

Falck, Oliver; Lameli, Alfred; Ruhose, Jens

Working Paper

The Cost of Migrating to a Culturally Different Location

CESifo Working Paper, No. 4992

Provided in Cooperation with:

Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Falck, Oliver; Lameli, Alfred; Ruhose, Jens (2014) : The Cost of Migrating to a Culturally Different Location, CESifo Working Paper, No. 4992, Center for Economic Studies and ifo Institute (CESifo), Munich

This Version is available at:

<https://hdl.handle.net/10419/103089>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



Working Papers

www.cesifo.org/wp

The Cost of Migrating to a Culturally Different Location

Oliver Falck
Alfred Lameli
Jens Ruhose

CESIFO WORKING PAPER NO. 4992

CATEGORY 4: LABOUR MARKETS

SEPTEMBER 2014

An electronic version of the paper may be downloaded

- from the SSRN website: www.SSRN.com
- from the RePEc website: www.RePEc.org
- from the CESifo website: www.CESifo-group.org/wp

CESifo

Center for Economic Studies & Ifo Institute

The Cost of Migrating to a Culturally Different Location

Abstract

Ever since Sjaastad (1962), researchers have struggled to quantify the psychic cost of migration. We monetize psychic cost as the wage premium for moving to a culturally different location. We combine administrative social security panel data with a proxy for cultural difference based on historical dialect dissimilarity between German counties. Conditional on geographic distance and pre-migration wage profiles, we find that migrants demand a (indexed with respect to local rents) wage premium of about 1 (1.5) percent for overcoming one standard deviation in cultural dissimilarity. The effect is driven by males, more pronounced for geographically short moves, and persistent over time.

JEL-Code: D510, J610, R230.

Keywords: migration costs, culture, internal migration, psychic cost.

Oliver Falck
Ifo Institute – Leibniz Institute for Economic
Research at the University of Munich
Poschingerstrasse 5
Germany – 81679 Munich
falck@ifo.de

Alfred Lameli
Research Centre Deutscher Sprachatlas
Hermann-Jacobsohn-Weg 3
Germany – 35032 Marburg
lameli@uni-marburg.de

Jens Ruhose
Ifo Institute – Leibniz Institute for Economic
Research at the University of Munich
Poschingerstrasse 5
Germany – 81679 Munich
ruhose@ifo.de

September 11, 2014

We thank George Bulman, Robert Fairlie, David A. Jaeger, Constantin Mang, Fabian Waldinger, Simon Wiederhold, Ludger Woessmann, and seminar participants at the Ifo Institute, 3rd workshop for regional economics in Dresden, University of Luxembourg, University of California-Santa Cruz, CUNY Graduate Center, and meeting of the Verein für Socialpolitik, Hamburg for helpful comments and discussion.

1. Introduction

The decision to migrate, and where exactly to go, is determined by comparing the costs and benefits of moving to the costs and benefits of alternatives. Benefits and costs can be monetary or non-monetary (Sjaastad 1962). Non-monetary migration costs include the psychic cost of moving from a familiar to an unfamiliar surrounding. As pointed out by Sjaastad, psychic cost is a result of tastes, which should be taken as given. Nevertheless, it is important to quantify psychic cost when analyzing rates of return to migration; otherwise, the rate of return to monetary resources allocated to migration is biased.

The internal migration literature typically uses geographic distance between the place of origin and destination as a catch-all proxy for various costs of migration, including psychic cost (cf. Greenwood 1975). The reason for using a catch-all proxy is that it is hard to find direct measures of psychic cost. Schwartz (1973, p. 1161) justifies the use of this particular catch-all proxy: “Psychic cost can be transformed into permanent transportation cost by figuring the needed frequency of visits to the place of origin so as to negate the agony of departure from family and friends”.

We monetize the psychic cost of migration as the wage premium that migrants demand when moving to a culturally different location. This approach is motivated by regional general equilibrium models in the tradition of Roback (1982). We assume that living in a culturally unfamiliar environment is comparable to a disamenity in the Roback model. Consequently, a potential internal migrant will move to a culturally unfamiliar environment only when she is compensated for this disamenity in the form of a higher wage and/or lower rent compared to her place of origin.

We use administrative social security panel data to identify internal migrants in Germany. Internal migrants are defined as job switchers for whom the job switch involves moving house from one county to another.¹ We merge the internal migrants’ wage profiles over time with information on the geographic and cultural distance between their counties of origin and destination. Cultural distance is calculated from unique data on historical dialect dissimilarity between German counties (Falck *et al.* 2012).

This historical dialect information comes from a government-funded dialect survey conducted in the German Empire at the end of the 19th century. At this time, dialects were still the prevalent languages of communication, often leading to significant problems in understanding between people from different regions or even nearby towns. As the most prominent expression of social identity, almost like a genome, historical dialects stored

¹ Thus, we do not study commuting. We are also not looking at gains to migration in general. McKenzie *et al.* (2010) have shown that these gains are hard to retrieve from non-experimental data. Therefore, we focus solely on the internal margin, i.e. looking only at individuals who have changed their place of work and place of residence and do not discuss outcomes from individuals who have changed their place of work without moving to another region.

information about past interactions across German counties over time. Our broad and evolutionary perspective of culture is thus similar to that of Guiso *et al.* (2006), who define culture as “those customary beliefs and values that ethnic, religious, and social groups transmit fairly unchanged from generation to generation.”

The linguistic situation changed when social and economic exchange was intensified after the founding of the empire. At that point, the national language (*Hochdeutsch*), which, until then, had been mostly reserved for written contexts, became increasingly adopted for speech also. At the same time, and considerably more so after World War II, German dialects show signs of both convergence and linguistic transfer from the national language. Obtaining explicit cultural consolidations at a very small geographic scale is thus made easier by using historical dialect data.

Our findings imply that, conditional on geographic distance and pre-migration quarterly wage profiles, internal migrants demand a (indexed with respect to local rents) wage premium of about 1 (1.5) percent for overcoming one standard deviation in dialect distance. This wage premium is most likely a lower-bound estimate for internal migrants since the county of immediate origin of an internal migrant is not necessarily the place where she was born and socialized. For those cases, however, we would not expect to find a systematic correlation between wage changes and dialect distance. The effect is driven by males, more pronounced for geographically short moves, and persistent over time. Considering higher polynomial functions of geographic distance in the regressions provides additional confidence that the effect of dialect distance is not only reflecting a non-linearity in the geographic distance effect. We also analyze those who have made multiple moves within a relatively short period and find that internal migrants who made a “wrong decision” in the first move correct this decision in the second move and demand a much higher wage premium.

The remainder of the paper is organized as follows. Section 2 describes the historical dialect data. Section 3 introduces the wage data for internal migrants in Germany. Section 4 explains our estimation strategy. Section 5 shows the baseline results. Section 6 provides a series of robustness checks. Section 7 reveals important effect heterogeneities with respect to gender, education, geographic distance, and multiple-times movers. Section 8 investigates the long-term impact of cultural distance. Section 9 concludes.

2. Historical Dialect Distance Between German Counties

Our proxy for cultural distance is based on historical dialect data from German localities. This unique source of data is derived from the language survey conducted for the Linguistic Atlas of the German Empire (*Sprachatlas des Deutschen Reichs*; data exploration between 1879 and 1888). Under the direction of the linguist Georg Wenker, pupils in more than 45,000 German schools were asked to translate 40 German sentences (more than 300 words) into

their local dialect.² One of the chief results of this project was the discovery of 66 prototypical characteristics of pronunciation and grammar that Wenker and his successors isolated during an extensive evaluation process (cf. Wrede *et al.* 1927). These characteristics are most relevant for structuring the German-language area.

Based on these prototypical characteristics, Falck *et al.* (2012) construct a dialect similarity matrix across all German counties (for more details, see Lameli 2013). For each county, the specific dialect is identified by the individual realization of the prototypical characteristics. The similarity between any two German counties is then quantified by counting the relative frequency of co-occurrences between any two profiles. We use this measure for further analysis, but, as we are dealing with the concept of cultural distance in this paper, we convert it from a similarity matrix into a distance matrix. The resulting dialect distance matrix across all counties has a dimension of 439×439 , with elements ranging between 0 (linguistic identity) to 1 (maximum linguistic distance). To illustrate, Figure 1 shows the dialect distance of all other counties to the city of Worms (Rhineland-Palatinate). The figure reveals that dialect distance is low for counties to the east, west, and north of Worms, but high for counties to the south of Worms.

<<Figure 1 about here>>

3. Internal Migration in Germany

Information on internal migration in Germany stems from the IAB Employment Panel. Based on the quarterly employment statistics of the Federal Employment Agency, the panel is a 2 percent subsample of the universe of employees who are subject to social security in Germany. Besides gross monthly wages, the data provide information on age, gender, educational attainment, nationality, and place of work and residence.³ Our sample period covers the years 1998 to 2006 and thus includes about 26 million quarterly observations from around 925,000 individuals. Since information on hours worked is not accurate in the IAB Employment Panel, we restrict our analysis to full-time employed individuals. However, there are still workers who receive zero wages even if they are full-time employed. We follow Card *et al.* (2013) and drop all workers with daily wages below 10 euro. Another problem is that the wage data are top-coded at the social security maximum. The number of workers affected by this restriction in the full sample is of the order of 10 to 12 percent of male workers and 1 to 3 percent of female workers (Card *et al.* 2013). The literature proposes imputing the missing wage information by assuming a normal wage distribution (Dustmann *et al.* 2009; Card *et al.* 2013). However, we restrict our sample to include only persons who have moved between two quarters. We find that only about 2 percent, either before or after the move, are top-coded. Thus, in total, we have only about 4 percent of top-coded observations. Therefore,

² The results are available in the form of phonetic protocols for each school, cf. <http://www.regionalsprache.de>.

³ To obtain the regional identifiers for the county of work and county of residence, we use the confidential weakly anonymous version of the scientific use file (see Schmucker and Seth 2009).

instead of using imputation methods, we check the robustness of our results by excluding this group and find that the results do not change.⁴ Finally, we restrict our sample to German citizens only.

We define internal migrants as individuals who have changed their county of residence and their county of work between two consecutive quarters. In some cases, the information on county of residence and work is missing. In these cases, we allow for an administrative lag of one quarter and determine whether the person has moved by comparing the work and residence status of the person in the wave before the missing entry with the wave after the missing entry.⁵ Our final sample contains 9,090 internal migrants. The internal migration rate in our sample is roughly 3 percent, which is comparable to official aggregate internal migration statistics for Germany.⁶

Panel A of Table 1 shows the distribution of wages four quarters before ($t-1$, $t-2$, $t-3$, $t-4$) and one quarter after the move ($t+1$). Wages are in 2010 prices, i.e., we adjust wages for the national consumer price index (Federal Statistical Office, 2014). The average monthly gross wage in 2010 prices before the move is € 2,867 and increases by 3.9 percent to € 2,980 after the move. To account for the fact that moving to a culturally unfamiliar environment might also be capitalized in rents, we also calculate an index wage based on local rents. We use rental prices averaged over the years 2004 to 2008 as reported by the Federal Institute for Research on Building, Urban Affairs and Spatial Development, as well as by the IDN ImmoDaten GmbH. The rental prices are transformed into a price index expressed in terms of the most expensive place, Munich. Munich receives a value of 1 and all other counties are ranked relative to it. The average monthly indexed gross wage in 2010 prices before the move is 5,200 and increases by 1.4 percent to 5,271 after the move (see Panel A of Table 1).

<< Table 1 about here >>

Another observation from Panel A of Table 1 is that the average wage for movers to counties farther away than the median dialect distance is higher than that of movers to counties closer than the median dialect distance. This is the case not only one quarter after the move but at each point in time. This suggests that these “far” movers have higher skills than “close” movers. However, these skills are also reflected in pre-move wages.

⁴ The social security data should only report wages until the social security maximum. However, there are a few cases in which the reported wage exceeded this amount. We restricted these cases back to the social security maximum. We also performed robustness checks by omitting the bottom and top 5 percent of the wage distribution and the results are not sensitive to this omission.

⁵ Omitting individuals with an administrative lag from the sample or controlling for them with an indicator variable does not change the results.

⁶ The average overall internal migration rate for the period 1998 to 2006 was 4.6 percent (own calculations based on official migration and population data of the Federal Statistical Office 2013). Since our sample consists only of working individuals subject to social security, the internal migration rate in our sample is slightly lower.

Panel B of Table 1 shows descriptive statistics for the distance data. The geographic distance definitely correlates with dialect distance. The mean geographic distance is 318 km (197.6 miles) for individuals who moved to a county farther away than the median dialect distance whereas the destination county is only 76 km (47.2 miles) away for the closer-than-median mover. On average, an internal migrant moves 200 km (124.3 miles) and experiences 0.372 in cultural distance by doing so.

Figure 1 has already indicated that geographic distance and dialect distance capture, at least partly, the same spatial variation which means that they are correlated. The obvious reason is that individuals from regions that are closer together interact more with each other. While Figure 1 illustrates the situation for Worms only, Figure 2 shows this relationship systematically. In Figure 2, we plot geographic distance versus the dialect distance of the movers in our dataset. We construct the figure by portioning the dialect distance into 20 equal sized bins (5 percentage intervals) and compute the mean geographic distance for each of the bins. The relationship between both distances shows that a higher dialect distance is associated with a higher geographic distance. One standard deviation increase in the dialect distance is associated with an increase in geographic distance by 130 km (80.8 miles). The curvature follows an s-shaped curve, with an accelerating increase in geographic distance at low levels of dialect distance and decreasing increases in geographic distance at higher levels of dialect distance. This curvature is in line with the argument that dialect distance (or cultural distance) might explain non-linearity in geographic distance. The positive correlation between geographic distance and dialect distance makes it important to control for geographic distance in the following analyses. We also control for non-linearities in geographic distance in some specifications. This can be viewed as a conservative approach since it removes some of the non-linearity that might have its origin in culture.

<<Figure 2 about here>>

The selection of individuals into moving across cultural borders can be seen in Panel C of Table 1. Above-median movers are more likely to have a university degree (33.9 percent vs. 26 percent) and to have attended the highest academic track in secondary school (15.2 percent vs. 13.5 percent). There is also a gender gap. The share of male migrants is higher in both the below-median mover group and in the above-median mover group. Age and (potential) experience are comparable across both groups.⁷ The average age of the movers is 32. The question arises, then, whether the wage earned at around 30 years of age is a meaningful reflection of an individual's lifetime productivity or earnings. Studies by Haider and Solon (2006), who look at the relationship of current and life-time earnings, and by Chetty *et al.* (2014), who look at the relationship of parental and child earnings, show that measures using wages at age 30 are fairly stable predictors of life-time earnings or intergenerational mobility,

⁷ Potential labor market experience is computed by $Age - 6 - Years\ of\ Education$.

respectively. Finally, slightly less than 60 percent of the internal migrants change the industry in which they work when they move.

4. Estimation Strategy

To deal with unobserved self-selection into different locations, we adopt an estimation strategy from the literature on the effects of training programs on wages (e.g., Ashenfelter and Card 1985; LaLonde 1986). The basic idea in this strand of literature is to use pre-treatment wages to control for unobserved selection into programs. Comparing individuals with similar pre-treatment wage profiles should mitigate the selection problem. McKenzie *et al.* (2010) evaluate the transferability of this estimation strategy to the context of gains to migration. They show that it is hard to retrieve the causal effect of migration on wages from non-experimental data. However, estimators conditioning on the pre-treatment wage performs best among non-experimental and non-IV estimators.⁸ Specifically, we estimate the following wage regression:

$$\begin{aligned} \log wage_{idt+1}^{indexed} = & \alpha + \beta Dialect\ Distance_{sd} + \sum_{j=1}^4 \gamma_j \log wage_{ist-j}^{indexed} \\ & + \lambda Geographical\ Distance_{sd} + \phi X_{it-1} + \mu_t + \varepsilon_{idt+1} \end{aligned} \quad (3)$$

The log of the indexed wage received by internal migrant i in destination d in the quarter after the move, i.e., at $t+1$, is regressed on the dialect distance between the origin county s and destination county d . The coefficient of interest is β , which is the wage premium in percent for overcoming one unit in dialect distance. The identification assumption under which the coefficient β would report the causal effect of dialect distance on the wage after the move requires that dialect distance not be correlated with unobserved individual characteristics. By including the last four quarterly wages before the move, $\sum_{j=1}^4 \log wage_{ist-j}^{indexed}$, we control for unobserved self-selection into different locations.

Local amenities, like schools, transport infrastructure, health care providers, shopping alternatives, or leisure facilities, and also disamenities, like pollution, congestion, and the like, are also capitalized in local wages and rents. However, the local amenity level should not bias our estimate as long as the difference in amenities in two counties are not correlated with

⁸ In addition, our setup allows for several improvements compared to the approach of McKenzie *et al.* (2010): We use quarterly data and several lags; describing the pre-treatment wage profiles more accurately. We look only at the internal margin and at internal migrants as opposed to the external margin and international migration. This should reduce the potential selection bias as overall migration costs are smaller. Conditioning on the sample of movers, all individuals are more likely to receive the same treatment (common support). Individuals who have only switched their place of work might be more dissimilar in unobserved characteristics compared to our baseline sample of individuals who switched the place of work and place of residence.

dialect distance. We further control for geographic distance between s and d .⁹ We also control for gender, education (five dummies), experience (and its square), and a dummy indicating an industry change accompanying the move.¹⁰ The quarter-year fixed effects μ_t capture all time-specific shocks. Finally, ε_{idt+1} is an idiosyncratic error term.¹¹

5. Wage Premium for Overcoming Dialect Distance

Table 2 sets out our baseline results. The sample is restricted to the internal migrants' first move.¹² Column (1) shows the association between dialect distance and post-migration log indexed wage conditional on geographic distance and quarter-year fixed effects. Dialect distance is in fact positively correlated with post-migration log indexed wage. Interestingly, conditional on dialect distance, the geographic distance enters negatively, which means that long-distance moves are associated with lower wages. In Column (2), we add the last four quarterly pre-migration log indexed wages to control for unobserved self-selection into different locations. The coefficient on dialect distance drops by almost a factor of four and almost all pre-migration wages are highly significant predictors of post-migration wages. This indicates that self-selection is indeed a serious issue and that neglecting pre-migration wages in the regression will lead to an upwardly biased estimate of the coefficient on dialect distance. After controlling for pre-migration wage profiles, adding further control variables in Column (3) hardly changes the picture. The coefficient decreases slightly to 0.075 but is still highly significant. Thus, a one standard deviation (about 0.2) increase in dialect distance increases the post-migration indexed wage by about 1.5 percent.

<< Table 2 about here >>

In Column (4) of Table 2 we provide an alternative specification in which we explain the log wage and control for the log rental price in the destination and the source county on the right-hand side of the regression. This specification allows us to compare the effect of dialect distance with collective wage agreements so as to get an impression of the importance of the effect. The log rental price in the destination county is a significant predictor of post-migration log wages. Thus, wages in areas with high rental rates are also relatively high. The rental price in the source county is not associated with the post-migration wage. The coefficient on the dialect distance decreases in this specification but is still comparable to the

⁹ In another specification, we also control for a higher polynomial function of geographic distance because it could be argued that cultural distance is only a non-linearity in geographic distance.

¹⁰ An alternative for using a dummy for the industry change is to use industry fixed effects. The results do not change.

¹¹ We use robust standard errors throughout the paper. In various robustness checks, we clustered standard errors at various levels. However, clustering at the origin county \times destination county, the origin county, or the destination county yield very similar standard errors.

¹² We analyze multiple-time movers in Section 7.

baseline specification. Increasing dialect distance by one standard deviation increases the post-migration wage by almost 1 percent.¹³

The indexed wages of internal migrants increase, on average, by about 1.4 percent from the quarter before the move to the first quarter after the move. This implies that the wage premium necessary to compensate for one standard deviation in dialect distance is about 107 percent of the average wage gain in 2010 prices from internal migration. The wage in 2010 prices increases from the quarter before the move to the quarter after the move by 3.9 percent. Thus, in 2010 nationwide prices, the wage premium has to be 26 percent. The effect size of 1 percent per standard deviation is sizeable when compared to the most recent (2013) collective wage agreements in Germany. For example, in the public sector, there was an agreed upon increase of 2.65 percent in nominal wages (ver.di 2013) and in manufacturing, an increase of 3.4 percent in nominal wages was negotiated (IG Metall 2013).

Figure 3 shows an added-variable plot where we use only the variation in the post-migration indexed wage that remains after taking account of the geographic distance, quarter-year fixed effects, and four quarterly pre-migration wages (blue-diamond) or conditional on the full control set (red-quadrat). The conditional post-migration indexed wage is then plotted against the residual dialect distance after taking out all variation that is due to the full control set.¹⁴ The figure reveals an almost linear relationship between residual dialect distance and the conditional post-migration indexed wage once the dialect distance crosses the 10th percentile (first two bins).

<< Figure 3 about here >>

6. Robustness Checks

In this section, we conduct a couple of robustness checks. For example, it could be that the observed effect is driven by moves to and from large agglomerations, which might differ from other counties in terms of amenities. To check this, we exclude the five largest cities in Germany (Berlin, Hamburg, Munich, Cologne, and Frankfurt) as destination and source counties (Column (1) of Table 3). Even though these cities account for almost a quarter of the mover sample, the coefficient of the regression stays virtually the same.¹⁵

<< Table 3 about here >>

Unfortunately, we do not know where the individuals in our sample were born and socialized, raising the concern that a migrant might not be attached to the county he or she

¹³ The results are comparable when we use a price index instead of rental rates. However, we think that rental rates are better able to capture amenities than are price levels.

¹⁴ The figure is a binned scatterplot where the residual dialect distance is binned into 20 equal-sized bins. The mean of the conditional post-migration indexed wage within each bin is then computed and plotted against the dialect distance.

¹⁵ In other specifications, we include dummies for moving from East to West Germany and for moving from West to East Germany or for changing states. The results are not affected by these dummies.

left.¹⁶ In this case, however, we would not expect to see any effect of cultural distance on post-migration wages. Thus, our baseline results should indicate a lower bound of the effect of cultural distance on migration wage gains.

To get some sense of the extent to which we underestimate the true effect of cultural distance on migration wage gains, we restrict the sample to those internal migrants who have not changed place of work or residence for a reasonable period before the move. Living in a region for a longer period could make a person more attached to that county than to the former home county (Burchardi and Hassan 2013). Given that our panel covers nine years, we restrict our analysis to those 1,815 individuals who resided and worked in the origin county for at least seven years and then moved to a different county during the last two years of our panel. The result of this procedure is shown in Column (2) of Table 3. The coefficient of dialect distance almost doubles, providing more support for our argument that the baseline effect is more of a lower bound and that being attached to a certain area for a longer period increases the cost of moving.

The last robustness check (Column (3) of Table 3) introduces various pair-wise historical and contemporaneous controls between the counties of origin and destination that might be correlated with both migration flows and historical dialect distance. We include the log difference in slope, the historical rail distance, a dummy for a different religion, the difference in share Catholics, the difference in the historical industry structure, the difference in the current industry structure, and weather controls as the difference in temperature, difference in sunshine duration, and difference in precipitation.¹⁷ None of these controls significantly change the coefficient on dialect distance.

A crucial assumption is that the four quarterly pre-migration wages sufficiently capture the migrant's unobserved ability. Table 4 introduces a more demanding specification by conditioning on a greater number of pre-migration wages. Columns (1) to (8) include up to two more years of quarterly wages. However, the coefficient on dialect distance remains comparable. Column (9) changes the setup and includes the wages in yearly intervals. The coefficient on dialect distance increases, which indicates that the quarterly wages capture the selection of internal migrants better than do yearly wages.¹⁸

<< Table 4 about here >>

¹⁶ For example, migration flows in the aftermath of World War II (e.g., refugees, ethnic Germans, etc.) might have substantially involuntarily reshuffled the German population with respect to cultural roots.

¹⁷ Data on log difference in slope, the historical rail distance, a dummy for a different religion, the difference in share Catholics, the difference in the historical industry structure, the difference in the current industry structure is taken from Falck *et al.* (2012). Climate data comes from the Deutscher Wetterdienst (DWD). We use long-term averages from 1961 to 1990. We mapped all weather monitoring stations to counties and calculated averages. We use state averages for missing county observations.

¹⁸ Using yearly averages instead of yearly wages leads to very similar results.

The next concern is the possibility that dialect distance captures non-linearities in geographic distance that do not have their origin in culture. Table 5 sets out several specifications that include non-linear geographic distance measures. Column (1) replicates the baseline regression for means of comparison. Column (2) includes the geographic distance of power two and three. The coefficient on dialect distance increases, which indicates that it does not capture strong non-linearities in geographic distance.

<< Table 5 about here >>

However, it could be that geographic distance is an insufficient distance proxy for dialect distance. Therefore, in Columns (3) and (4) of Table 5 we use the travel distance between counties by car in minutes as an alternative geographic distance measure.¹⁹ However, the travel time could be affected by dialect distance as well because it is very likely that transportation hubs and networks have developed along travel routes. Column (3) shows a specification in which we include the travel distance instead of the geographic distance. The coefficient of dialect distance decreases but remains highly significant. When we include travel distance to the power two and three, we see that the coefficient increases slightly again. However, the results of this exercise indicate that there are only minor nonlinear effects, if any, of geographic distance that are picked up by dialect distance.

Table 6 uses alternative measures of dialect distance to check the robustness of our results. To this point, we have used a metric measure of dialect distance. However, it could be that cultural space is dependent not only on gradual differences but on categorical ones. That is, the decision to move could be due to a difference between, for example, “Swabian” and “Bavarian” as such and not to the actual gradual difference between the counties within the Swabian and Bavarian region. To test for the impact on migration of categorical differences between smaller regions we use a classification introduced by Lameli (2013) that captures the most prominent 13 dialect areas in Germany. The measure results from bootstrapped hierarchical cluster analysis, based on the measurement of linguistic similarity of German counties. Column (1) of Table 6 sets out the results. The coefficient is positive and significant. A one standard deviation in the dialect distance by language area (1.04) leads to 1.11 percent higher post-migration indexed wages.

<< Table 6 about here >>

As the most important linguistic difference between German dialects is that between Low German (northern part of Germany) and High German (southern part), we further construct a dummy that substantiates the particular locality of the counties and tests for movements within the two larger areas of Low German and High German. Column (2) of Table 6 includes a dummy for moving from a High German county to a Low German county, a dummy for moving from a Low German county to a High German county, and a dummy for

¹⁹ Data are provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development.

moving from a High German county to another High German county. The omitted category is moving from a Low German county to another Low German county. The results show that the effect of dialect distance remains robust when testing for the north-south distinction. We find, however, a slight north-south divide, indicating the relevance of a categorical conceptualization of cultural space. Wages are positively affected by migration from south to north, but negatively affected by a migration from north to south.

7. Effect Heterogeneity

The question arises as to whether there is a group of individuals that is driving the baseline results. To answer this question, we first split the sample by (i) age, (ii) gender, (iii) education, (iv) education \times gender, (v) distance of the move, and (vi) occupational change. The results are summarized in Table 7.

<< Table 7 about here >>

Table 7, Panel A stratifies the sample between young (below age 30) and older (above age 30) movers. In Column (1), we look only at movers who are 30 or younger to discover whether age plays a crucial role in overcoming cultural distance, as argued by Schwartz (1973). The coefficient is large and significant. The coefficient on dialect distance for older movers in Column (2) is smaller and not significant. This indicates that our results are more driven by young movers than by older movers. Schwartz (1973) further argues that the interaction of geographic distance with age should indicate the importance of the psychic cost of migration. Therefore, we interacted geographic distance with age. In this specification (not shown), the interaction is not significant and the effect of dialect dissimilarity remains unchanged, indicating that dialect dissimilarity better captures the psychic cost of migration than does an interaction between geographic distance and age.

Panel B of Table 7 shows that the wages of men are more responsive to culture than those of women. Possibly this is because in most families the male adult is the household head and his place of work largely determines where the family lives. We also see that low- and medium-qualified migrants find culture more of a barrier to migration than do higher qualified migrants.²⁰ However, the difference between the groups is not large. Panel C shows that within the group of men, it is again the group of lower qualified migrants that shows a larger coefficient, but the differences are not significant. The results for women are insignificant again and the coefficient for lower qualified women is slightly higher than for higher qualified women. Panel D reveals that the effect is mainly coming from shorter-distance moves, that is, moves less than 300 km from the former home county. Thus, the wage increases from moving to a more culturally distant county are not driven by long-

²⁰ The group of low- and medium-qualified migrants consists of those with a degree from the lowest and middle academic track with and without vocational education and training (VET). We also include people for whom level of education is unknown. However, the picture does not change by omitting this group. The group of high-qualified people is comprised of those having a degree from the highest academic track or a university degree.

distance moves as one might have expected. We also looked at the subsample of internal migrants who also switch occupation when they move (Panel E). Compared to occupational stayers, switchers are compensated more for their move to a dialect-dissimilar county.

We also analyze in more detail the 567 two-time movers in our sample.²¹ Recall that the total time period under analysis is nine years, meaning that every second move occurs within a relatively short time window. For the second move, we use the dialect distance and geographic distance between the origin county of the first move and the destination county of the second move. This should mimic the potential direct move to the destination county in the second move. All other control variables (quarterly pre-treatment wages, education, experience, age, etc.) are taken from the second move. Interestingly, almost 34 percent (194 migrants) of the two-time movers in our sample return in the second move to exactly the same county from which they came. However, only 32 of the 194 repatriates return to the same firm.²²

Table 8 shows the results of the two-time mover analysis by first and second move and by timing of the move, that is, whether the migrant moved another time after or before eight quarters (two years). Panel A shows the results with repatriates included and Panel B shows the results without this group. The first move shows, independent of the timing, that the coefficients are larger than in the baseline sample. This indicates that these particular people, who we know are going to move again within the next nine years, value culture highly. The second move is more interestingly. The coefficient for those who moved another time within eight quarters is almost seven times as large as the baseline coefficient. The above findings lead us to view these two-time movers as people who made the wrong decision about where to live and work for the first move and are now willing to sacrifice a lot more money in return for a more familiar environment.

<< Table 8 about here >>

8. Persistence of Wage Premium

We now turn to the question of whether the initial effect directly after the move is persistent over time. To this end, we look at wage growth after the first move by estimating the regression in Equation (2).

$$\begin{aligned} \left[\log wage_{idt+k}^{indexed} - \log wage_{idt+1}^{indexed} \right] / k = & \alpha + \beta Dialect Distance_{sd} + \gamma \log wage_{ist+1}^{indexed} \\ & + \lambda Geographical Distance_{sd} + \phi X_{it-1} + \mu_t + \varepsilon_{idt+1} \end{aligned} \quad (2)$$

²¹ There are some individuals who moved more than two times, but this group is too small for an in-depth investigation.

²² “Repatriates” are those who move to their previous county of residence and again work in their previous county of work. Thus, migrants who return to their previous home county but work in a different county than before are not repatriates.

Conditional on the logged initial wage level after the move, we regress the average yearly wage growth from period $t+1$, i.e., the first quarter after the move, to period $t+k$, on dialect distance. Thereby, k takes a maximum value of 32 (quarters), i.e., we analyze wage growth within a maximum of eight years after the move. Note that by extending the growth period of analysis year by year, the number of internal migrants remaining in the sample drops significantly, until finally, in the analysis of eight-year post-move wage growth, there are less than 700 internal migrants. All other control variables remain equivalent to the baseline model. Due to a “catching-up” process, we expect that migrants who moved to more culturally dissimilar counties will exhibit lower wage growth rates. Table 9 shows the results for the three- to six-year wage growth rates. The coefficient on the logged initial wage level after the move shows that internal migrants with initially higher wages after the move generally have lower wage growth in the future. However, dialect distance is not significantly associated with future wage growth. Thus, we conclude that the initial wage sacrifice is persistent over time.

<< Table 9 about here >>

9. Conclusion

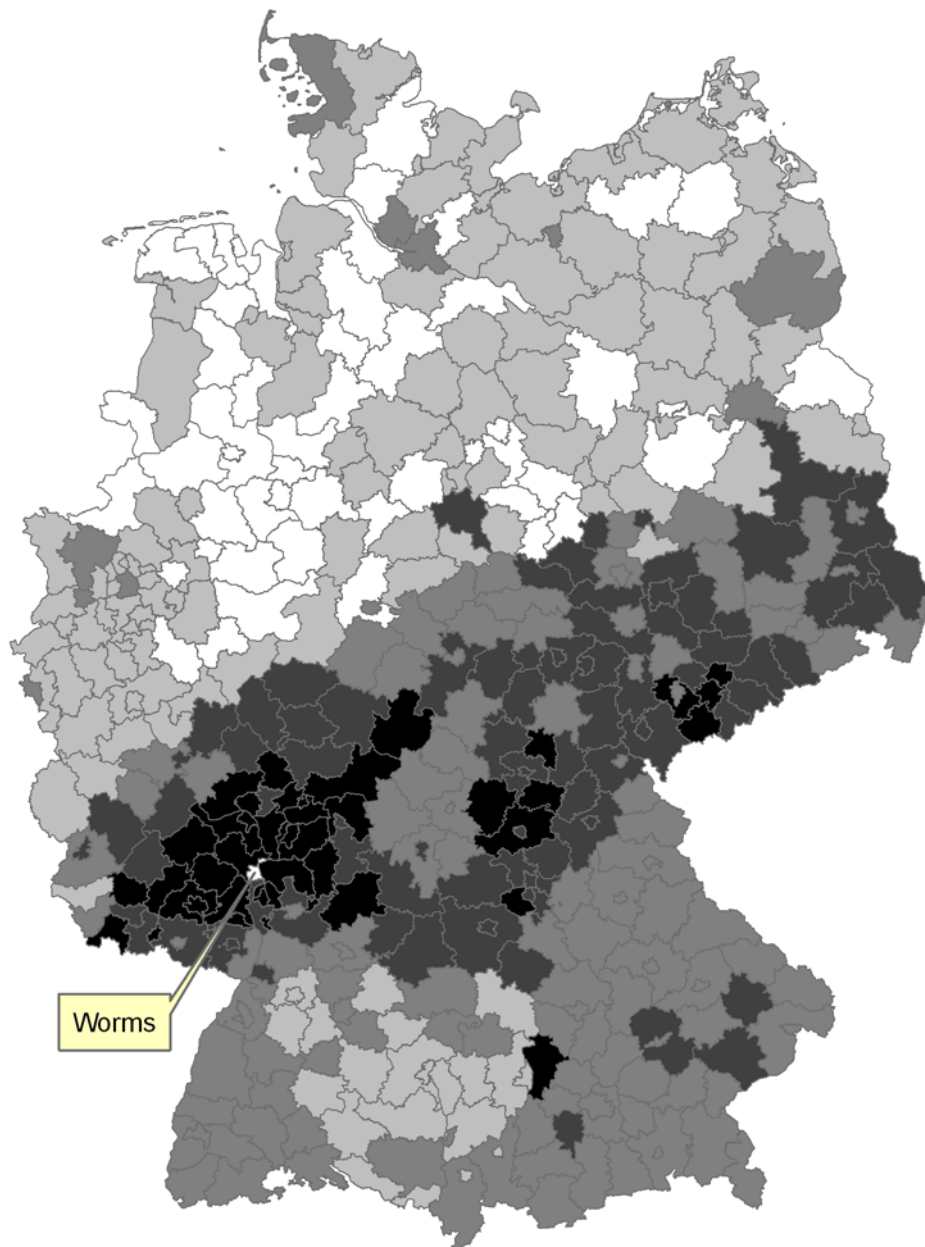
In this paper, we monetize the psychic cost of migration by combining administrative social security panel data with a proxy for cultural difference that is based on historical dialect distance between German counties. Internal migrants demand a (indexed with respect to local rents) wage premium of about 1 (1.5) percent for a one standard deviation in dialect distance. Compared to the general wage gain associated with internal migration, as well as to general wage increases negotiated in recent collective agreements, this wage premium, which is arguably a lower-bound estimate, is economically substantive and persistent over time. Our results imply that analyses of rate of return to migration that do not consider this psychic cost of migration overestimate the rate of return allocated to migration.

Literature

- Ashenfelter, Orley C. and David Card (1985), Using Longitudinal Structure of Earnings to Estimate the Effect of Training Programs. *Review of Economics and Statistics*, 67(4), 648–660.
- Burchardi, Konrad B. and Tarek A. Hassan (2013), The Economic Impact of Social Ties: Evidence from German Reunification. *Quarterly Journal of Economics*, 128(3), 1219–1271.
- Card, David, Jörg Heining, and Patrick Kline (2013), Workplace Heterogeneity and the Rise of West German Wage Inequality. *Quarterly Journal of Economics*, 128(3), 967–1015.
- Chetty, Raj, Nathaniel Hendren, Patrick Kline, Emmanuel Saez, and Nicholas Turner (2014), Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States. *Quarterly Journal of Economics*, forthcoming.
- Dustmann, Christian, Johann Ludsteck, and Uta Schönberg (2009), Revisiting the German Wage Structure. *Quarterly Journal of Economics*, 124(2), 843–881.
- Falck, Oliver, Stephan Heblich, Alfred Lameli, and Jens Suedekum (2012), Dialects, Cultural Identity, and Economic Exchange. *Journal of Urban Economics*, 72(2–3), 225–239.
- Federal Statistical Office (2013), Bevölkerung und Erwerbstätigkeit, Fachserie 1, Reihen 1.2 und 1.3.
- Federal Statistical Office (2014), Consumer price indices, <https://www.destatis.de/EN/FactsFigures/Indicators/ShortTermIndicators/Prices/pre110.html>.
- Greenwood, Michael J. (1975), Research on Internal Migration in the United States: A Survey. *Journal of Economic Literature*, 13(2), 397–433.
- Guiso, Luigi, Paula Sapienza, and Luigi Zingales (2006), Does Culture Affect Economic Outcomes? *Journal of Economic Perspectives*, 20(2), 23–48.
- Haider, Steven and Gary Solon (2006), Life-Cycle Variation in the Association Between Current and Lifetime Earnings. *American Economic Review*, 96(4), 1308–1320.
- IG Metall (2013), Collective Wage Agreement in the Manufacturing Sector 2013, <http://www.igmetall.de/SID-49F5A1E2-969B8B98/metall-tarifunde-2013-bayerisches-ergebnis-in-allen-11891.htm>
- LaLonde, Robert J. (1986), Evaluating the Econometric Evaluations of Training Programs with Experimental Data. *American Economic Review*, 76(4), 604–620.
- Lameli, Alfred (2013), *Strukturen im Sprachraum. Analysen zur arealtypologischen Komplexität der Dialekte in Deutschland*. De Gruyter, Berlin, Boston.
- McKenzie, David, John Gibson, and Steven Stillman (2010), How Important is Selection? Experimental vs. Non-Experimental Measures of the Income Gains from Migration. *Journal of the European Economic Association*, 8(4), 913–945.

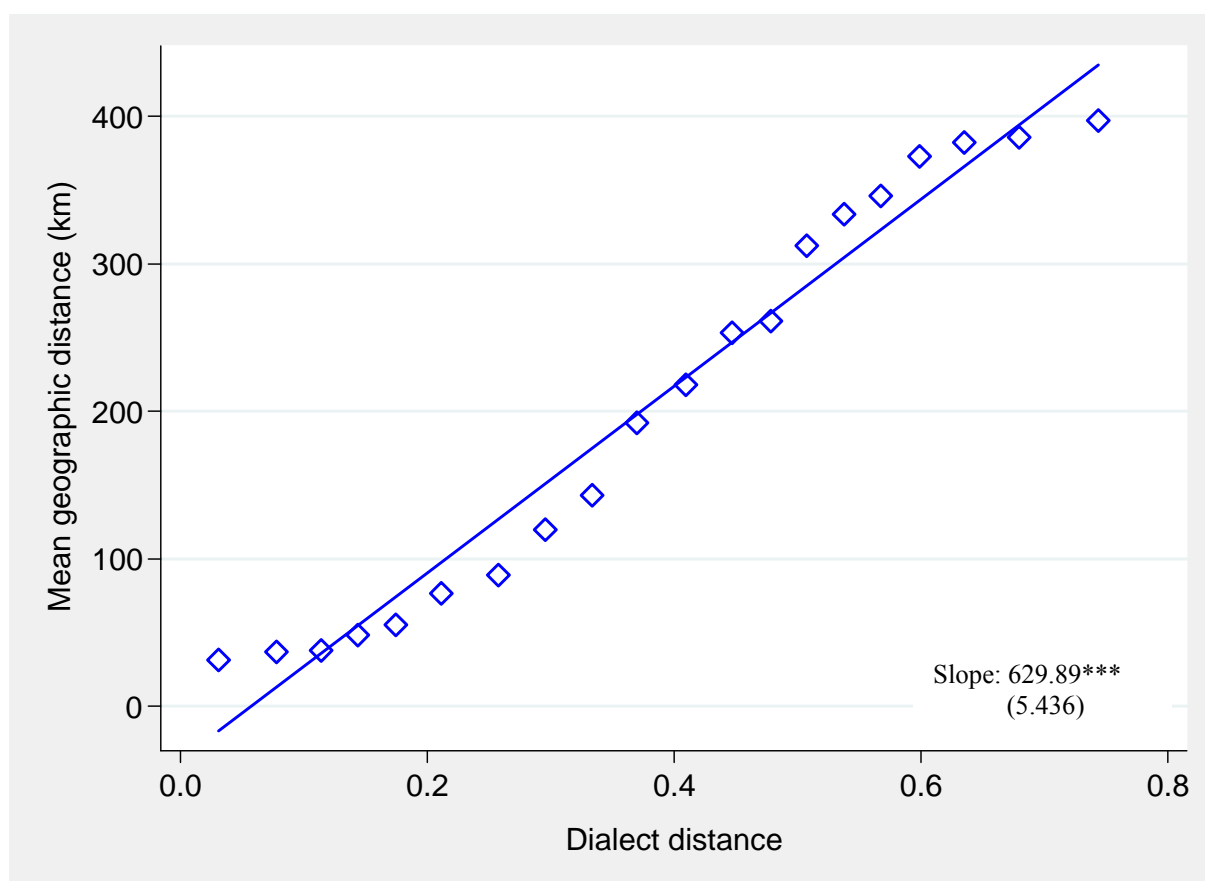
- Roback, Jennifer (1982), Wages, Rents, and the Quality of Life. *Journal of Political Economy*, 90(6), 1257–1278.
- Schmucker, Alexandra and Stefan Seth (2009), BA-Beschäftigtenpanel 1998–2007 Codebuch, FDZ Datenreport 01/2009, Bundesagentur für Arbeit Nürnberg.
- Schwartz, Aba (1973), Interpreting the Effect of Distance on Migration. *Journal of Political Economy*, 81(5), 1153–1169.
- Sjaastad, Larry A. (1962), The Costs and Returns of Human Migration. *Journal of Political Economy*, 70(5), 80–93.
- ver.di (2013), Collective Wage Agreement in the Public Sector 2013, <http://www.verdi.de/themen/geld-tarif/tarifunde-oeffentlicher-dienst-der-laender-2013/++co++a5c366fa-784c-11e2-8d18-52540059119e>
- Wrede, Ferdinand, Walther Mitzka, and Bernhard Martin (1927), Deutscher Sprachatlas. Auf Grund des von Georg Wenker begründeten Sprachatlas des Deutschen Reichs. Elwert, Marburg.

Figure 1: Dialect Distance—The Case of Worms



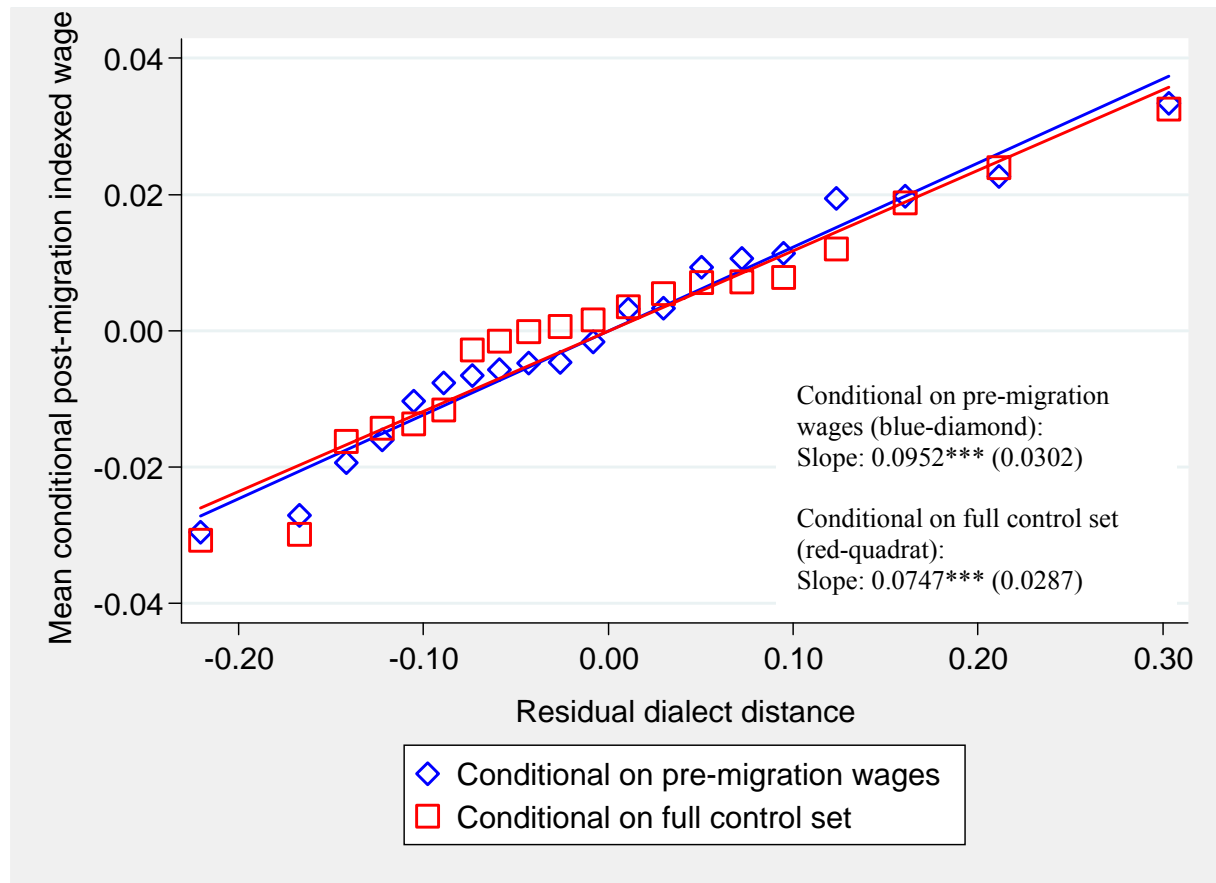
Notes: The figure shows dialect distance of all districts to the reference point Worms (20% intervals of dialect distance). Degrees of dialect distance (from highest to lowest) are indicated by: white, grey, black.

Figure 2: Geographic Distance and Dialect Distance



Notes: The figure shows a binned scatterplot of geographic distance on dialect distance. The figure is constructed by binning dialect distance into 5-percentile point bins (so that there are 20 equal-sized bins) and computing the mean geographic distance within each bin. The slope coefficient and (robust) standard error in parentheses are obtained from a regression on the micro data. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 3: Added-Variable Plot of Dialect Distance and the Post-Migration Wage



Notes: The figure shows a binned scatterplot of conditional post-migration indexed wages on residual dialect distance. The conditional post-migration indexed wages are obtained from residuals from regressions on the geographic distance, quarter-year fixed effects, and the last four quarterly pre-migration wages (blue-diamond) or additionally on education dummies (4), male, experience, experience squared, and an industry change dummy (red-quadrat). The residual dialect distance is obtained from residuals from regressions on the geographic distance, quarter-year fixed effects, the last four quarterly pre-migration wages, education dummies (4), male, experience, experience squared, and an industry change dummy. The figure is constructed by binning dialect distance into 5-percentile point bins (so that there are 20 equal-sized bins) and computing the mean conditional post-migration indexed wage within each bin. Coefficients and robust standard errors in parentheses are obtained from regressions on the micro data. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1: Descriptive Statistics

Variable	Total sample		Dialect distance			
	Mean (SD)	Min Max	below median		above median	
	Mean (SD)	Min Max	Mean (SD)	Min Max	Mean (SD)	Min Max
<i>Panel A: Wage data</i>						
Wage in 2010 prices (t+1)	2,980 (1,291)	240 5,692	2,857 (1,266)	248 5,692	3,098 (1,303)	240 5,692
Wage in 2010 prices (t-1)	2,867 (1,285)	222 5,698	2,758 (1,257)	222 5,698	2,971 (1,302)	250 5,686
Wage in 2010 prices (t-2)	2,852 (1,301)	223 5,692	2,744 (1,270)	223 5,654	2,956 (1,323)	225 5,692
Wage in 2010 prices (t-3)	2,825 (1,319)	221 5,716	2,719 (1,288)	225 5,686	2,926 (1,340)	221 5,716
Wage in 2010 prices (t-4)	2,806 (1,329)	221 5,716	2,705 (1,298)	227 5,670	2,903 (1,351)	221 5,716
Indexed wage in 2010 prices (t+1)	5,271 (2,402)	300 15,836	5,180 (2,405)	300 14,992	5,358 (2,397)	319 15,836
Indexed wage in 2010 prices (t-1)	5,200 (2,371)	273 14,398	5,034 (2,353)	273 14,398	5,358 (2,378)	467 13,838
Indexed wage in 2010 prices (t-2)	5,174 (2,398)	273 14,476	5,010 (2,371)	273 14,475	5,331 (2,414)	341 13,915
Indexed wage in 2010 prices (t-3)	5,129 (2,432)	225 14,570	4,968 (2,407)	225 14,570	5,282 (2,446)	431 13,930
Indexed wage in 2010 prices (t-4)	5,100 (2,444)	227 14,586	4,951 (2,424)	227 14,586	5,243 (2,455)	359 13,928
<i>Panel B: Distance data</i>						
Dialect distance	0.372 (0.207)	0 0.833	0.189 (0.103)	0 0.364	0.548 (0.104)	0.379 0.833
Geographic distance (km)	200 (170)	1 818	76 (72)	1 595	318 (150)	15 818
<i>Panel C: Individual characteristics</i>						
Lowest and middle academic track, without VET	0.019	0 1	0.021	0 1	0.017	0 1
Lowest and middle academic track, with VET	0.523	0 1	0.572	0 1	0.477	0 1
Highest academic track	0.144	0 1	0.135	0 1	0.152	0 1
University	0.300	0 1	0.260	0 1	0.339	0 1
Education unknown	0.014	0 1	0.012	0 1	0.015	0 1
Male	0.557	0 1	0.570	0 1	0.545	0 1
Age	32.038 (8.049)	18 63	31.965 (8.307)	18 62	32.108 (7.794)	18 63
Experience	11.687 (8.083)	0 43	11.790 (8.335)	0 43	11.587 (7.835)	0 43
Industry change	0.588	0 1	0.578	0 1	0.598	0 1
Observations	9,090		4,444		4,646	

Notes: Summary statistics are based on the baseline sample. Only the first observed move is considered for individuals who moved several times. We have full information on 567 individuals, or 6.2 percent, who moved two times during our time period. Wage data and data on individual characteristics are drawn from the IAB Employment Panel. Wages are denoted in 2010 Euros by using the consumer price index from the Federal Statistical Office (2014). The distance data are from Falck *et al.* (2012). Standard deviations are not computed for dummy variables. The variable t indicates the timing of the move. $t+1$ denotes the first observation after the move, $t=0$ denotes the move, and $t-1$ denotes the quarter before the move. *Experience* represents potential labor market experience and is computed by $\text{Age} - 6 - \text{years of schooling}$. *Years of schooling* is assumed to be equal to 10 years for *lowest and middle academic track without VET*, 13 years for *lowest and middle academic track with VET*, 13 years for *highest academic track without VET*, 15 years for *highest academic track with VET*, 17 years for *university*, and 10 years for *education unknown*. We merged *highest academic track without VET* and *highest academic track with VET* into one education category.

Table 2: Dialect Distance and Post-Migration Wages

<i>Dependent variable:</i>	<i>Log indexed wage (t+1)</i>			<i>Log wage (t+1)</i>
	(1)	(2)	(3)	(4)
Dialect distance	0.3872*** (0.0389)	0.0952*** (0.0302)	0.0747*** (0.0287)	0.0486** (0.0234)
Geographic distance (km)	-0.00035*** (0.00005)	-0.00012*** (0.00004)	-0.00013*** (0.00003)	-0.000002 (0.000029)
Log indexed wage (t-1)		0.342*** (0.0272)	0.2608*** (0.0256)	
Log indexed wage (t-2)		0.1137*** (0.0334)	0.088*** (0.0301)	
Log indexed wage (t-3)		-0.0134 (0.0376)	-0.0098 (0.0334)	
Log indexed wage (t-4)		0.2000*** (0.0293)	0.1509*** (0.0267)	
Log wage (t-1)				0.3799*** (0.0273)
Log wage (t-2)				0.0984*** (0.0307)
Log wage (t-3)				0.0178 (0.035)
Log wage (t-4)				0.0897*** (0.0286)
Log rental price (t+1)				0.1984*** (0.0144)
Log rental price (t-1)				-0.0216 (0.0158)
Lowest and middle academic track, with VET			0.0869*** (0.0332)	0.0635** (0.029)
Highest academic track			0.2002*** (0.0346)	0.1685*** (0.0304)
University			0.3537*** (0.0344)	0.2939*** (0.0305)
Education unknown			0.167*** (0.0473)	0.1114*** (0.0408)
Male			0.0928*** (0.0081)	0.0765*** (0.007)
Experience			0.0124*** (0.0017)	0.0059*** (0.0015)
Experience squared x 10 ⁻⁴			-2.7144*** (0.5098)	-1.2637*** (0.4391)
Industry change			-0.0542*** (0.0073)	-0.0366*** (0.0061)
Quarter-year fixed effects	YES	YES	YES	YES
Observations	9,090	9,090	9,090	9,090
R ²	0.0225	0.4399	0.4994	0.4997

Notes: The indexed wage is the gross wage in 2010 prices divided by the index of the rental rate. The log rental price at $t+1$ is the average rental price in the destination county and the log rental price is the average rental price in the source county. Only the first observed move is considered for individuals who moved several times. The omitted education category is *lowest and middle academic track, without VET*. Robust standard errors in parentheses. $t = 0$ denotes the time of the move. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Robustness Checks

	<i>Dependent variable: Log indexed wage (t+1)</i>		
	(1)	(2)	(3)
	5 largest cities excluded	7 years at origin	Pair-wise controls
Dialect distance	0.0741** (0.0303)	0.1295** (0.0653)	0.0961*** (0.0282)
Geographic distance (km)	-0.000149*** (0.000038)	-0.000158** (0.000078)	-0.00012*** (0.00004)
Log indexed wage (t-1)	0.286*** (0.0297)	0.3601*** (0.0623)	0.2988*** (0.0259)
Log indexed wage (t-2)	0.0903** (0.0357)	-0.0103 (0.0783)	0.0789*** (0.0302)
Log indexed wage (t-3)	0.0304 (0.0403)	0.0937 (0.0586)	-0.0114 (0.0332)
Log indexed wage (t-4)	0.1224*** (0.0317)	0.0692* (0.0363)	0.1483*** (0.0261)
Lowest and middle academic track, with VET	0.0422 (0.0321)	0.053 (0.0748)	0.0879*** (0.0322)
Highest academic track	0.1383*** (0.0341)	0.1549** (0.0773)	0.1950*** (0.0335)
University	0.3092*** (0.0339)	0.3271*** (0.0768)	0.3408*** (0.0333)
Education unknown	0.1164** (0.0456)	0.162* (0.0932)	0.1680*** (0.0461)
Male	0.0919*** (0.0089)	0.1335*** (0.0189)	0.0921*** (0.0078)
Experience	0.0075*** (0.0018)	0.0086** (0.0038)	0.0097*** (0.0016)
Experience squared x 10 ⁻⁴	-1.5633*** (0.5601)	-2.2194** (1.1222)	-2.0864*** (0.4936)
Industry change	-0.0484*** (0.0079)	-0.0527*** (0.017)	-0.0518*** (0.0071)
Quarter-year fixed effects	YES	YES	YES
Observations	6,946	1,815	9,090
R ²	0.5395	0.5327	0.5350

Notes: Column (1) drops the five largest cities (Berlin, Hamburg, Munich, Cologne, Frankfurt) as destination and source counties. Column (2) conditions the sample on having lived at least seven years in the county of origin. Column (3) includes several pair-wise controls: log difference in slope, historical rail distance, different religion dummy, difference in share Catholics, difference in historical industry structure, and the difference in the current industry structure, difference in temperature, difference in sunshine duration, and difference in precipitation. The indexed wage is the gross wage in 2010 prices divided by the index of the rental rate. Data on bilateral controls come from Falck *et al.* (2010) and from the Deutscher Wetterdienst (DWD) for the climate data. Only the first observed move is considered for individuals who moved several times. $t = 0$ denotes the time of the move. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Adding More/Other Pre-Migration Wages

	<i>Dependent variable: Log indexed wage (t+1)</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dialect distance	0.0790*** (0.0294)	0.0637** (0.0299)	0.0629** (0.0308)	0.0550* (0.0319)	0.0666** (0.0334)	0.0821** (0.0347)	0.0916** (0.0368)	0.0846** (0.0386)	0.0858** (0.0372)
Log indexed wage (t-5)	0.0777*** (0.0229)	0.0706* (0.0426)	0.0731 (0.0445)	0.0668 (0.0498)	0.0563 (0.0517)	0.04 (0.0532)	0.0316 (0.0571)	0.0331 (0.0604)	
Log indexed wage (t-6)		0.0211 (0.0318)	-0.0415 (0.0472)	-0.042 (0.053)	-0.0507 (0.0572)	-0.0334 (0.0585)	-0.0384 (0.0632)	-0.0466 (0.0663)	
Log indexed wage (t-7)			0.0746** (0.0288)	0.0602 (0.0512)	0.0583 (0.0556)	0.067 (0.0597)	0.0682 (0.0637)	0.0859 (0.0665)	
Log indexed wage (t-8)				0.0291 (0.0321)	-0.0369 (0.0506)	-0.0723 (0.0577)	-0.0652 (0.0635)	-0.0914 (0.0694)	
Log indexed wage (t-9)					0.0932*** (0.0307)	0.0643 (0.0422)	0.0616 (0.0462)	0.0612 (0.0502)	
Log indexed wage (t-10)						0.0577* (0.0298)	0.0454 (0.04)	0.0659 (0.0443)	
Log indexed wage (t-11)							0.0225 (0.0254)	-0.0123 (0.0366)	
Log indexed wage (t-12)								0.0317 (0.0311)	
Mean log indexed wage (t-1 to t-4)									0.4161*** (0.0279)
Mean log indexed wage (t-5 to t-8)									-0.0281 (0.030)
Mean log indexed wage (t-9 to t-12)									0.1017*** (0.0204)
Quarter-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	8,517	7,949	7,392	6,845	6,225	5,692	5,099	4,681	5,411
R ²	0.5048	0.5137	0.522	0.5225	0.5208	0.5283	0.5276	0.5293	0.519

Notes: Only the first observed move is considered for individuals who moved several times. The indexed wage is the gross wage in 2010 prices divided by the index of the rental rate. *Controls:* geographic distance, education dummies, male, experience, experience squared, and industry change. Regressions in Columns (1) to (8) contain pre-migration log indexed wages from $t-1$, $t-2$, $t-3$, and $t-4$. Robust standard errors in parentheses. $t = 0$ denotes the time of the move. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Non-Linearities in Distance

	<i>Dependent variable: Log indexed wage ($t+1$)</i>			
	(1)	(2)	(3)	(4)
Dialect distance	0.0747*** (0.0287)	0.0846*** (0.0324)	0.0603** (0.0291)	0.0640** (0.0315)
Geographic distance (km)	-0.00013*** (0.00003)	0.00002 (0.00018)		
Travel distance			-0.00014*** (0.00005)	0.00029 (0.00025)
Geographic distance (km) squared x 10^{-5}		-0.0924 (0.064)		
Geographic distance (km) cubic x 10^{-5}		0.00012* (0.00007)		
Travel distance (min) squared x 10^{-3}				-0.002** (0.001)
Travel distance (min) cubic x 10^{-5}				0.0003** (0.0001)
Log indexed wage (t-1)	0.2608*** (0.0256)	0.2608*** (0.0255)	0.2614*** (0.0256)	0.2614*** (0.0255)
Log indexed wage (t-2)	0.088*** (0.0301)	0.0874*** (0.030)	0.0882*** (0.0301)	0.0868*** (0.0301)
Log indexed wage (t-3)	-0.0098 (0.0334)	-0.0095 (0.0334)	-0.0099 (0.0335)	-0.0091 (0.0334)
Log indexed wage (t-4)	0.1509*** (0.0267)	0.1514*** (0.0267)	0.1512*** (0.0268)	0.1514*** (0.0267)
Lowest and middle academic track, with VET	0.0869*** (0.0332)	0.088*** (0.0333)	0.0865*** (0.0332)	0.0868*** (0.0333)
Highest academic track	0.2002*** (0.0346)	0.2015*** (0.0347)	0.1992*** (0.0346)	0.2*** (0.0346)
University	0.3537*** (0.0344)	0.3552*** (0.0345)	0.3525*** (0.0344)	0.3531*** (0.0344)
Education unknown	0.167*** (0.0473)	0.1686*** (0.0474)	0.1661*** (0.0474)	0.1673*** (0.0474)
Male	0.0928*** (0.0081)	0.0932*** (0.0081)	0.093*** (0.0081)	0.0936*** (0.0081)
Experience	0.0124*** (0.0017)	0.0124*** (0.0017)	0.0123*** (0.0017)	0.0124*** (0.0017)
Experience squared x 10^{-4}	-2.7144*** (0.5098)	-2.7138*** (0.5089)	-2.7126*** (0.5097)	-2.7249*** (0.509)
Industry change	-0.0542*** (0.0073)	-0.0538*** (0.0073)	-0.0542*** (0.0073)	-0.0537*** (0.0073)
Quarter-year fixed effects	YES	YES	YES	YES
Observations	9,090	9,090	9,090	9,090
R ²	0.4994	0.4997	0.4991	0.4994

Notes: Only the first observed move is considered for individuals who moved several times. The indexed wage is the gross wage in 2010 prices divided by the index of the rental rate. The omitted education category is *lowest and middle academic track, without VET*. Robust standard errors in parentheses. $t = 0$ denotes the time of the move. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Alternative Dialect Measures

	<i>Dependent variable: Log indexed wage (t+1)</i>	
	(1)	(2)
Dialect distance by language area	0.0106** (0.005)	
Dialect distance		0.0582* (0.0307)
Moving from High German to Low German		0.0847*** (0.0148)
Moving from Low German to High German		-0.0955*** (0.0144)
Moving from High German to High German		-0.0425*** (0.0095)
Geographic distance (km)	-0.000104*** (0.000031)	-0.000131*** (0.000033)
Log indexed wage (t-1)	0.2619*** (0.0255)	0.2687*** (0.0252)
Log indexed wage (t-2)	0.0874*** (0.0301)	0.0866*** (0.0298)
Log indexed wage (t-3)	-0.0095 (0.0335)	-0.0077 (0.0331)
Log indexed wage (t-4)	0.151*** (0.0267)	0.1476*** (0.0265)
Lowest and middle academic track, with VET	0.0857*** (0.0332)	0.0795** (0.0332)
Highest academic track	0.1998*** (0.0345)	0.1924*** (0.0346)
University	0.3532*** (0.0343)	0.3445*** (0.0344)
Education unknown	0.1664*** (0.0474)	0.1652*** (0.047)
Male	0.0924*** (0.0081)	0.0912*** (0.008)
Experience	0.0125*** (0.0017)	0.0126*** (0.0017)
Experience squared x 10 ⁻⁴	-2.7449*** (0.51)	-2.7804*** (0.5094)
Industry change	-0.0541*** (0.0073)	-0.0516*** (0.0072)
Quarter-year fixed effects	YES	YES
Observations	9,090	9,090
R ²	0.4992	0.5093

Notes: *Moving from High German to Low German* indicates a move from a county in which mostly High German is spoken to a county in which mostly Low German is spoken. *Moving from Low German to High German* indicates a move from a county in which mostly Low German is spoken to a county in which mostly High German is spoken. *Moving from High German to High German* indicates a move from a county in which mostly High German is spoken to a county in which mostly High German is spoken. The omitted category is *Moving from Low German to Low German*. The indexed wage is the gross wage in 2010 prices divided by the index of the rental rate. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Effect Heterogeneities

	Dependent variable: Log indexed wage ($t+1$)			
	(1)	(2)	(3)	(4)
Panel A: Age				
	Age			
	< 30	≥ 30		
Dialect distance	0.0930** (0.0404)	0.0494 (0.0407)		
Observations	4,384	4,706		
R ²	0.3948	0.5042		
Panel B: Gender and education				
	Gender		Education	
	Men	Women	Low, medium	High
Dialect distance	0.1046*** (0.0367)	0.0367 (0.0451)	0.0844** (0.0406)	0.0669 (0.0410)
Observations	5,063	4,027	5,051	4,039
R ²	0.5057	0.4027	0.3615	0.4351
Panel C: Gender \times education				
	Men		Women	
	Low, medium	High	Low, medium	High
Dialect distance	0.1143** (0.0548)	0.0934* (0.0492)	0.0519 (0.0598)	0.0215 (0.0700)
Observations	2,727	2,336	2,324	1,703
R ²	0.3522	0.3872	0.3377	0.3457
Panel D: Geographic distance				
	< 200 km	< 300 km	≥ 200 km	≥ 300 km
Dialect distance	0.0984** (0.0402)	0.1179*** (0.0356)	0.0534 (0.0545)	-0.0279 (0.0702)
Observations	5,325	6,575	3,765	2,515
R ²	0.5155	0.5112	0.4862	0.4822
Panel E: Occupational change				
	Occupational information available		Occupational switchers	Occupational stayers
Dialect distance	0.0806** (0.0313)		0.1154** (0.0506)	0.0423 (0.0383)
Observations	7,337		3,479	3,858
R ²	0.5089		0.4638	0.5757

Notes: Low and medium education corresponds to the lowest and middle academic track with and without VET, plus unknown education. High education corresponds to the highest academic track plus university education. Only the first observed move is considered for individuals who moved several times. The indexed wage is the gross wage in 2010 prices divided by the index of the rental rate. All regressions include quarter-year fixed effects, four quarterly pre-migration wages, individual controls, and geographic distance controls. *Individual controls:* education, male, experience, experience squared, industry change. *Geographic distance controls:* geographic distance. Robust standard errors in parentheses. $t = 0$ denotes the time of the move. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Two-Time Mover Analysis

<i>Dependent variable: Log indexed wage ($t+1$)</i>				
	(1)	(2)	(3)	(4)
	First move		Second move	
	≥ 8 quarters	< 8 quarters	≥ 8 quarters	< 8 quarters
<i>Panel A: With repatriates</i>				
Dialect distance	0.2907* (0.1752)	0.1208 (0.1881)	0.0363 (0.1411)	0.5027*** (0.1559)
Observations	245	322	245	322
R ²	0.5813	0.5157	0.7002	0.5616
<i>Panel B: Without repatriates</i>				
Dialect distance	0.3145 (0.2001)	0.2570 (0.2693)	0.1621 (0.1570)	0.6122*** (0.1932)
Observations	192	181	192	181
R ²	0.6224	0.5166	0.7074	0.6019

Notes: Repatriates are those individuals who move back to their county (or counties) of origin (both county of work and county of residence) in the second move. The *second move* uses the dialect and geographic distance between the source county of the first move and the destination county of the second move. The indexed wage is the gross wage in 2010 prices divided by the index of the rental rate. All regressions include quarter-year fixed effects, four quarterly pre-migration wages, individual controls, and geographic distance controls. *Individual controls:* education, male, experience, experience squared, industry change. *Geographic distance controls:* geographic distance. $t = 0$ denotes the time of the move. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Long-Run Effects

	<i>Dependent variable: $[\log \text{ indexed wage } (t+k) - \log \text{ indexed wage } (t+1)]/k$</i>							
	<i>k = 4</i>	<i>k = 8</i>	<i>k = 12</i>	<i>k = 16</i>	<i>k = 20</i>	<i>k = 24</i>	<i>k = 28</i>	<i>k = 32</i>
Dialect distance	0.0088* (0.0048)	0.0034 (0.0034)	0.0022 (0.003)	0.0005 (0.0026)	0.0003 (0.0024)	0.0022 (0.0024)	-0.0001 (0.0029)	-0.0002 (0.0044)
Log indexed wage (t+1)	-0.0431*** (0.0035)	-0.0338*** (0.0022)	-0.028*** (0.0017)	-0.0223*** (0.0015)	-0.0194*** (0.0013)	-0.0166*** (0.0013)	-0.0164*** (0.0014)	-0.015*** (0.0021)
Observations	8,209	6,872	5,875	4,910	4,076	3,142	1,923	698
R ²	0.0922	0.1224	0.119	0.1317	0.1333	0.1271	0.1491	0.1627

Notes: Only the first observed move is considered for individuals who moved several times. The indexed wage is the gross wage in 2010 prices divided by the index of the rental rate. All regressions include quarter-year fixed effects, individual controls, and geographic distance controls. *Individual controls:* education, male, experience, experience squared, industry change. *Geographic distance controls:* geographic distance. Robust standard errors in parentheses. $t = 0$ denotes the time of the move. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.