the upward bias in the returns to skills, however, estimation results for the migration model with uncorrected and corrected returns to skills yielded very similar results which likely reflects their high positive correlation. We thus refrain from any attempt to correct our estimated returns, especially since transferring the methodology proposed by Dahl is not straightforward in a context where we have repeated polychotoous choices across a ten year period.

[9] One problem is that there are gaps in the employment record, whenever an individual is out of labour force, self-employed, a civil servant or unemployed without any receipt of unemployment transfers. For this reason, following Fitzenberger and Wilke (2010), we count non-employment periods only as unemployment if there has been at least one initial receipt of unemployment benefits.

a particular year t in region j:

$$I_{ijt} = \begin{cases} 2 \quad if \quad d_{ijt} = 365 \\ 1 \quad if \quad 0 < d_{ijt} < 365 \\ 0 \quad if \quad d_{ijt} = 0 \end{cases}$$

Individual i's observed number of employed days depends on the probability of being employed all-year-long ($I_{ijt} = 2$), employed between 0 and 365 days ($I_{ijt} = 1$) and being unemployed all year long ($I_{ijt} = 0$). According to the law of total probability, the conditional number of days employed in region j at time t can be written as

$$E[d_{ijt}|X_{it}] \quad = \quad P(I_{ijt} = 1|X_{it})E[d_{ijt}|I_{ijt} = 1, X_{it}] + P(I_{ijt} = 2|X_{it})365]. \tag{10}$$

The conditional probabilities $P(I_{ijt} = 0|X_{it})$, $P(I_{ijt} = 1|X_{it})$ and $P(I_{ijt} = 2|X_{it})$ are estimated for each region and year by predicting conditional probabilities within a multinomial logit framework. The conditioning set is the same as in equation (9) except for establishment size which is not available in the two percent random sample of the data set. The expected number of days employed conditional on being employed between 0 and 365 days, $E[d_{ijt}|I_{ijt} = 1, X_{it}]$, is estimated running separate region- and year-specific OLS-regressions. Just as with wages, we then calculate the mean and standard deviation of the predicted employment distribution for each region and year. When comparing the official unemployment rate across the ten year period to the share of days not employed that is implied by our employment measure, we found very similar patterns, confirming that our measure captures a meaningful concept.

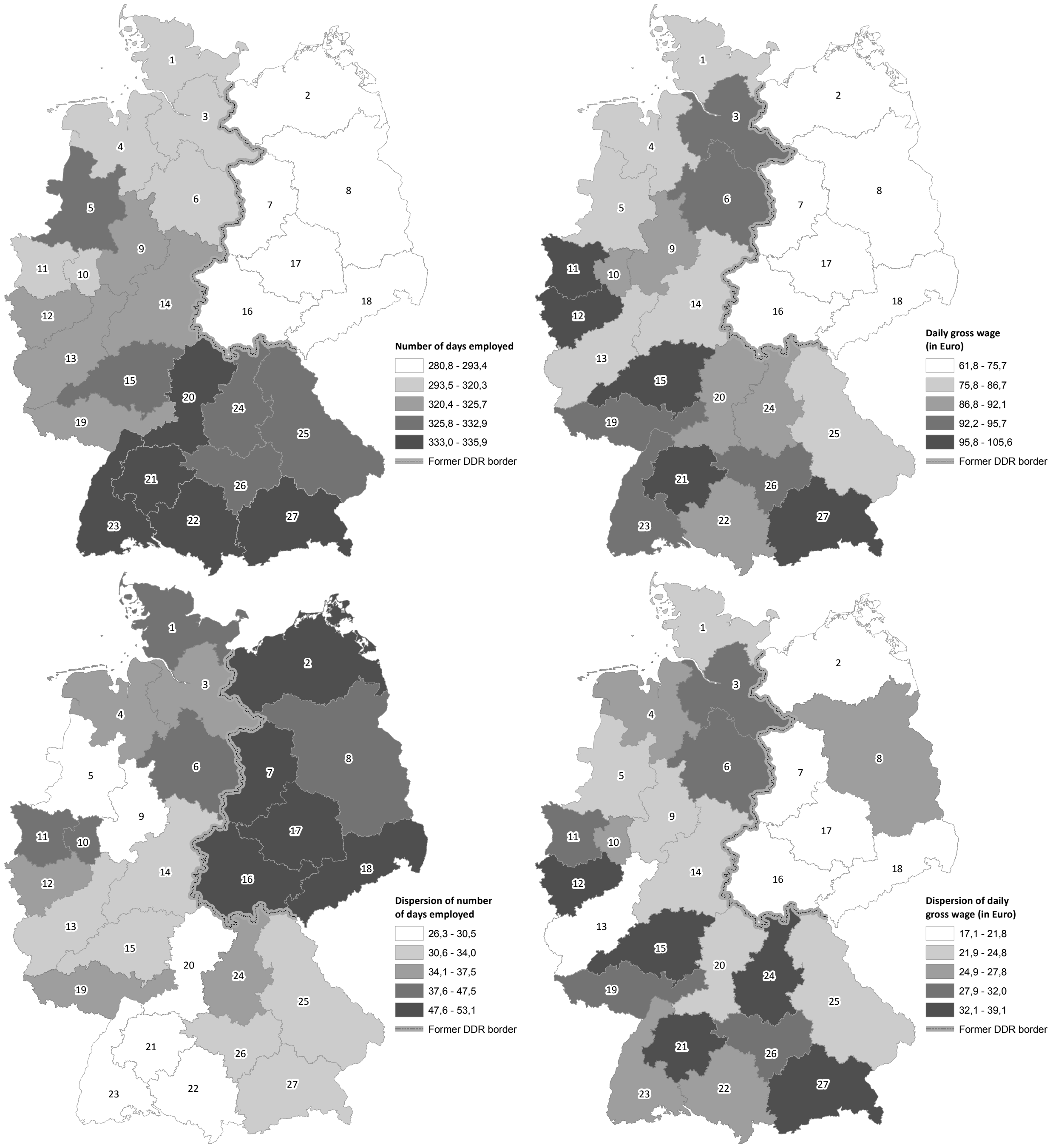
Figure 2 shows the average parameters of the employment and wage distribution across the ten year period. For better interpretation we use the mean and standard deviation of the exponentiated predicted log wage. We mainly find the expected east-west divide, with average wages and average employment in western Germany clearly exceeding levels in eastern Germany. However, we also find some disparities between southern and northern Germany, with the latter being in a less favorable labour market situation. Moreover, the absolute wage dispersion in eastern Germany is below the wage dispersion in western Germany, although in relative terms in percent of the mean wage, wage inequality is quite comparable between both parts of the country as has also been suggested by Burda and Hunt (2001) and Gernandt and Pfeiffer (2009) for the time period after 1995. In contrast, the employment dispersion in eastern Germany strongly exceeds the level of employment inequality in western Germany. Thus, the risk of being unemployed is not only higher on average in eastern Germany, but is also distributed more unequally among the local workforce.

Note that our regional indicators are highly correlated, posing a challenge for the identification of the model. However, since we distinguish 27 regions, there is still a lot of variation on the level of labour flows. Moreover, we exploit the time variation in each of the flows between the 27 regions. Thus, while in a cross-section perspective the east-west divide dominates the picture, our later estimation approach exploits the variation in the skill content of each labour flow across the ten year period and relates this to changes in interregional disparities. In the subsequent analysis, these refer to the difference between the receiving and the sending region in the standardized wage and employment parameters and are denoted as $\Delta\mu_w$, $\Delta\mu_e$, $\Delta\sigma_w$ and $\Delta\sigma_e$. An increase of one unit in $\Delta\mu_w$, for instance, thus corresponds to a one standard deviation higher mean wage in the receiving relative to the sending region. Note that we mitigate a simultaneity bias by measuring flows between June 30th of two consecutive years while the wage distribution relates to June 30th prior to observing the flows. Since for the employment distribution, we need information for an entire year, the corresponding parameters are estimated for the year prior to observing the destination state in the next year so that there is some but only a limited overlap between the timing of flows and the estimation of the regional employment distribution.

4 Descriptives

In order to provide descriptive evidence on the proposed selection mechanism, Table 2 shows all 7,020 gross labour flows as well as corresponding interregional returns to skills measures for the time period 1995-2004. We thereby distinguish flows between and within eastern and western Germany due to the large differences in the regional characteristics between both parts of the country, as pointed out in section 3. The flows are ranked according to their average standardized observable skill level, that is we standardized the skill level of each migrant before calculating the average skill level for each gross labour flow. We then rank all flows according to their average standardized skill level and create quintiles of this distribution. The lowest quintile among the east-west flows, for

Figure 2: Parameters of the Regional Wage and Employment Distribution at the Level of 27 Aggregated Planning Regions



instance, corresponds to the 20% of all east-west flows with the lowest skill level, while the fifth quintile captures the 20% of all flows with the highest skill level.

If the predictions of the theoretical framework hold, we would expect interregional differences in all four parameters to increase across these quintiles. Column (4) to (7) thus show the interregional differences as defined in the previous section. We find that within all flow directions most of

Table 2: Interregional Differentials by Quintile of the Labour Flows Ranked According to Their Average Observable Skill Level S_{kj} by Flow Direction, 1995-2004

Quintile of observable skills distribution	Observations: (1) Number of flows	(2) Number of movers (in 1000)	(3) Average standardized skill level	Interregional standardized values: (4) Average wage $\Delta\mu_w$	(5) Average employment $\Delta\mu_p$	(6) Wage dispersion $\Delta\sigma_w$	(7) Employment dispersion $\Delta\sigma_p$
			EAST-WEST FLOWS				
1	251	81	0.11	1.97	2.07	-0.19	-1.67
2	252	101	0.25	1.97	1.92	-0.16	-1.63
3	252	92	0.32	2.13	1.92	0.02	-1.71
4	252	94	0.38	2.23	1.96	0.22	-1.82
5	253	60	0.49	2.37	2.01	0.40	-1.91
			WEST-EAST FLOWS				
1	251	55	0.06	-2.12	-2.13	-0.23	1.72
2	252	69	0.20	-2.09	-2.12	-0.03	1.83
3	252	69	0.27	-2.07	-2.04	0.07	1.84
4	252	60	0.35	-2.18	-1.87	-0.09	1.70
5	253	45	0.48	-2.20	-1.72	-0.01	1.66
			WEST-WEST FLOWS				
1	839	615	0.11	-0.07	-0.08	-0.17	0.10
2	840	607	0.24	-0.07	-0.07	-0.12	0.08
3	840	566	0.30	-0.02	0.01	-0.02	-0.01
4	840	451	0.37	0.05	0.04	0.10	-0.05
5	841	257	0.47	0.11	0.10	0.20	-0.11
			EAST-EAST FLOWS				
1	59	49	-0.10	-0.05	-0.01	-0.12	0.01
2	60	65	0.01	0.03	0.03	0.05	-0.03
3	60	84	0.07	-0.03	-0.05	0.03	0.04
4	60	78	0.13	-0.10	-0.04	-0.21	-0.01
5	61	54	0.21	0.14	0.06	0.24	-0.01
Total	7,020	3,551					

the parameters respect the expected ranking across the quintiles. Labour flows with higher skill levels thus tend to move to regions with higher interregional values compared to less skilled labour flows. However, the ranking for the employment dispersion is decreasing when the ranking of the mean employment is increasing and vice versa. One explanation may be that regions with high average employment tend to have a lower employment dispersion so that $\Delta\mu_p$ and $\Delta\sigma_p$ are strongly negatively correlated with $\rho = -0.51$. We will thus have to run multivariate analyses in order to disentangle the effects. Still, the descriptive evidence tends to confirm that skilled migrants move to regions with relatively higher skill premiums in terms of both wages and employment.

Also, note that the average mover even of the least skilled flows in Table 2 has an above-average skill level, thus confirming once again that movers are a positive selection with regard to observable skills. Moreover, we find differences in the average skill levels across quintiles of different flow directions with flows within eastern Germany being least skilled. Relating such differences to the interregional differences in Figure 2, however, may be misleading since the average skill level should also be affected by other factors than regional differentials in wages and employment such as, for example, amenity differentials. For this reason, keep in mind that our aim is not to fully explain the observed skill composition, but to test whether changes in the skill composition of flows are related to changes in the interregional differences in employment and wages as theoretically predicted.

Hence, a better descriptive test is to look at how changes in employment and wage differentials across time on the flow level are related to changes in the skill composition. Of course, such an analysis is not feasible for the 702 available flows. As an example, we thus focus on the flow between eastern and western Germany which is of particular interest given the strong interregional differences that still persist after reunification. Figure 3 shows the corresponding income differential π calculated based on equation (4) for an individual with average ($\upsilon = 0$), above-average ($\upsilon = 1$) and below-average ($\upsilon = -1$) skills. In 1995, an average individual earns 10.000 euro more in western than in eastern Germany. This income differential increases up to 16.000 euro in 2001 reflecting deteriorating average employment chances in eastern relative to western Germany while wage differentials remain rather constant. In 2001, the increase in the income differential came to a halt before stagnating from thereon. In light of this development, we expect an increasing net loss of migrants in eastern Germany until 2001.

The spread between the upper and the lower line in Figure 3 reflects the skill premium for skilled ($\upsilon = 1$) relative to unskilled individuals ($\upsilon = -1$). The increasing gap between the income differentials of skilled and unskilled workers until 2001 reflects the increasing skill premium in western as compared to eastern Germany that is mainly related to the deteriorating average employment chances in eastern relative to western Germany and, in addition, to an increasing employment dispersion in western as compared to eastern Germany. Hence, according to theory we should observe an increasing net loss of skills from eastern to western Germany similar to net migration.

Figure 3: Income Differential $\Delta\pi(\upsilon) = \pi^{west}(\upsilon) - \pi^{east}(\upsilon)$ for an Average-Skilled ($\upsilon = 0$), High-Skilled ($\upsilon = 1$) and Low-Skilled ($\upsilon = -1$) Individual, 1995-2004

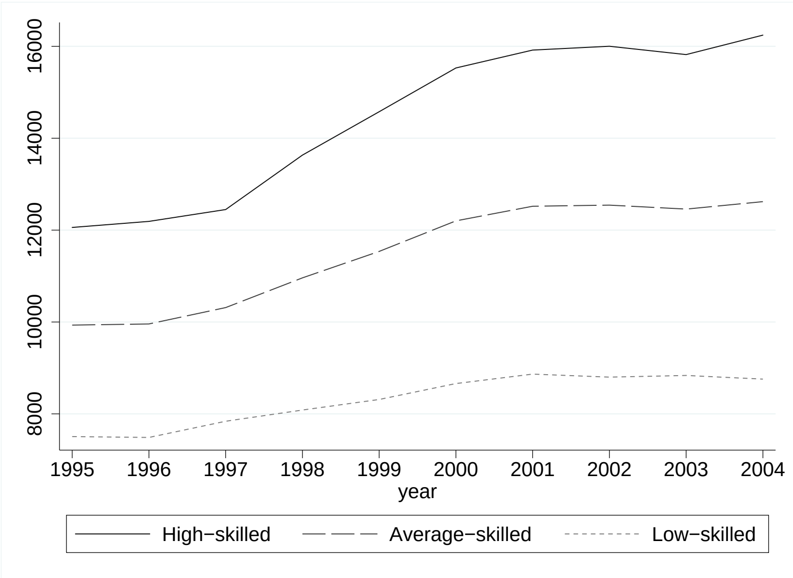
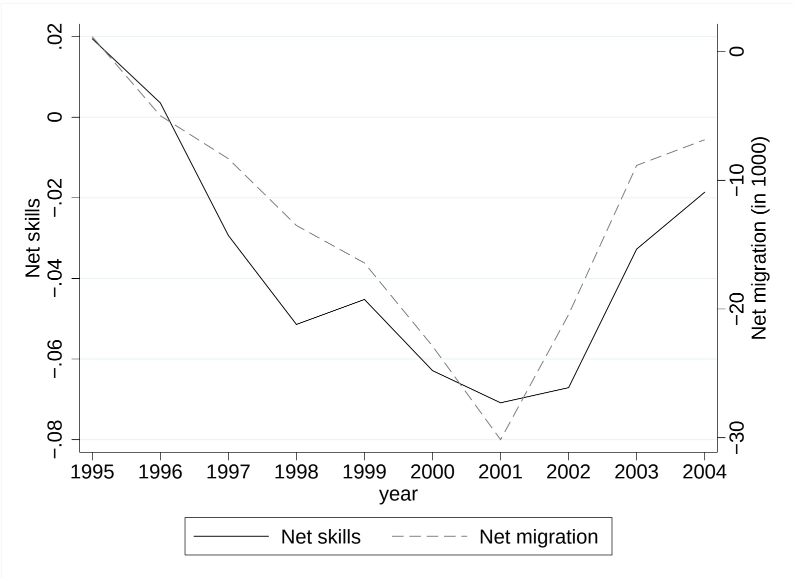


Figure 4: Net Migration and Net Skill Transfer in Eastern Germany, 1995-2004



Indeed, Figure 4 shows that the net loss of migrants as well as the net loss of skills in eastern Germany increased until 2001 and thus confirms the above derived predictions. In particular, in 2001 about 30.000 more migrants moved from eastern to western Germany than vice versa. Moreover, the average east-west migrant became more skilled relative to the average west-east migrant, thus aggravating the already existing brain drain with regard to observable skills. While this development is consistent with the development of income differentials until 2001, the somewhat decreasing net loss in migrants and skills after 2001 cannot be fully explained by the income differentials after 2001.

5 Empirical Analysis

In order to identify the determinants of the average skill level of gross migration flows we exploit the variation in the average observable skill level across 7,020 gross labour flows that we observe during the time period between 1995-2004. The panel is balanced, that is for all 702 region pairs we have 10 year observations. Since unobserved effects in the error term such as amenity differentials are likely to be correlated with regional wages and employment, a simple Ordinary Least Squares (OLS) regression should be biased. Therefore, we estimate the following labour flow fixed effects (FE) panel model:

$$S_{kjt} = \beta_0 + \beta_1 \Delta\mu_w + \beta_2 \Delta\mu_e + \beta_3 \Delta\sigma_w + \beta_4 \Delta\sigma_e + c_{kj} + u_{kjt} \tag{11}$$

where S_{kjt} refers to the average observable skill of a migrant moving from region k to j in a particular year $t = 1, ..., 10$ with $k \neq j$. The right hand side of equation (11) contains the interregional differences in the returns to skills, namely the differences in wages and employment between the destination region j and the region of origin k as defined in section 3.2. The composite error consists of the flow fixed effect c_{kj} as well as an idiosyncratic error term u_{kjt}. Hence, the above model controls for time-constant flow-specific unobserved effects such as time-invariant amenity differentials and explicitly allows the explanatory variables to be correlated with the flow-specific fixed effect.

The results for the skill selectivity are presented in column (3) and (4) of Table 3 in addition to estimations for the migration level in columns (1) and (2). We complement our analysis of skill selectivity with these additional estimates in order to test whether our specification replicates migration patterns that have been found in the literature. In particular, we would expect absolute migration to increase with rising interregional differentials in mean wages and mean employment, while measures of employment and wage dispersion should not affect the migration level.

Model (1) shows the results for the log of the average number of migrants, while model (2) looks at the migration rate that results from dividing the average number of migrants by the population size in the sending region. Since there have been pronounced population movements in Germany within the last decade, the migration rate that takes account of the changing regional population size is the preferred model. As expected, increasing mean wages and mean employment chances in the receiving relative to the sending region raises gross migration levels. Moreover, consistent with similar studies on internal migration, employment differentials have a stronger impact than wage differentials (McCormick 2007, Ederveen et al. 2007, Puhani 2001). While an increase in the mean wage differential by one standard deviation increases the migration rate by 14 percent, an increase in the mean employment differential by one standard deviation increases the migration rate by almost 28 percent. Somewhat surprisingly, however, we also find a positive and significant effect for the employment dispersion. For wages, no such effect on absolute migration can be found. The estimations on absolute migration therefore mainly confirm the usual determinants of gross migration that have been found in previous studies.

Turning to the estimations of main interest, column (3) and (4) show the effects of regional wage and employment differentials on the average skill level of a flow measured in log wage points (see section 3). While column (3) shows the pooled OLS results that assume time-constant flow-specific factors to be uncorrelated with the covariates, column (4) shows the above discussed labour-flow fixed effects model. In the pooled OLS model we add the distance between regions in logs to control for major differences across flows in the costs that are related with moving from k to j. In column (4), such effects are absorbed in the fixed effects. Although most of the coefficients in column (3) show the expected signs, the results for the regional mean wage differential are negative and significant. Also, the positive coefficient for the employment dispersion is insignificant. The results of the pooled OLS model therefore do not correspond to the theoretical predictions. Moreover, adding labour-flow fixed effects in column (4) yields different and much more plausible outcomes and thus demonstrates that the pooled OLS model is apparently biased by time-constant interregional differentials. For most previous studies that are based on exploiting cross-sectional variation only, this puts doubt on the reliability of the findings and suggests the need for better taking account of unobserved

Table 3: Absolute Size and Average Skill Level of Gross Labour Flows, 1995-2004

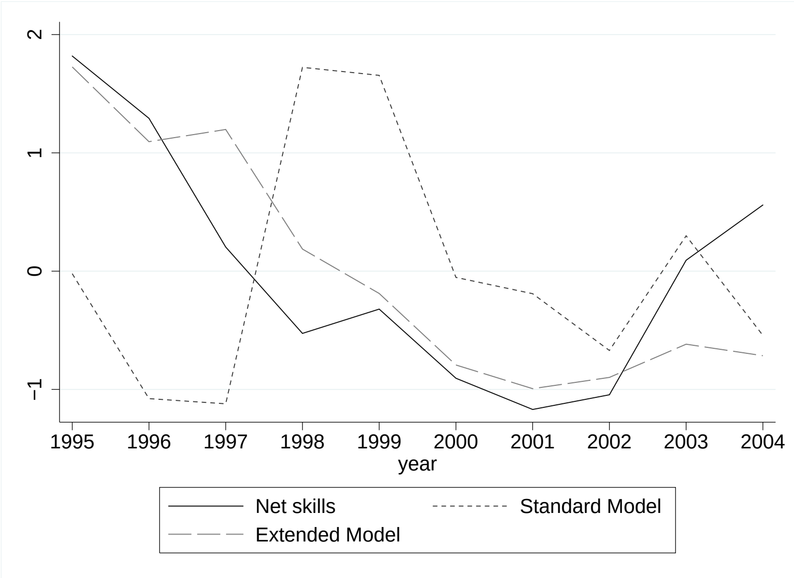
	(1) Absolute migration (log)	(2) Migration rate (log)	(3) Average skills pooled OLS	(4) Average skills FE	(5) Average skills FE
Mean wage ($\Delta\mu_w$)	0.163***	0.140**	-0.008***	0.008	-0.011
	(2.68)	(2.57)	(-3.29)	(0.37)	(-0.56)
Mean empl. ($\Delta\mu_e$)	0.215***	0.277***	0.019***	0.027***	
	(14.70)	(20.81)	(6.49)	(6.18)	
Wage dispersion ($\Delta\sigma_w$)	0.012	0.016	0.012***	0.011	0.004
	(0.47)	(0.73)	(8.45)	(1.50)	(0.57)
Empl. dispersion ($\Delta\sigma_e$)	0.199***	0.171***	0.011	0.023***	
	(9.77)	(9.09)	(1.51)	(3.18)	
Distance (log)			0.035***		
			(13.06)		
Constant	5.453***	-7.644***	4.020***	4.217***	4.217***
	(575.39)	(-885.65)	(255.48)	(1192.10)	(1173.54)
N	7020	7020	7020	7020	7020
F	177	156	154	168	196
R^2	0.321	0.356	0.254	0.339	0.332
$Adj.R^2$	0.319	0.354	0.252	0.338	0.331
$RMSE$	0.199	0.191	0.112	0.085	0.085

Note: robust t-statistics in parenthesis; Significance levels: * 10%, ** 5%, *** 1%; All models include year dummies. FE denotes labour-flow fixed effects models.

labour-flow related heterogeneity.

In particular, column (4) shows positive and significant effects of regional differentials in employment. To be more precise, an increase in the mean number of employed days by one standard deviation in the receiving relative to the sending region increases the skill level of the average migrant by 0.027 log wage points. For an average gross wage income of 79.4 euro per day, this effect would be equivalent to an increase of the daily gross wage of an average migrant by 2.17 euro. Similarly, the average migrant following a labour flow to a region with an employment dispersion that exceeds the employment dispersion in the sending region by one standard deviation is more skilled by 0.023 log wage points. In contrast, coefficients related to the wage level and wage dispersion are small and insignificant. The estimations thus show that the skill composition of a labour flow is mainly driven by regional differences in the employment rather than the wage distribution.

Figure 5: Prediction of East-West Migration Selectivity Based on the Standard and Extended Borjas Model, 1995-2004



Moreover, when comparing these estimates to the results of the standard Borjas model that includes only regional differentials in mean wages and wage dispersion, their impact remains insignificant as shown in column (5). In order to compare the performance of the standard and extended model, we predict the pattern of migration selectivity between eastern and western Germany for the years 1995-2004 based on models (4) and (5). We then compare the predicted net skill transfer from eastern to western Germany of both models with the observed pattern as described in section 4. As Figure 5 shows, the predictions of the extended model are much better able to explain the observed net skill loss in eastern Germany compared to the standard model. The test underlines the importance of extending the Borjas model to allow for regional differences in employment chances.

Of course, looking at the impact of regional wage and employment differentials on the skill composition does not tell us much about which migrants drive the results. As an example, we could get the same theoretically proposed effects with high-skilled individuals being attracted to regions with a high return in wages or employment, by unskilled individuals being distracted from these regions or a combination of both. From the predictions in section 2, we would expect individuals to be increasingly attracted to regions with higher mean wages and mean employment the higher their skill level. In addition, we would expect individuals with below-average skills to be distracted from regions with a high wage and employment dispersion while individuals with above-average skills should be attracted to these regions.

In order to test these predictions, we determine the quintiles of the observable skill distribution, i.e wage distribution as estimated in section 3.1, in each year in order to ensure that the skill distribution is not affected by average nominal wage increases across time. We then compute migration rates for the five quintiles for each of the 702 flows across the ten year period, i.e. we calculate the absolute number of migrants from k to j by quintile and divide these numbers by the size of the population in k of the corresponding skill quintile. The first quintile therefore contains the rate by which individuals ranking in the lowest quintile of the skill distribution follow a particular migration path.

The results are shown in Table 4. As expected, the effects of mean wage and employment differentials tend to be positive for all quintiles, although an increasing and significant pattern across quintiles can be found for the mean employment differential only. Thus, the related positive selection in Table 3 seems to be the result of migratory responses along the entire skill distribution. In contrast, mean wage differentials significantly affect migration choices for the best skilled individuals only. Since this group is more likely to earn a wage independent of any centrally bargained tariff, wage rigidities may be less pronounced for this group. In that case, mean wage differentials likely reflect regional differences in income opportunities for the group of high-skilled individuals only and so it appears plausible that we find significant effects for the fifth quintile only.

Regarding the effect of the wage dispersion, we find no consistent pattern across all five quintiles, but a negative significant effect for the second and a positive significant impact for the fourth quintile that are both in line with the theoretical predictions. In contrast, the employment dispersion has a significantly positive and increasing impact on migration along the skill distribution. The related positive selection effect in Table 3 thus results from this increasing patterns rather than individuals with below-average skills avoiding regions with a higher employment inequality. While this may seem at odds with the theoretical predictions, we think that this observation is the result of two empirical facts.

First of all, the empirical distribution of the number of employed days turned out to be bi-modal with the majority of individuals being almost always employed. Thus, although the risk of unemployment is spread unequally across individuals, only a rather small share of individuals appears to be affected by a positive unemployment risk. If these individuals were the least skilled as postulated in the theoretical framework, however, we would expect a negative sign for the lowest quintile only and insignificant effects for the remaining quintiles. As an alternative explanation, we think that unobservable skills play a major role. Due to the relevance of unobservable skills in determining an individual's employment chances, even the individual with the highest observable skill level has a non-zero chance of unemployment, while even the individual with the lowest observable skill level may be continuously employed. Therefore, an increasing employment inequality may be beneficial for the majority of individuals with favorable unobservable characteristics within each skill quintile, yet the share of those for whom an increasing employment inequality increases the risk of unemployment decreases across the quintiles of the observable skill distribution. As a result, we get a continuously increasing pattern of positive coefficients across quintiles in Table 4. This pattern thus reveals that the theoretical framework is too simplistic to realistically capture the effect of unequal employment chances on the selectivity of migrants.

6 Robustness

The main problem with the previous labour flow fixed effect model is that it assumes the independent variables to be uncorrelated with past and possibly current realizations of the error term. However, migration could be both the cause and consequence of regional wages and employment. In fact, several studies explicitly examine the effect of selective migration on the development of regional wages and employment (Fratesi and Riggi 2007, Burda and Wyplosz 1992). Although the timing of the dependent and independent variables rule out a direct simultaneity between interregional differences and the skill composition of labour flows, the described dynamics may still bias the previous labour flow fixed effects estimations.

In order to deal with endogenous regressors and reverse causality, we estimate the average skill level of the gross labour flows with the first-difference General Methods of Moments (GMM) estimator as proposed by Arellano and Bond (1991). The estimator is designed for panel data, where the

Table 4: Log Migration Rates by Quintile of the Skill Distribution, Labour Flow Fixed Effects Estimation 1995-2004

	1. Quintile	2. Quintile	3. Quintile	4. Quintile	5. Quintile
Mean wage ($\Delta\mu_w$)	0.135	0.060	0.100	0.094	0.207***
	(1.42)	(0.77)	(1.46)	(1.50)	(3.09)
Mean empl. ($\Delta\mu_e$)	0.184***	0.220***	0.281***	0.319***	0.330***
	(10.12)	(12.73)	(17.65)	(20.98)	(20.02)
Wage dispersion ($\Delta\sigma_w$)	-0.005	-0.058**	0.030	0.072***	0.034
	(-0.14)	(-1.99)	(1.13)	(3.08)	(1.39)
Empl. dispersion ($\Delta\sigma_e$)	0.112***	0.138***	0.165***	0.156***	0.214***
	(3.02)	(4.77)	(6.22)	(6.89)	(9.72)
Constant	-8.432***	-7.863***	-7.580***	-7.341***	-7.451***
	(-503.85)	(-631.41)	(-679.18)	(-738.16)	(-697.07)
N	6959	7013	7015	7018	7020
F	48	69	112	147	132
R^2	0.105	0.142	0.230	0.312	0.333
$Adj-R^2$	0.104	0.140	0.229	0.310	0.331
$RMSE$	0.391	0.308	0.266	0.226	0.233

Note: robust t-statistics in parenthesis; Significance levels: * 10%, ** 5%, *** 1%; All models include dummies for the origin and destination region.

number of time periods, T, is small and the number of observations, N, is large. The underlying idea is to instrument the endogenous variables in the differenced equation using the lagged versions of the endogenous variables. As Arellano and Bond (1991) note, lagged variables dated t-2 and earlier can potentially be orthogonal to the error and therefore act as valid instruments.[10]

In addition, we not only test this difference GMM for the average skill level of our gross flows, but also run this test for the average skill level relative to the skill level of the sending region. Such a test would be unnecessary if, as assumed by the theoretical framework, there was a skill distribution such that the position of an individual within this distribution is region-invariant. However, this need not be the case, especially between eastern and western Germany that had separate educational systems until 1990. In fact, we do find differences in the average skill level of the regional population, especially between eastern and western Germany. While some of these differences may be the result of previous skill-selective migration, such differences may also indicate that the skill distribution is not region-invariant.

[10]The model is also estimated with the System GMM estimator proposed by Blundell and Bond (1998). Since the Sargan/Hansen-Test was rejected in most of the System GMM estimations, we only present the results for the Difference GMM estimator.

Table 5 reports the Difference GMM results for both the average absolute and the average relative skill level of a migrant. Thus, in the latter case, migrants may now be skilled relative to the source population despite being unskilled compared to other flows. Still, we would expect the sorting of skills across space to follow the same predicted pattern as before. In all models, we use all available lags of the dependent variable and of the four returns to skills variables dated t-6[11] and earlier as instruments for the transformed equation. In addition, models (2) and (4) add lags of the independent variables in order to allow for the possibility that there is a time lag between regional differentials and migratory responses. According to Table 5, the orthogonality restrictions of the instruments and the estimated residuals are accepted in all models by the Sargan and Hansen Test. As a test for autocorrelation, we conduct the Arellano-Bond Test on the residuals in differences. The $AR(2)$-Test rejects the hypothesis of autocorrelation of second order which argues against a dynamic model with lags of the dependent variable. In fact, including lags of the dependent variable turned out to be insignificant in all models.

Model (1) shows that results remain quite robust when taking into account both the potential endogeneity of the regressors, therefore confirming the results in Table 3. The size of the coefficient for the mean employment differential is, however, slightly higher compared to the basic flow fixed effects model in Table 3. The same pattern holds when using the relative skill measure in column (3). When adding lags of the independent variables, the significant effect of mean employment disappears, while the contemporaneous employment dispersion continues to attract better skilled migrants on average. Note, however, that all lags are insignificant, thus suggesting that lagged responses to regional income differentials are not relevant such that models (1) and (3) remain the preferred specifications.

Overall, the robustness checks confirm our previous findings. Interestingly, therefore, it seems to be more important to take account of time-constant interregional differences that seem to strongly bias cross-sectional estimations than taking care of the potential endogeneity of the regressors due to reversed causality.

[11]The Sargan and Hansen Test on the joint validity of the instruments failed to pass the test for lags dated prior to t-6.

Table 5: GMM-Estimation of the Average and the Relative Average Skill Level of Gross Migration Flows

	(1) Average skills	(2) Average skills	(3) Relative average skills	(4) Relative average skills
Mean wage ($\Delta\mu_w$)	-0.186	-0.115	-0.195	-0.179
	(-1.52)	(-0.68)	(-1.60)	(-1.05)
Mean empl. ($\Delta\mu_e$)	0.094**	0.066	0.090**	0.035
	(2.16)	(1.05)	(2.11)	(0.56)
Wage dispersion ($\Delta\sigma_w$)	0.034	0.044	0.030	0.050
	(1.24)	(1.39)	(1.10)	(1.59)
Empl. dispersion ($\Delta\sigma_e$)	0.031**	0.030**	0.022*	0.025*
	(2.45)	(2.05)	(1.72)	(1.71)
L.Mean wage ($\Delta\mu_w$)		-0.012		0.061
		(-0.09)		(0.44)
L.Mean empl. ($\Delta\mu_e$)		0.001		0.027
		(0.04)		(0.88)
L.Wage dispersion ($\Delta\sigma_w$)		0.023		0.015
		(0.91)		(0.60)
L.Empl. dispersion ($\Delta\sigma_e$)		0.021		0.017
		(1.43)		(1.19)
N	6318	5616	6318	5616
Sargan (p-value)	0.160	0.102	0.264	0.189
Hansen (p-value)	0.291	0.260	0.437	0.436
AR1 (p-value)	0.000	0.000	0.000	0.000
AR2 (p-value)	0.355	0.464	0.226	0.477
Instruments	39	38	39	38

Note: robust t-statistics in parenthesis; Significance levels: * 10%, ** 5%, *** 1%; GMM estimations are one-step estimates.

7 Conclusion

This paper examined the factors driving the skill-composition of labour flows in Germany by complementing the Borjas framework on the skill selectivity of internal migration with an employment-based selection mechanism. This extension is motivated by repeated hints in the existing literature that the scope for regional wage bargaining and, thus, regional wage differentiation may be weak in labour markets that are dominated by central wage bargaining. As a consequence, it may be employment rather than wages that respond to shocks and create regionally varying income chances. Unlike the standard model, the extended framework predicts that the average skill level of a migrant should be a positive function not only of regional differentials in wage inequality, but also of differentials in mean wages and mean employment chances as well as in employment inequality, i.e. differences in how employment chances are spread across the workforce.

Being able to exploit the variation in the skill composition of 702 gross labour flows across a ten year period, we test these predictions based on a labour-flow fixed effects model that takes account of time-constant flow-specific unobservables such as amenity differentials. Comparing the outcomes to pooled OLS results indicates that controlling for time-constant unobservables on the flow level is important in order to prevent biased estimates. This puts doubt on the reliability of previous cross-sectional estimates.

The findings suggest that, as expected, regional differentials in the employment distribution turn out to be important. In particular, a region attracts an increasingly skilled inflow of migrants, the higher is its average employment rate (i.e. the lower its unemployment rate). The same is true for an increasing employment inequality. The less equal employment chances are spread across the regional workforce, the more a region attracts an increasingly skilled inflow of migrants. In contrast, regional differentials in the wage distribution exert no significant effect on the skill composition of labour flows in Germany. These findings turn out to be robust when using a Difference GMM estimator that takes account of an endogeneity of the regressors resulting from a possibly reversed causality.

Hence, this paper suggests that when wages tend to be rather inflexible at a regional scale, the allocation of human capital across space may be driven by regionally varying employment chances rather than wages. Using the flow between eastern and western Germany as an example, the paper demonstrates that the extended model has a much better predictive power for the observed skill composition between both parts of the country than the standard model that allows for a wage-based selection mechanism only. These findings are relevant beyond Germany whenever regional wage rigidities prevent flexible wage adjustments.

From a policy perspective, these results indicate that attempts to control migration flows in order to prevent an extensive brain drain should not focus on wage policies alone. In fact, attempts to artificially speed up wage convergence as has been the case in eastern Germany in the years following reunification, are likely to decrease employment rates, thereby again fostering an increased brain drain. In fact, the average east-west migrant became more skilled relative to the average west-east migrant, thus aggravating the already existing brain drain with regard to observable skills.

From the perspective of eastern Germany as a whole, this brain drain is likely to continue. In particular, the regional wage and employment distributions suggest that both the mean income differential as well as the returns to skills in terms of income are lower in eastern than in western Germany. For skilled individuals, there are thus no good reasons to stay in eastern Germany such that a net outflow of skills is likely to continue. Moreover, although the penalty from lacking certain skills in western Germany is higher than in eastern Germany, the higher mean income may still result in a net outflow of unskilled individuals as is, in fact, the case. As a consequence, both the net loss of population and skills is likely to continue as long as eastern Germany is not able to make a competitive offer within the unified Germany.

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