

Competition, Mobility and Immigration*

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JOB MARKET PAPER

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Abstract

We study the effects of immigration on wages using matched employer-employee data from Germany throughout the opening of the German labor market to Central and Eastern Europe in 2011. We show that migrants and native-born workers are highly segregated across firms, even within narrowly defined markets, and that migrants are over-represented at low wage firms. Motivated by these facts, we derive the effects of a migrant labor supply shock on wages in a model of worker sorting across heterogeneous firms. Segregation moderates wage effects by reducing competition, and workers exposed to competition respond by reallocating across firms. To test these predictions, we extend the Card (2001) shift-share to isolate firm-specific migrant labor supply shocks. Consistent with the model, we find that firms cut wages and shed German workers, but that workers move to higher wage firms with lower migrant shares. Our results suggest that inter-firm mobility is an important means by which the labor market adjusts to supply shocks, and can help explain the prevalence of null wage effects found in the literature.

* Corresponding author: Sam Gyetvay, sam.gyetvay@gmail.com. Sam thanks Thomas Lemieux, Raffaele Saggio and David Green for their generous guidance and support. We also thank Davit Adunts, Michael Amior, Paul Beaudry, Gorkem Bostanci, Sydnee Caldwell, David Card, Vitor Farinha-Luz, Nicole Fortin, Giovanni Gallipoli, Andreas Hauptmann, Jeffrey Hicks, Florian Hoffmann, Philipp Jaschke, Patrick Kline, Samuel Norris, Jesse Perla, Federico Ricca, Heather Sarsons, Kyungchul Song, Isaac Sorkin, Ignat Stepanok, Ehsan Vallizadeh, participants at Berkeley Labor Lunch and the Stanford SITE 2023 Micro and Macro of Labor Markets Conference. We also thank Pierre-Loup Beauregard, Yige Duan, Sarah Fritz, Pascuel Plotkin, Jan Rosa, Catherine van der List, and all other past and present members of the UBC PhD Labour Group. All errors are our own.

What are the effects of immigration on wages in receiving country labor markets? In the extensive literature focused on this question, a preponderance of studies have estimated very modest wage effects of market-level immigration shocks on the wages of native-born workers. Remarkably, this lack of wage response has been found even among groups of workers who are similarly skilled and presumably in close competition with migrants (Card, 1990, Dustmann, Schönberg, and Stuhler, 2017, Signorelli, 2023).

How can it be that the wages of workers in direct competition with migrants *don't* fall in response to native labor supply shocks? Since the pioneering work of Jean B. Grossman (Grossman, 1982), applied labor economists have primarily interpreted such evidence through the lens of a perfectly competitive labor market with a representative firm. Modest wage effects among similarly skilled workers can arise in such models when migrant and native-born labor are imperfect substitutes in production (Card, 2009, Ottaviano and Peri, 2012, Manacorda et al., 2012).

One way in which migrant and native-born workers differ starkly—and which is not captured by the above class of model—is in the kinds of firms they work at. Previous research has shown that native-born workers are highly segregated from each other in the labor market (Åslund and Skans, 2009, Glitz, 2014), and that firms explain a substantial portion of the native-migrant earnings gap (Dostie et al., 2023, Arellano-Bover and San, 2023). In the past decade, research in labor economics has demonstrated that worker-firm sorting plays a central role in the determination of the gender wage gap (Card, Cardoso, and Kline, 2016), the effects of minimum wages (Dustmann, Lindner, Schönberg, Umkehrer, and vom Berge, 2022), and earnings inequality (Song, Price, Guvenen, Bloom, and von Wachter, 2019). An increasing acknowledgement of the role of firms has also raised interest in imperfectly competitive models of the labor market (Card, Cardoso, Heining, and Kline, 2018).

In this paper, we study how firm-wage setting and worker-firm sorting shape the wage effects of immigration. We combine a theoretical analysis of worker sorting across heterogeneous firms in an imperfectly competitive labor market with an empirical analysis of matched

employer-employee data. Our results provide a novel account of what David Card has termed “the elusive search for negative wage impacts of immigration” (Card, 2012): firms *do* reduce wages in response to increases in migrant labor supply, but native-born workers respond by moving to other firms. This reallocation is possible since migrants are concentrated in a relatively small set of low-wage firms and hence highly segregated from native-born workers in the labor market. Importantly, this mechanism still operates even when natives and migrants are perfect substitutes in production within every firm. Firm wage dispersion and worker-firm sorting, rather than imperfect substitutability within firms, are the primary drivers.

Our empirical analysis uses administrative matched employer-employee data from Germany over the period 2005-19. These data, which permit us to observe the nationality of each worker across all firms for virtually the entire German labor market, provide an unparalleled view into the patterns of sorting across firms by migrant and native-born workers. We focus on the opening of the German labor market to Central and Eastern Europe beginning in 2011 following the EU Enlargements of 2004 and 2007.¹ This period saw rapid immigration from the EU Enlargement Nations (EUN) of Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia. Between 2011 and 2019, the number of workers from EUN countries employed in Germany increased by over 1.2M. The policy-driven nature of the shock, the 7-year delay between EU product and labor market integration, and the fact that migration to Germany was low and stable in the 2005-10 pre-period make this episode an ideal natural experiment for the purposes of our study.

We begin by documenting three descriptive facts. First, migrant and native-born workers are highly segregated across firms. This segregation remains high even within narrow labor markets defined by intersections of industry and geography.² Second, migrants are over-represented among the lowest paying firms. This sorting doesn’t just reflect the fact

¹This episode was studied in two previous papers: Iling (2023) and Hammer and Hertweck (2022).

²These findings are consistent with those documented Glitz (2014) for Germany during the period 1975-2008, Åslund and Skans (2009) for Sweden, and Hellerstein and Neumark (2008) for the United States.

that migrants are employed at firms that employ other low-skilled workers, but holds when measuring wages by firms' wage premia estimated by two-way fixed effects regressions that account for worker sorting (Abowd, Kramarz, and Margolis, 1999, Card, Heining, and Kline, 2013).³ Dustmann, Ku, and Surovtseva (2021) find that EUEN migrants to Germany during the period 2004-12 are more willing to accept jobs in lower-paying firms in part due to lower real prices in their origin country, where part of their earnings are spent. Third, we provide evidence suggesting that recent migrants find jobs through intranational co-ethnic networks. This is consistent with survey data from the German Socioeconomic Panel documenting that 43.8% of migrants employed in Germany during the period 2010-14 found their jobs through referrals (Alaverdyan and Zaharieva, 2022).⁴ We show that the intranational referral channel is particularly strong for EUEN migrants.

Motivated by these facts, we study how a migrant labor supply shock affects market-level wages in a model of worker sorting across heterogeneous firms. Sorting is driven by workers' information about jobs, preferences for firms' non-wage attributes, and labor supply elasticities. Migrant workers will be concentrated in low-wage firms and segregated from native-born workers when they are more likely to be informed about low-paying jobs, when they have different preferences for non-wage attributes than natives, and when they supply labor more inelastically than natives. In this case, the effect on market-level average native wages will be attenuated by worker-firm sorting. We show that the effect of sorting on market-level wage effects can be decomposed into two components, which we term competition and mobility. The competition component reflects the effect of a migrant supply shock holding native-born employment shares across firms fixed. Segregation across employers reduces the extent of direct within-firm competition. Employers' capacity to cut native-born wages in response to increased migrant labor supply is reduced when there is limited overlap

³This is consistent with evidence from Canada (Dostie, Li, Card, and Parent, 2023), Spain (Damas de Matos, 2017) and Israel (Arellano-Bover and San, 2023) finding that moving up the "job ladder" to higher wage premium firms is an important component of migrants' wage convergence.

⁴The role of employee referrals for migrant wage growth in Germany was previously studied by Dustmann, Glitz, Schönberg, and Brücker (2016).

between the two groups. The mobility component reflects the effect of a migrant supply shock holding wages fixed. Native-born workers exposed to competition may move firms to avoid negative wage effects. If they move to higher wage firms on average, this reallocation effect will partially offset the wage declines caused by direct within-firm competition.

To test the model’s predictions, we estimate the effects of migration supply shocks on both workers and firms. We identify firm level migrant labor supply shocks using a shift-share that interacts firms’ pre-policy ethnic composition with country-specific post-policy national growth rates.⁵ Taking advantage of the sharp policy-driven nature of the shock, we embed the shift-share into a generalized difference-in-difference design and estimate event studies over the period 2008-14. These event-studies allow us to trace out the dynamic effects and to test for parallel pre-trends. Consistent with the model, we find that firms exposed to inflows of EUEN workers cut wages and shed German workers. Wage effects are largest for Germans with lower levels of education.

We find that the wages of incumbent foreign workers fall by a similar magnitude as those of their German counterparts. Within firms, the relative wage between the two groups remain constant. Both facts are consistent with a high degree of substitutability between migrant and native-workers within firms. Many previous studies have found that, in contrast to the native-born, incumbent migrants do experience wage declines in response to market-level immigration shocks (Card, 1990). Our results suggest an explanation: migrants experience larger negative wage impacts because they tend to work in the same firms as incoming migrants. In terms of our theoretical framework, the competition component is much stronger for migrants, and so the mobility component would have to be even stronger to compensate. Segregation across firms can therefore explain both the lack of wage effects across natives, *and* the presence of negative effects among migrants.

To measure reallocation effects, we estimate the effects of both firm-level and market-level shocks on incumbent workers. The effects of firm-level shocks on workers allow us to observe

⁵A similar approach is used by Malchow-Møller, Munch, and Skaksen (2012) and Egger, Auer, and Kunz (2022) using data from Denmark and Switzerland, respectively.

how the wages, employment, and across-firm mobility patterns of workers initially employed by firms exposed to EUEN inflows—as measured by the firm-level shift-share of their initial employer—evolve over the period 2011-14. Incumbent workers at exposed firms move to high wage firms with lower foreign shares and experience modest wage increases on average. We also find that workers move to firms located further away from their place of residence, suggesting that workers are trading off a higher disutility from commuting for higher wages. We find at most small effects on the number of days spent in nonemployment, suggesting that reallocations across firms, rather than exits to nonemployment, are the relevant margin of adjustment for this group.

Our final set of results measure the effects of market-level shocks on workers. Using market-level shocks allows us to estimate effects for a broader group of workers than the firm-level shocks, which only capture effects on incumbent workers at highly exposed firms. We measure exposure to EUEN inflows at the market-level using a traditional shift-share based on geographically-defined markets, and focus on heterogeneous effects across the firm wage distribution. This is motivated by the observation that the EUEN migrant labor supply shock was primarily a shock to low wage firms.⁶ Consistent with our effects using firm-level shocks, we find that workers in more exposed labor markets who are initially employed by firms in the bottom deciles of the firm wage distribution are more likely to move to higher wage firms and more likely to move to firms with *lower* shares of EUEN migrants. Workers at the top of the firm-wage distribution, by contrast, have no detectable reallocation effect. This is consistent with the fact that the EUEN migrant shock is concentrated in the bottom deciles of the firm wage distribution.

We contribute to the literature on the wage effects of immigration by providing a novel explanation for the muted market-level wage effects of immigration. We provide direct evidence of how the distribution of migrant inflows across firms, changes within firms, and changes in worker sorting interact in shaping the market-level effects of immigration on

⁶Amior and Stuhler (2022) also estimate effects across quantiles of the firm wage distribution for an immigration wave in Germany during the early 1990s.

wages. While other studies have estimated the effects of market-level shocks on firm-level outcomes (Beerli, Ruffner, Siegenthaler, and Peri, 2021, Dustmann and Glitz, 2015, Brinatti and Morales, 2021, Amior and Stuhler, 2022), our firm-level estimates isolate effects among the precise firms that EUC migrants entered.

Our estimates of the effects of firm-specific immigration shocks on wages and employment provide a distinct margin of variation from estimates obtained using lotteries in over-subscribed visa programs such as the H-1B (Doran, Gelber, and Isen, 2022, Brinatti, Chen, Mahajan, Morales, and Shih, 2023) and H-2B (Clemens and Lewis, 2022, Amuedo-Dorantes, Arenas-Arroyo, Mahajan, and Schmidpeter, 2023). Firms participating in visa programs must shoulder a substantial administrative burden to hire specific types of workers, and face additional legal restrictions on the wages they can pay.⁷ By contrast, the EUC workers in our study enjoy essentially unlimited access to the German labor market on par with native-born Germans, find jobs through standard channels, and the firms employing them face no restrictions on the wages they set. If lottery studies identify the effect of a marginal expansion of visa caps, our estimates are analogous to the U.S. opening its borders to Central and South America.

While firm level evidence is valuable, our results caution against the extrapolation of evidence on the effects of firm level shocks to market or aggregate effects, and our theoretical model provides a coherent framework for rationalizing the differences. Due to the small number of visas allotted, lottery studies capture idiosyncratic firm level effects. However, in the context of a large market-level shock, the distribution of migrant supply shocks across firms is highly concentrated in some pockets of the labor market.

The mechanism we propose is related to but distinct from the one put forward by Peri

⁷The H-1B captures firms hiring college-educated workers in specialized occupations, while H-2B captures firms hiring non-farm low-skilled labor for an intermittent or seasonal contract. Firms applying to the H-2B need to petition two separate federal agencies, the Department of Labor (DOL) and the Department of Homeland Security. Laws restrict participating firms from changing the wage of employment of domestic workers in response to the lottery outcome. Wages for H-2B workers are fixed by the federal government at the average wage for the occupation in the region as calculated by the Bureau of Labor Statistics, and each participating firm must receive a certification from the DOL maintaining that no adverse wage or employment effects will arise as the result of the hiring.

and Sparber (2009), which emphasizes native-born workers' reallocation towards *occupations* intensive in communication-language tasks. Rather than comparative advantage, our mechanism emphasizes supply-side reallocation across firms. Our mechanism operates even among workers who provide manual-physical labor tasks, and to workers who remain engaged in the same occupation.

We contribute to the literature on the study of immigration in imperfectly competitive labor markets by including worker-firm sorting. Amior and Manning (2023) and Amior and Stuhler (2022) have argued that firm monopsony power amplifies the negative wage effects of immigration when firms are unable to wage discriminate against migrant workers. Relative to the models in these papers, the wage effects of monopsony in our model are more muted. In an extension of our model considered in **Section B.3**, we show that uniform wage setting *strengthens* the impact of the mobility channel.

Perhaps most closely related is Brinatti and Morales (2021), who study the effect of immigration on German establishments during the period 2003-10. The authors motivate their analysis by documenting that the immigrant share of the wage bill is higher for larger firms. They endogenize this pattern in a model where firms pay a fixed cost to hire migrant workers, which only the most productive firms are willing to pay. During the period we study, migrants primarily sorted into low wage firms. This is intuitive given the policy change we study, which lowered costs of hiring immigrants from EU enlargement countries to essentially zero for all firms. Instead of firms' hiring costs, our theoretical model focuses on immigrant workers' labor supply decision in driving sorting. Relative to Brinatti and Morales (2021) who use a general equilibrium model to quantify the aggregate welfare effects of immigration, we provide a partial equilibrium analysis focused on wage effects, with a particular focus on the relationship between these effects at the market- and firm-level. Mahajan (2022) also considers the role of firms in absorbing new immigration shocks in the US, with a focus on firm entry and exit.

The rest of the article is organized as follows. **Section 2** describes the data. **Section**

3 provides background on the policy. **Section 4** presents our main descriptive results. **Section 5** presents the model and states the main theoretical results. **Section 6** explains the construction of the shift-share, tests of identifying assumptions, and the main firm-level results. **Section 7** presents our worker-level estimates. **Section 8** concludes.

2 Data

Our analysis is based on data drawn from German social security records that have been assembled and maintained by the Institute for Employment Research (IAB) of the German Federal Employment Agency (BA). These are longitudinal employer-employee data, containing unique employer and employee identifiers for all private sector workers and firms in Germany with the exception of civil servants and the self-employed. Data are collected in daily spells and contain information on earnings, occupation and part-time or full-time status.⁸

These data also contain demographic information on workers, including their age, gender, level of education and, most importantly for our analysis, country of citizenship.⁹ We define a unique nationality for each worker as the earliest non-missing value of citizenship observed, and proxy migrant workers' date of immigration to Germany by the first year they are observed in the data. These data allow us an unparalleled view of the ethnic composition of firms at any point in time.¹⁰

In accordance with German data privacy regulations restricting the use of full population individual-level microdata, we employ a “collage” of data-sets at various levels of aggregation

⁸The employer identifiers in the data (which we refer to as “firms” throughout) may refer to multiple work sites owned by the same firm located in the same industry and municipality.

⁹Demographic variables come from a combination of German social security records and process-generated data from German’s federal employment agency. We impute missing values of education according to [Fitzenberger, Osikominu, and Völter \(2006\)](#) and impute missing values of working hours according to [Ludsteck and Thomsen \(2016\)](#).

¹⁰Not all administrative data-sets contain such rich information on country of citizenship. This has prompted researchers to use ingenious methods to identify foreign citizens. For example, [Bernstein, Diamond, Jiranaphawiboon, McQuade, and Pousada \(2023\)](#) are able to identify workers who were not born in the US by comparing the year an individual’s social security number was assigned with their year of birth. However, they are not able to observe specific country of origin.

and using different sampling schemes. To this end, we create two custom data-sets from the BA’s Employment Biographies (BeH) data file. The first data-set is a firm-level annual panel encompassing the universe of workers and firms. The second data-set is a proper subsample of individual-level micro-data targeted to our research design. The third data-set is a representative sample of individual level micro-data created by the Research Data Centre (FDZ) of the BA. We now provide a brief description of each of these data-sets in turn.

2.1 Firm Panel (BeH)

Our firm panel, which we primarily use in the descriptive analysis in [Section 4](#), is constructed from a 100% sample of employment spells over the period 2005-19. For every firm-year, we calculate the number of workers, average daily wage, and annual earnings within every combination of occupation, period of entry, full/part-time, nationality, gender, and age group.¹¹ For example, these data allow us to observe the number of Polish men aged 18-29 employed full-time in a manual-routine intensive occupation who immigrated to Germany between 2010-14, within each firm, each year.

We further merge in information on each firm’s industry and geographic location from the Establishment History Panel (BHP, [Eberle and Schmucker, 2017](#)). We merge in AKM firm effects calculated by [Lochner, Seth, and Wolter \(2023\)](#) for the periods 2003-10 and 2011-17. We impute missing firm effects as in [Dustmann, Lindner, Schönberg, Umkehrer, and vom Berge \(2022\)](#). For details of the imputation, see [Section A.1](#).

2.2 Custom Worker-Firm Panel (BeH)

Our second custom sample was constructed specifically for the firm-level shift-share research design in [Section 6](#). We employ a two-level sampling design. We first identify all firms who

¹¹We group occupations into 5 levels following the classification of [Dengler, Matthes, and Paulus \(2014\)](#). We group nationalities into 75 levels by taking the 50 nationalities with the largest population share in Germany in 2019, and then grouping all other countries into 25 sub-regions. We group ages into three levels: 18-29, 30-49, 50+. We group period of entry into four periods: pre-2005, 2005-9, 2010-14, and 2015-19, and calculate it for both Germans and non-Germans.

employed at least one EUEN worker between 2005-10. We drop firms with fewer than 10 employees and more than 2000 employees in 2005, as well as firms in the Agriculture and Temp Agency industries. We then take a 50% random sample from this set of firms and identify the set of all workers who worked at least one day in a sampled firm during the period 2005-2019. Our final data set contains all employment spells of all sample workers over the period 2005-19. We process the data following the procedure outlined in [Dauth and Eppelsheimer \(2020\)](#), including the imputation of working hours, education, and of top-coded censored wage observations.

2.3 Representative Worker-Firm Panel (SIEED)

Our final data-set is the Sample of Integrated Employer Employee Data (SIEED), a data set created by the Research Data Centre (FDZ) of the BA ([Schmidtlein, Seth, and Vom Berge, 2020](#)). The SIEED uses a similar two-step sampling design to our custom sample, but begins with a representative sample of firms. We process the SIEED using the same procedure as our custom sample.

3 Policy Background

Our empirical analysis focuses on the opening of the German labor market to Central and Eastern Europe following the 2004 and 2007 Enlargements of the European Union. Between May 2011 and January 2014, workers from Bulgaria, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia were granted essentially unrestricted access to the German labor market.

This policy change led to sudden and rapid employment and population inflows of EU Enlargement Nationals (EUEN), as depicted in [Figure 1](#) and [Figure C1](#), respectively. Between 2010 and 2019, the number of EUEN workers employed in the German labor market increased from approximately two hundred thousand to over a million ([Table C1](#)) and the

EUEN share of employment increased from 0.2% to 1.3%. EUEN inflows accounted for the majority of immigrant inflows into the German labor market during the period 2010-14, accounting for 55% of migrant employment growth and 16% of total employment growth.

Several features make this episode a useful “natural experiment” for the study of the labor market effects of immigration. First, the sharp surge in migrants inflows in 2011 is driven by a policy change and not by changes in the strength of the German labor market, making it easier to separate the “push” of supply from the “pull” of demand. Second, EUEN inflows from 2005-10 were modest or flat, as was immigration to Germany as a whole. This stable pre-period allays concerns about biases arising from serially correlated shocks in persistent immigration waves raised by [Jaeger, Ruist, and Stuhler \(2018\)](#). Finally, Germany delayed labor market opening for seven years following EU enlargement.¹² The lengthy gap between integration of product and labor markets allows us to separately identify the effects of labor market opening. If product and labor markets had opened simultaneously (as was the case for other EU states such as the UK, Ireland and Sweden), it would be challenging to disentangle the effects of labor and product market integration. The 7-year delay provides a comfortably long gap for product market effects to have stabilized.

4 Descriptive Analysis

In this section, we provide a descriptive analysis, with a focus on the sorting of migrants and Germans across firms. We begin by providing summary statistics detailing the demographic and labor market characteristics of EUEN migrants, and compare them those of other migrant groups and various segments of the German workforce. Next, we characterize the types of firms that EUEN migrants entered. The firm-level characteristics that best predict EUEN inflows are paying a low wage and having a higher pre-reform share of EUEN workers. The correlation between pre-2011 EUEN share and subsequent EUEN migrant inflows

¹²This is the longest allowable time-span under the EU’s “2 + 3 + 2” regulation. The only other country to delay labor market integration for the full 7-year period was Austria.

is primarily driven by a strong intranational correlation. We quantify the intranational correlation (which we call the “firm-level ethnic enclave effect”) for a large number of countries and find that is particularly pronounced for EUEN countries. This suggests that EUEN migrants rely on intranational coethnic networks to find out about job opportunities. This is relevant to the interpretation of the firm-level research design in **Section 6**, as it suggests that pre-reform country share generate differential exposure to post-reform inflows. Lastly, we quantify the degree of firm-level segregation between German workers and both EUEN and non-EUEN migrants, both in the aggregate and within markets delineated by the intersection of industry and commuting zones. firm-level segregation diminishes the within-firm exposure of German workers to EUEN inflows by approximately 40% within a given market, on average. This relates to one of the central components of our argument: that segregation reduces the scope of within-firm competition between migrants and native-born workers.

4.1 Characteristics of EUEN Migrants

Table 1 compares the demographic and labor market characteristics of the EUEN migrant workers with earlier EUEN migrants, foreign workers from other countries, and Germans. The 2010-14 cohort of EUENs were disproportionately male, young, had lower levels of education, were more likely to be employed in low-skilled occupations, and worked at smaller firms, when compared to earlier cohorts of immigrants, or to Germans. 60% were male, 23.4% have a high school diploma or lower, over 30% are under 30 years old, and nearly 55% are employed in an unskilled occupation. However, when compared to non-EUEN migrants of the same cohort they are broadly similar. One aspect in which the 2010-14 EUEN cohort stand out compared to other immigrants during this period is their high rate of labor force attachment. 64.3% of EUEN workers were employed full-time, a number higher than almost any other group.

4.2 Which Firms Did EUEN Migrants Enter?

The migrant labor supply shock following the opening of the German labor market to the EU Enlargement Nations in 2011 was primarily a shock to the lowest wage firms. The top panel of **Figure 2** plots the share of workers who are EUEN foreigners within each firm wage decile for the years 2005, 2010, 2014 and 2019. The EUEN share in the bottom two deciles increased from about 1% in 2005 to around 4% in 2014, and then nearly doubled again, reaching around 8% by 2019. By contrast, the upper deciles, particularly the top tercile, saw very small increases, with the EUEN share remaining around 1% by 2019.

The bottom panel of **Figure 2** plots the total foreign (i.e., including both EUEN and non-EUEN foreign workers). While the overall foreign share increased much more at higher deciles than the EUEN share, the increase at lower deciles is close to the EUEN, increasing from around 10% in 2010 to over 20% in 2019. This means that the migration shock to low wage firms primarily consisted of EUEN workers.

This relationship is not just driven by the sorting of low-skilled workers into low-skilled firm. **Figure C3** plots the same relationship as in **Figure 2**, but with deciles of AKM firm fixed effects on the horizontal axis.¹³ Since these firm effects come from two-way fixed effects regressions that include a full set of worker fixed effects, they fully control for worker characteristics and identify employer wage policies. The two sets of figures are nearly identical, suggesting that EUEN migrants' over-representation in low wage firms is not just driven by worker characteristics.

The last two figures showed that the EUEN migrant shock was primarily a shock to low wage firms. However, it could be that this is merely a residual effect of sorting on other firm characteristics that are negatively correlated with the wage level. For example, perhaps EUEN migrants are more likely to work in small firms, but conditional on firm size, they are no more likely to work at low wage firms. Similarly, it could be that EUEN migrants are

¹³We use firm effects calculated by [Lochner, Seth, and Wolter \(2023\)](#) which are in turn based on the analysis of [Card, Heining, and Kline \(2013\)](#). Firm effects are calculated from a two-way fixed effects regression $\log w_{it} = \alpha_i + \psi_{J(i,t)} + \beta X_{it} + \varepsilon_{it}$ where i indexes workers and j indexes firms. ψ_j are the firm fixed effects.

concentrated in low wage industries, or low wage regions, but are not more likely to work in low wage firms within an industry or region. To investigate whether this is the case, we run a descriptive regression at the firm level which estimates which baseline firm characteristics¹⁴ predict EUEN inflows during the period 2011-14. The dependent variable is the gross EUEN migrant inflow in 2014, normalized by baseline firm size. Controls include dummies for firm wage deciles as well as flexible controls for firm size, industry, region, and a range of other firm characteristics. The regression allows us to see which characteristics predict EUEN migrants inflows conditional on all other characteristics. Specifically, we estimate the regression

$$\frac{M_{j,2014}^{EUEN,New}}{\bar{L}_{j,2005-9}} = \alpha_{CZ(j)} + \alpha_{Ind(j)} + \alpha_{WageDecile(j)} + \alpha_{Size(j)} + \beta X_{j,2005-9} \quad (1)$$

where $M_{j,2014}^{EUEN,New}$ is the number of EUEN migrants from the 2010-14 cohort employed at firm j in 2014, $\bar{L}_{j,2005-9}$ is the mean firm size of firm j between 2005-9, $\alpha_{CZ(j)}$ and $\alpha_{Ind(j)}$ are commuting zone and industry fixed effects, $\alpha_{WageDecile(j)}$ and $\alpha_{Size(j)}$ are fixed effects for firm wage decile and a set of firm size bins, and $X_{j,2005-9}$ is a vector of continuous firm-level covariates measured over the period 2005-9. X_j includes the share of EUEN foreigners, share of non-EUEN foreigners, share of workers aged 18-29, share of workers aged over 50, share male, share of workers in a manual non-routine task-intensive occupation, and share of workers in a manual routine task-intensive occupation. Both the dependent variable $M_{j,2014}^{EUEN,New} / \bar{L}_{j,2005-9}$ and the continuous covariates X_j were normalized by their standard deviation to facilitate comparison of magnitudes. **Figure 3** plots the coefficient estimates and associated 95% confidence intervals.

Two main patterns stand out. First, wages remain a very powerful predictor of EUEN inflows, even after introducing a battery of controls. A firm in the bottom 2 deciles of the firm wage distribution will have over a 0.1 standard deviation higher EUEN inflow in 2014 than a firm in the 5th decile. This effect is over 4 times as strong as the comparable effect for being in the smallest wage bin. Second, among continuous covariates, the pre-reform

¹⁴Baseline characteristics are measured during the period 2005-9.

EUEN share is by far the most powerful predictor of subsequent EUEN inflows. A firm with a one-standard deviation higher EUEN share in 2005-9 on average has over 20% of a standard deviation higher inflow of new EUEN workers in 2014. The magnitude of all other partial correlations are at most half the size.

4.3 EUEN Migrants Find Jobs Through Intranational Networks

The previous result establishes that the share of EUEN workers at a firm over the pre-period 2005-9 is a powerful predictor of EUEN inflows during the period 2011-14. Our next set of results show that this relationship is largely due to *intranational* coethnic correlations: workers from Poland entering the German labor market in 2011-14 are more likely to work at firms that had employed other Polish workers during the pre-period 2005-9. We suggest that these correlations can be interpreted as evidence that information about jobs flows through intranational social networks (Granovetter, 1995). Furthermore, the strength of intranational ties are particularly strong among the Central and Eastern European EU enlargement countries.

To measure the strength of the intranational correlation of migration flows between the pre-period 2005-9 and the period 2011-14, we estimate the following regression at the firm (j) by country (c) level:

$$\frac{M_{jc,2011-2014}^{New}}{L_{j,2011-2014}} = \alpha_j + \alpha_c + \gamma_c \cdot \frac{M_{jc,2005-9}}{L_{jc,2005-9}} + \epsilon_{jc} \quad (2)$$

where $M_{jc,t_0-t_1}^{New}$ (M_{jc,t_0-t_1}) is the number of (recent) migrants from country c in firm j in the period $t_0 - t_1$, L_{j,t_0-t_1} is the total employment at firm j in over the period $t_0 - t_1$, and α_j and α_c are a set of firm and country fixed effects. We construct the data set to include all combinations of firm and country, including “zeroes” (representing firm-country pairs with no observed workers). The coefficients γ_c capture the strength of the intranational correlation of within-firm migration flows for each country c . Since the regression includes firm fixed effects

α_j , these coefficients are not just picking up countries hired by firms hire many migrants. Likewise, since the regression includes country fixed effects α_c , the coefficients γ_c are not just picking up countries with large aggregate inflows spread across all firms.

Figure 4 plots the coefficient estimates $\hat{\gamma}_c$ and associated 95% confidence intervals for **Equation 2** for the countries with the 30 largest foreign population shares in Germany as well as the EUEN countries (which are bolded and colored dark green). Two features stand out. First, the estimates display a striking degree of heterogeneity. Some countries have a very strong partial correlation well above 0.5, while others are closer to zero. Second, the EUEN are among the countries with the very highest values of $\hat{\gamma}_c$. Czechia, Romania, Poland, Bulgaria and Hungary make up 5 out of the top 7 countries when ranked by $\hat{\gamma}_c$.

This evidence is consistent with EUEN workers having limited information about job opportunities, and finding out about jobs through their social networks. It is also consistent with survey evidence from the German socio economic panel finding that 43.8% of migrants employed in Germany during the period 2000-14 report having found their jobs through referrals, compared to 31.5% for Germans (Alaverdyan and Zaharieva, 2022). While we are not able to directly observe referrals or social networks in our data, the patterns we document suggest that information about jobs flowing through intranational social networks are a key driver of EUEN migrants' firm choice.

This finding guides both our theoretical model and our firm-level research design. In **Section B.1**, we show our firm-level labor supply equations can be micro-founded by a limited information model where migrants' information about jobs depends on their country of origin. The model clarifies the conditions under which firm-level country shares in the pre-period are valid instruments for subsequent inflows, which in turns informs the exogeneity tests in **Section 6**.

4.4 Segregation Across Firms

In this section, we show that EUEN migrants and native-born workers are highly segregated from each other in the labor market. Specifically, they are highly segregated across firms, even within labor markets defined by intersections of industry and geography. The high level of segregation significantly reduces the level of within-firm exposure that the average German worker in a given industry and city faces. In our theoretical results in **Section 5**, we show that the market-level wage effects depend on a measure of within-firm exposure. The estimates in this suggestion suggest that segregation reduces the direct within-firm exposure of the average German worker by about 40%.

We begin with a visualization of the distribution of segregation within a few large labor markets. **Figure 5** plots the “segregation curves” (Duncan and Duncan, 1955) for the hospitality and manufacturing industries in three cities: Berlin, Hamburg, and Munich. Segregation curves are closely related to the Lorenz from the wealth inequality literature (Lorenz, 1905) from which the familiar Gini index is derived. The horizontal axis is the cumulative share of Germans, ranked by the share of their co-workers who are EUEN migrants. The vertical axis is the cumulative share of foreigners. The dashed grey line is the 45 degree line. In the case of “perfect zero segregation” where every German has the same share of EUEN co-workers, the segregation curve would coincide with the 45 degree line.

In hospitality, around 40% of Germans are employed at firms with zero EUEN coworkers. In manufacturing, this number is about 20%. In both industries, about 50% of EUEN workers employed in firms that collectively employ about 5% (the top vignile) of Germans. The distribution of within-firm exposure to EUEN migrants is therefore highly concentrated among a relatively small number of Germans, among whom exposure is high. These two industries are not exceptional in their degree of segregation; in **Figure C2**, we plot segregation curves for the construction and retail industries.

While segregation curves are useful for visualizing the distribution of exposure, they aren’t directly informative about how segregation impacts the exposure of the average German.

This is most closely related to the notion of competition in the model in [Section 5](#). [Figure C4](#) plots, for every industry commuting zone pair, the EUEN share in the market on the horizontal axis and the average German’s share of coworkers who are EUEN on the vertical axis. It is a scatter-plot where every dot represents a market, and the size of the dots are proportional to their total employment. The 45 degree line represents the case of perfect zero segregation, and the horizontal axis (i.e., the points where the average German’s coworker share is equal to zero) represents perfect segregation. Labor markets within the “cone” defined by these two lines have intermediate levels of segregation. We also plot the line of best fit from an (employment-weighted) OLS regression. The slope coefficient on the line of fit is about 0.58, suggesting that segregation reduces the coworker share of the average German by about 40%, conditional on their industry and commuting zone.

To conclude our analysis of firm-level segregation, we calculate a series of segregation indices. We begin by calculate a sequence of indices that summarize the degree of segregation in the German labor market as a whole, as well as the level of segregation within markets. We show that the majority of observed segregation is not due to migrants working in different labor markets than German workers, but working at different firms within markets. This summarizes the segregation curves discussed above in a single set of statistics across all markets.

Following [Glitz \(2014\)](#), we begin by calculating the [Duncan and Duncan \(1955\)](#) unconditional Index of Dissimilarity (ID) across all firms, and then report adjusted indices that condition on industry and geography. The unconditional index is calculated as

$$ID_{\text{Uncond}} = \sum_j \left| \frac{M_j}{L_j} - \frac{M}{L} \right| \times 100$$

where M_j is the number of migrant workers at firm j and L_j is the total number of workers at firm j , and M and L are the total number of migrants and workers. Adjusted indices measure the deviation of ID_{Uncond} from an index calculated on data simulated from a distribution

which takes into account the firm characteristics such as size, industry and location.¹⁵ The adjusted index is equal equal to the difference between the unconditional and the random index, normalized by 100 minus the random index

$$ID_{\text{Adj}} = \frac{ID_{\text{Uncond}} - ID_{\text{Rand}}}{100 - ID_{\text{Rand}}}.$$

The results are presented in **Table 2**. We calculate segregation indices for EUEN foreign workers, as well as for all foreign workers. We also report separate indices for recent (i.e., post-2011) migrants from each group. Indices are calculated for the years 2014 (top panel) and 2019 (bottom panel). We drop all singleton firms from the analysis.

The first column, which contains unadjusted indices for all workers, shows extremely high levels of segregation for all groups, with recent EUENs having an index of dissimilarity of nearly 85, close to the maximum possible value of 100. The second column contains a simple adjusted model that considers all workers to be in a common market (i.e., $k(j) = K$ for all k). This model adjusts for biases arising from small units or when the number of minority workers is not sufficiently large relative to the number of units (Carrington and Troske, 1997), but does not condition on the distribution of migrants across industries and regions. This simple adjustment decreases the level of the indices, but they still remain elevated. The adjusted index for recent EUENs is above 70. The last two columns adjust for commuting zone (CZ) and finally for the intersection of industry and CZ. Adjusting for CZ makes only a marginal difference compared to the simple adjustment (the value for recent EUENs falls to 68.8), suggesting that the spatial distribution is not a significant driver of

¹⁵Adjusted indices are calculated by first simulating the number of migrant and German workers according to $\tilde{M}_j \sim \text{Binom}(m_{k(j)}, L_j)$ and $\tilde{N}_j \sim \text{Binom}(1 - m_{k(j)}, L_j)$, where $k(j) \in \{1, \dots, K\}$ is a partition of firms into K markets¹⁶ and $m_k = \frac{\sum_{\ell: k(\ell)=k} M_\ell}{\sum_{\ell} L_\ell}$ is the migrant share of market k . We then calculate the “random” index

$$ID_{\text{Rand}} = \sum_j \left| \frac{\tilde{M}_j}{\tilde{M}_j + \tilde{N}_j} - \frac{M}{L} \right| \times 100.$$

We repeat this for R replications and take the average $\bar{ID}_{\text{Rand}} = \frac{1}{R} \sum_r ID_{\text{Rand},r}$. We run $R = 30$ replications for each conditional index.

segregation. Conditioning on industry-CZ, however, yields a larger reduction with the index for recent EUENs falling to approximately 55. However, even conditioning on these fine cells, measured segregation remains very high. The index of dissimilarity may be interpreted as the fraction of workers who would need to be moved to create an equal distribution, so an index of 55 means that over half of workers would need to be moved to equalize differences in exposure across firms within industry-CZ cells.

5 Model

As shown in the previous section, the immigration wave that the German economy experienced following the opening of its labor market to the EU Enlargement nations of Central and Eastern Europe in 2011 had several particular characteristics. The EUEN migrants who entered Germany were over-represented at low wage firms, they seemed to have found jobs through their intranational social networks, and they are highly segregated from Germans, even within narrowly-defined labor markets. The migration supply shock was not evenly distributed across firms; it was absorbed by a small minority of firms, and only a small minority of German workers faced direct competition.

In nearly all economic analyses of immigration, only the aggregate size of a shock relative to total employment in the market determines wage effects. But as shown in **Figure C4**, the distribution of migrants across firms can dramatically reduce the within-firm exposure of the average native-born worker. How does the distribution of a labor supply shock across firms shape market-level wage effects?

To understand this question and form testable empirical predictions, we study a simple model of worker sorting across heterogeneous firms based on the model in **Card, Cardoso, Heining, and Kline (2018)**. The model features a non-degenerate firm wage distribution: high wage firms and low wage firms co-exist within the same labor market. This is made possible by worker heterogeneity. Workers vary in their preferences for firms' non-wage attributes

as well as in their information about job opportunities. By allowing the preferences and information to differ systematically between migrants and natives, the model allows for general patterns of sorting. Information is a particularly important channel for migrants, who often find jobs before arriving in the country.¹⁷ The fact that different firms pay different “wage premia” means that shocks that cause a reallocations of workers across firms can affect wages. It also means that idiosyncratic firm-specific labor supply shocks affect firm-level wages. Both of these features are key to the results.

Worker heterogeneity also gives rise to a form of imperfect competition often referred to as monopsony: firms face upward-sloping (rather than horizontal) labor supply curves. Firms are not “wage-takers” who take wages as given and choose a level of employment, as in a perfectly competitive labor market, but rather “wage setters” who choose wages and employment jointly to maximize profits. All else equal, in order to increase output, a firm must move up its labor supply curve by raising wages. Access to new migrant labor provides firms with the opportunity to grow without raising wages. Firms with access to large and stable inflows of migrant labor may therefore be able to keep wages low relative to their competitors.

The model considered in this section is an intentionally stripped down “minimalist” model that abstracts from many interesting or realistic features in order to focus attention on our key mechanisms. However, our results do not rely on these simplifications. In **Section B**, we provide results for a much more general model.¹⁸

The economy is populated by J firms and a mass N of native-born and M migrant workers. Each firm posts a wage w_j . Labor supply to firm $j \in \{1, \dots, J\}$ is given by

$$N_j = N\lambda_N w_j^\beta a_{Nj} \qquad M_j = M\lambda_M w_j^\beta a_{Mj},$$

¹⁷[Straubhaar \(2014\)](#) presents evidence that most EUN migrants had already secured a job before immigrating to Germany.

¹⁸The extended model adds imperfect substitution between native-born and migrant workers, heterogeneous labor supply elasticities and productivity of native and migrant-born labor, and an imperfectly competitive product market.

where $\lambda_N = (\sum_k w_k^\beta a_{Nk})^{-1}$ and $\lambda_M = (\sum_k w_k^\beta a_{Mk})^{-1}$ are migrant and native indexes and β is the elasticity of labor supply to the firm which firms treat as fixed. The parameters a_{Nj} and a_{Mj} are firm-specific “intercepts” that we allow to differ between native and migrant workers.

The interpretation of the intercepts depends on the micro-foundation that underlies the above labor supply curves. In **Section B.1**, we provide a formal micro-foundation for these supply curves using a limited information discrete choice model (Manski, 1977, Goeree, 2008, Abaluck and Adams-Prassl, 2021).¹⁹ We provide an informal summary here. Workers derive utility from wages and from firms’ non-pay characteristics. Examples of non-pay characteristics include commuting distance, schedule flexibility, and workplace culture. In addition, not every worker is aware of every firm in the entire labor market. Variation in preferences and information across workers is partly idiosyncratic and part systematic.²⁰ The terms a_{Nj} and a_{Mj} reflect the systematic component of variation in preferences and information, and they are allowed to vary across natives and migrants. These parameters break the mechanical link between firm wages and employment, and permit rich sorting patterns.

In Card, Cardoso, Heining, and Kline (2018), as well as every other paper we are aware of that uses this framework, a “pure preference” model is used where a_{Nj} and a_{Mj} reflect only differences in the valuation of non-wage “amenities.” In **Section B.1**, we build on arguments from Abaluck and Adams-Prassl (2021) and show that a hybrid preference-limited information model can always be re-parameterized to a pure preference model.

Firms sell a quantity $Y_j = A_j \cdot L_j^{1-\eta}$ of a good, where $L_j = M_j + N_j$. Migrant and native-born labor are identically productive and are perfect substitutes within every firm. Firms

¹⁹Other labor economics papers that assume limited information include Bassier (2023) and Tschopp (2017).

²⁰For example, no two workers have the same exact commuting distance to any given firm, but a centrally-located firm will have a lower average commuting distance than one located in a distant exurb. Likewise, nearly every German knows about the supermarket chain Aldi (of which there are over 4000 outlets across the country), but only a small and arbitrary subset of workers are aware of jobs at any particular local “mom-and-pop” grocer.

differ in their productivity A_j and in unobserved non-wage attributes valued by workers. η is assumed to be between 0 and 1, in which case production within the firm is decreasing returns to scale. Firms set wages w_j to maximize profits subject to labor supply, treating λ_N as fixed. First-order conditions imply that

$$\log w_j = \log \psi_j + -\eta \log L_j$$

where

$$\psi_j = \left(\frac{\beta}{\beta + 1} \right) \cdot (1 - \eta) A_j$$

is the firm wage premium paid by firm j . The first term in the product is a wage markdown (which takes the familiar Lerner index form) due to the firm’s exercise of its monopsony power. ψ_j represent the “rents” firms share with their workers.²¹

In this model, a firm-specific labor supply shock lowers wages whenever it increases total employment at the firm. This is due to decreasing returns to scale at the firm level: as the firm expands, the marginal product of labor declines. The effects on market-level average native-born wages, however, are not simply the sum of the within-firm effects holding employment constant. As workers move across firms in response to the change in wages induced by the shock, the re-allocation across firms with different wage premia ψ_j will also affect market-level wages.

Our main theoretical result establishes how the joint distribution of a_{Nj} , a_{Mj} and ψ_j shape the market-level average wage effects of a market-level immigration shock. To do so, we derive the total effect of an arbitrary migrant supply shock ($d \log M_1, \dots, d \log M_J$) on

²¹In this model, rent-sharing arises due to asymmetric information. If firms were able to observe workers’ choice sets or their idiosyncratic preferences, they could make “custom” wage offers to each worker at the level that makes the worker indifferent between the firm and their next best option. Without this information, each firm posts a wage at which some workers are *infra-marginal*: they would be willing to work at the firm lower wages. Since the firm can’t tell who these workers are, the workers capture the rents.

average native-born log wages

$$\log \bar{w}_N = \sum_j \left(\frac{N_j}{N} \right) \log w_j = \sum_j s_{Nj} \log w_j,$$

taking into account both direct within-firm and indirect cross-firm effects:

$$d \log \bar{w}_N = \sum_k \sum_j \left(\frac{\partial}{\partial M_k} s_{Nj} \log w_j \right) d \log M_k.$$

This depends on how firm wages $\log w_j$ respond, and also on how native employment shares s_{Nj} respond. By the product rule, we have the following decomposition:

$$d \log \bar{w}_N = \underbrace{\sum_k \sum_j s_{Nj} \cdot \frac{\partial \log w_j}{\partial \log M_k} \cdot d \log M_k}_{\text{Competition}} + \underbrace{\sum_k \sum_j \frac{\partial s_{Nj}}{\partial \log w_k} \cdot \log w_{Nj} \cdot d \log M_k}_{\text{Mobility}}.$$

We refer to competition as the effect on wages holding the distribution of natives across firms fixed, while mobility is the effect on native re-allocation across firms holding wages fixed.

Our main theoretical result, which we prove for a generalized model that nests the current one as a special case, shows that the market-level wage effect is equal to

$$\begin{aligned} d \log \bar{w}_N &= \alpha_0 + \kappa d \log \lambda_N \\ &\quad - \eta \sum_k s_{Nk} \tilde{m}_k d \log M_k \\ &\quad - \left(\frac{\eta \beta}{1 + \eta \beta} \right) Cov(\log \psi_j, \tilde{m}_j d \log M_k) + \eta \left(\frac{\eta \beta}{1 + \eta \beta} \right) Cov(\log \bar{a}_j, \tilde{m}_j d \log M_k), \end{aligned} \tag{3}$$

where α_0 is an intercept term containing the change in wages when exposure to the immigration shock $\tilde{m}_k d \log M_k$ is independently distributed across firms, \tilde{m}_j is a monotonic transformation of m_j ,²² and \bar{a}_j is a weighted average of a_{Nj} and a_{Mj} . For markets where then migrant share is small, \bar{a}_j will be close to a_{Nj} .

²² $\tilde{m}_j = \frac{m_j^2}{1 + \beta \eta (1 - m_j)}.$

The terms on the first line represent the wage effects when exposure to the migrant shock is independently distributed across firms, as well as the effect of the shock on the native index λ_N which captures all indirect cross-firm effects. The second term represents the direct effect of competition, and is equal to the within-firm migrant exposure of the average German worker. This term is closely related to the foreign coworker shares we calculated in [Figure C4](#), and the term will generally be smaller when the average German has a lower foreign coworker share. The coefficient is negative, implying that when competition is greater, so is the fall in average native wages. The terms on the third line correspond to the mobility component. The first term, which also enters negatively, measures the strength of the correlation between firm wage premia and exposure to immigration. As shown in [Figure 2](#) and [Figure 3](#), EUEN inflows are strongly negatively correlated with firm wages. This therefore attenuates wage effects, pushing them up towards zero. The final term measures the correlation between the migrant inflow and the non-wage sorting parameters a_{Nj} . Since amenities are not observed, the sign of this term is ambiguous. However, the high levels of segregation observed suggest that the correlation is small or negative. Intuitively, if migrants enter firms with higher a_{Nj} , re-allocation will tend to be towards firms with higher ψ_j .

In [Section B.2](#), model is extended to accommodate imperfect substitution between native-born and migrant workers, heterogeneous labor supply elasticities and productivity of native and migrant-born labor, and an imperfectly competitive product market. The model, despite being more general, remains tractable. In [Section B.3](#), we consider an extension where labor supply elasticities between natives and migrants differ but firms are not able to wage discriminate ([Amior and Stuhler, 2022](#), [Amior and Manning, 2023](#)).

We conclude our theoretical analysis with a discussion of identification. Why can't we just regress observed migrant inflows on changes in log wages? The reason is that migrant inflows are correlated with changes in unobserved productivity or demand shocks. This

simultaneity bias can be observed in the following demand and supply system:

$$d \log w_j = d \log \psi_j - \eta \frac{\partial \log L_j}{\partial \log M_j} d \log M_j - \eta \frac{\partial \log L_j}{\partial \log N_j} d \log N_j$$

$$d \log M_j = d \log \lambda_M + \beta d \log w_j + d \log M a_{Mj}.$$

In the system above, we can also see that $d \log M a_{Mj}$ is a valid instrument since it only affects wages through migrant labor supply. While a_{Mj} are not directly observable, it is possible to construct a valid instrumental variable that can be constructed using data on the ethnic composition of each firm. Specifically, we can instrument for $d \log M_j \approx dM_j/M_{j0}$ (where the 0 subscript denotes data calculated in a pre-period) by a firm-level version of the Card (2001) immigrant enclave shift-share IV:

$$Z_j = \sum_c \frac{M_{cj0}}{M_{j0}} \cdot \frac{dM_c}{M_{c0}}.$$

The shift-share satisfies relevance if $Cov(Z_j, d \log M_j) > 0$, which holds as long as

$$\sum_c \frac{dM_c}{M_{c0}} Cov(M_{cj}/M_{j0}, M_j) > 0.$$

As we showed in the descriptive regression in **Figure 3**, firm-level EUEN shares over the period 2005-9 were strongly predictive of subsequent EUEN inflows, conditional on Non-EUEN foreign shares. This suggests that the above equation is likely to hold in practice.

The exclusion restriction holds as long as $Cov(Z_j, d \log \psi_j) = 0$, which is equivalent to

$$\sum_c \frac{dM_c}{M_{c0}} Cov(M_{cj}/M_{j0}, d \log \psi_j) > 0.$$

Note that in this model, the ratio M_{cj}/M_{j0} does not depend on the pre-period wage w_{j0} :

$$\frac{M_{cj0}}{M_{j0}} = \frac{M_c \lambda_{M_c} a_{M_c j}}{\sum_{c'} M_{c'} \lambda_{M_{c'}} a_{M_{c'} j}}.$$

Intuitively, since the shift-share only uses information on the relative composition of migrants from different countries within each firm, as long as migrants from different countries have the same labor supply elasticity, the wage cancels out.

6 Firm-Level Analysis

In this section we estimate the effects of firm-specific immigration shocks on firm-level wages and employment. In the model, migrant supply shocks cause firms to cut wages and lead to outflows of German workers. We test this prediction empirically by estimating quasi-experimental shocks using firm’s ethnic composition in the pre-period. In this section, we use the custom firm panel described in [Section 2.2](#).

6.1 Construction of Firm-Level Shift-Share

Motivated by the discussion in the previous section, we construct the empirical analogue of the firm-level shift-share:

$$z_j = \sum_{c \in \text{EUEEN}} \frac{M_{cj,2005-7}}{L_{j,2005-7}} \cdot \frac{\Delta M_c}{M_{c,2010}},$$

where $M_{cj,2005-7}$ is the number of worker-years worked by workers from country c in firm j over the period 2005-7, L_j is the number of worker-years at firm j between 2005-7, ΔM_c is the gross aggregate national inflow of workers from country c into Germany since 2010, and $M_{c,2010}$ is the total number of workers from country c employed in Germany in 2010. In order to capture exposure related to the 2011 policy change, the shift-share is only calculated using the EU Enlargement countries.

We estimate dynamic effects by estimating event-study regressions of the form

$$y_{jt} = \alpha_j + \alpha_t + \gamma_t z_j + \epsilon_{jt} \tag{4}$$

where α_j and α_t are firm and year-fixed effects, γ_t are the event-study coefficients which we

normalize to 0 in 2010. We estimate event-studies over the period 2008-14. Estimates $\hat{\gamma}_t$ over the pre-period 2008-10 can be used to test for parallel pre-trends. We end the event-study in 2014 for two reasons. First, in 2015 Germany passed a federal minimum wage (Dustmann et al., 2022). This policy differentially affected low wage firms and is likely correlated with our treatment. Second, 2015-16 were the peak years of the Germany refugee crisis. Differential exposure to either shock correlated with z_j would invalidate the parallel trends assumption. We therefore focus on the period 2011-14 in which EUEN migration was the primary shock affecting the labor market, in order to bolster the odds of parallel trends holding.

6.2 Shift-Share Validation

We subject z_j to several validation tests. Goldsmith-Pinkham, Sorkin, and Swift (2020) show that two-staged least squares using a shift-share like z_j as instrument is equivalent to over-identified GMM where the shares $M_{cj,2005-7}/L_{j,2005-7}$ for each country c are the instruments, for a particular weight matrix. They suggest inspecting the weights and verifying that they are non-negative. While we do not focus on “second-stage” 2SLS estimates, and rather consider the “reduced form” effects in a generalized difference-in-difference framework that uses z_j as a continuous measure of exposure, it would be challenging to interpret our estimates if they were not a convex combination of country-specific effects. The third column of **Table C4** (labeled α) gives the “Rotemberg” weights for each EUEN country. Reassuringly, all weights are non-negative. Poland and Romania alone account for over 60% of the weights, with Bulgaria, Hungary, and Czechia collectively account for under 30%, and Slovakia, Lithuania and Latvia accounting for about 10%. Interestingly, the weights roughly line-up with the coefficients from the firm-level intranational migration correlation from **Figure 4**.

Since our firm-level regressions contain a firm fixed effect, the effects are estimated from variation across time (i.e., before and after labor market opening in 2011) within-firms. The main identifying assumption is therefore that $Cov(z_j, \Delta\epsilon_j) = 0$. That is, the shift-share is

uncorrelated with firm-level *changes* in unobservable determinants of employment or wages over time. To validate this assumption, we run a series of regressions of the form

$$\Delta y_j = \alpha + \beta z_j + u_i,$$

where $\Delta y_j = y_{j,2010} - y_{j,2008}$ is the change in outcome y at firm j between 2008 and 2010, and plot coefficient estimates $\hat{\beta}$ and associated confidence intervals in **Figure C5**.²³ To facilitate visual comparison, we normalize Δy_j by the standard deviation of $y_{j,2010}$. Consistent with the identifying assumption, firms with higher exposure to EUEN inflows as measured by z_j were not differentially changing across a battery of observed outcomes. Firms’ occupational composition (as measured by the share of workers in manual routine, manual non-routine, cognitive routine occupations), the share of male workers at the firm, and the wages paid to both Germans and foreign workers (both measured broadly and within on age and education groups), are nearly uncorrelated with our measure of exposure.

6.3 Firm-Level Results: Effects on Migrant Inflows

Figure 6 plots the event-studies for firm-level net migrant inflows. The dependent variable is $\Delta M_{jt}^{EUEN} / L_{j,2010}$ (shown in the solid green line) and $\Delta M_{jt}^{Non-EUEN} / L_{j,2010}$ (shown in the dashed dark green line), where ΔM_{jt}^{EUEN} ($\Delta M_{jt}^{Non-EUEN}$) is the change in the number of (Non-)EUEN workers employed by firm j between t and 2010. The event-study for EUEN inflows is the “first-stage.” Firms with higher exposure saw a sharp increase in EUEN exposure beginning in 2011. The timing of the increase coincides with the policy change, and the flat pre-trend suggests that high exposure firms were not on a different trend in the years leading up to the reform going into place.

We interpret the event-study for Non-EUEN Foreign inflows as a test of the validity of the research design. If z_j were correlated with some unobserved factor that drove migrant

²³We use the period 2008-2010 since z_j is constructed using shares calculated from the period 2005-7, which may create some mechanical correlation.

sorting, we would expect to see large inflows of non-EUEN foreign workers as well as EUEN workers. However, the non-EUEN coefficients are statistically insignificant through 2012 and remain small in magnitude in 2013 and 14. Perhaps more importantly, they show no differential change around 2011.

6.4 Firm-Level Results: Employment

Figure 7 plots the coefficients from the event-study regression in **Equation 4** where the dependent variable is employment growth relative to 2010 at firm j . It also decomposes the contribution of German and foreign-born net employment inflows. Specifically, we use the identity

$$\frac{\Delta L_{jt}}{L_{j,2010}} := \frac{L_{jt} - L_{j,2010}}{L_{j,2010}} = \frac{\Delta N_{jt}}{L_{j,2010}} + \frac{\Delta M_{jt}}{L_{j,2010}}$$

where N_{jt} is the number of German workers employed at firm j in year t and M_{jt} is the number of migrant workers.

The estimates connected by a solid green line correspond to total employment growth $\frac{\Delta L_{jt}}{L_{j,2010}}$. Firm-level employment was stable during the pre-period, suggesting that firms with higher exposure were not experiencing differential employment growth prior to 2011. After 2011, employment increases. However, this increase in employment is entirely due to increases in net migrant inflows. The coefficient in 2014 implies that a 10 percentage point increases in predicted EUEN inflow 2011-14 (z_j) corresponds to about a 5 percentage point increase in net migrant inflows. Overall employment growth is lower due to the negative effect of German employment, which contributes about a 1.5 percentage point decline for the same change in exposure.

6.5 Firm-Level Results: Wages

Figure 8 plots the coefficients from the event-study regression in **Equation 4** where the dependent variable is the log wage of Germans who were employed full-time by firm j over

the entire period 2008-14 in year t . By restricting the sample to these “firm stayers”, we fully adjust for changes in worker composition. This is important since, as we have just seen, the supply shock caused a change in the composition of workers. If changes in employment are correlated with unobserved skills, this would bias the wage effects. The magnitude of the coefficient in 2014 implies that a 10 percentage point increase in z_j decreases wages by 12.5%.

Figure 9 plots the coefficients from the same regression, for each of three education groups: workers with a high school education or less, workers with a vocational degree, and university educated workers. The effects are strongest among the high school-educated, small but still negative for those with a vocational degree, and zero for university-educated workers. This is consistent with the inflow of EUEN migrant workers being primarily low-skilled, and therefore in most direct competition with EUEN migrants.

The top panel of **Figure 10** plots the coefficients from the regression where the dependent variable are log wages of German firm stayers (i.e., the regression where the dependent variable are log wages of German firm stayers), but in addition overlays coefficients from the regression for foreign firm stayers. Estimates across the two groups are very similar in magnitude and their trends follow each other closely. This suggests that, as in our model, these wage declines represent overall declines in firm-level wages. The bottom panel of **Figure 10** plots estimates from a regression where the dependent variable is the log of the ratio of German to foreign stayers’ wages (i.e., the dependent variable is $\ln(w_{Mj}^{Stay}/w_{jMj}^{Stay})$). The relative wages between the two groups of workers remain constant through the inflow. This is consistent with a high degree of substitutability between migrant and native-born workers within firms.

7 Worker-Level Analysis

In this section we turn to the worker level and estimate the effects of exposure to EUEN migrant supply shocks at both firm- and market-level. In **Section 7.1**, we estimate the

effects of the firm-level exposure (as measured by the firm-level shift-share of their 2010 employer $z_{j(i),2010}$) on incumbent workers. In 7.2, we estimate the effect of shocks at the local-labor market level.

7.1 Effects of Firm-Level Shocks on Workers

We estimate effects of firm-level shocks by running a series of regressions of the form

$$\Delta y_i = \alpha + \gamma z_{j(i),2010} + \beta X_i + \epsilon_i \quad (5)$$

where i indexes workers, j indexes firms (so that $j(i, 2010)$ refers to workers i 's employer in 2010), $\Delta y_i := y_{i,2014} - y_{i,2010}$ refers to the change in worker i 's outcome between 2010 and 2014, z_j is the shift-share of firm j , and X_i is a vector of controls. Worker controls include polynomials in age, experience, and tenure (all in 2010), as well as dummies for education and gender. Firm controls include industry, commuting zone, and firm size ventile fixed effects, corresponding to the sector, location, and size of i 's 2010 employer. The regression is run on the same sample of firms as in **Section 6**. Each coefficient comes from a separate regression. Standard errors are clustered at the firm level, where firm corresponds to the worker's employer in 2010. Coefficient estimates $\hat{\gamma}$ and are displayed in **Table 3**.

The results are consistent with the predictions of the model. Incumbent workers at exposed firms move to higher wage firms (as measured by AKM firm wage premia). Focusing on the estimates in the third column of **Table 3**, which include a full set of worker and firm controls, a 10 percentage point increase in z_j is associated with 5 percentage point foreign inflow. This is similar in magnitude to the estimates presented in the previous section. A 10 percentage point increase in z_j is associated with in firm wage by 4.2 log points, an increase in the wage by 1.6 log points, and an increase in commuting distance by 2 log points. This is consistent with workers at exposed firms moving to higher wage firms. The increase in commuting distance suggests that workers are moving to firms located further away from

their place of residence, trading off disutility from longer commutes for higher wages. Workers also move to firms with lower foreign shares. There is no effect on the cumulative number of days employed over the period 2011-14, suggesting that reallocations occurred through relatively seamless “employment-to-employment” transitions without substantial increase in time spent nonemployed.

To check that effects are not driven by trends in exposed workers’ outcomes that pre-date the 2011-14 period, we run a second set of “triple-difference” regressions of the form

$$\Delta y_{i,t} = \alpha_t + \gamma_1 z_{j(i),2010} + \gamma_2 z_{j(i),2010} \cdot Post_t + \beta_t X_i + \epsilon_{i,t} \quad (6)$$

where $t \in \{2015, 2009\}$ and $Post_t$ is an indicator for $t = 2014$. Coefficient estimates $\hat{\gamma}$ and are displayed in **Table C6**. Estimates are similar in magnitude to those in **Table 3**, and if anything slightly higher (which likely represents a modest degree of mean-reversion).

7.2 Effects of Market-Level Shocks on Workers

As we saw in **Figure 2**, the EUN migrant supply shock was concentrated in the lowest deciles of the firm wage distribution. Motivated by this observation, we estimate the effects of market-level supply shocks on changes in the characteristics of workers’ employers between 2010 and 2014 stratified by the firm wage of their employer in 2010. We should expect to find reallocation effects only among workers who were initially employed at the bottom of the firm wage distribution. Workers at higher quantiles offer a useful placebo.

We group each worker i based on the decile of the AKM firm effect of their 2010 employer, $\psi_{J(i),2010}$. We run regressions regressions

$$\Delta y_i = \alpha_d + \gamma_d \cdot z_{r(i),2010} + \beta_d X_i + \epsilon_i \quad (7)$$

where $\Delta y_i = y_{i,2014} - y_{i,2010}$ is the change in outcome y for worker i between 2014 and 2010. $z_{r(i),2010}$ is a shift-share constructed in the same way as the firm-level shift-share in the

previous section, but calculated at the district level.²⁴ X_i is a vector of covariates including worker i 's age, gender, level of education (high school, vocational, or university-educated), experience, as well as the non-EUEN foreign migrant share of their 2010 district. This last control is included in order to remove the effect of non-EUEN inflows, which were larger at higher quantiles of the firm wage distribution (see the bottom panel of **Figure 2**). The regression is run for Germans only and clustered at the district level.

Figure 11 plots the coefficients $\hat{\gamma}_d$ and associated 95% confidence intervals for the regression in **Equation 7** where the outcome is equal to the change in the AKM firm effect of worker i 's employer between 2010 and 2014: $\Delta y_i = \psi_{J(i,2014)} - \psi_{J(i,2010)}$. The coefficients are scaled so that they represent the effect of a 5 percentage point increase in the shift-share z_r . Workers in the bottom decile who in markets with a predicted 5 percentage point EUEN migrant inflow move to firms with approximately 7 log points higher AKM firm effects. The effect decreases monotonically in the first 5 deciles then becomes flat and statistically insignificant above the 5th decile. This is consistent with reallocation effects shifting workers to higher paying firms. **Figure C9** shows that this result is robust to alternative measures of firm wages, such as the mean log wage of FT workers (top panel) or a version of the AKM firm effect that includes imputed values (see **Section A** for details of the imputation).

In **Figure 12**, the outcome is equal to the change in the EUEN foreign share of worker i 's employer, calculated over the period 2011-14. That is $\Delta y_i = m_{j(i,2014),2011-14}^{EUEN} - m_{j(i,2010),2011-14}^{EUEN}$. Note that since the EUEN foreign share is calculated over the entire period 2011-14 for both terms in the difference, this does not represent inter-temporal increases in EUEN share. Rather, they represent between-firm differences. As in the previous figure, effects are concentrated in the bottom 5 deciles, with effects the 5th decile and above flat and statistically insignificant. This suggests that workers in exposed markets were more likely to move to firms with lower EUEN shares.

Since firm EUEN shares are calculated during the period 2011-14, it's possible that

²⁴There are 401 districts (*kreis*) in Germany.

the patterns observed are partly mechanical; that is, the low EUEN shares may represent movements of Germans into firms and not movement away from firms with higher EUEN share. To remove this bias, the bottom panel of ?? plots the coefficients for the same regression as **Figure 12** but where the dependent variable is the average firm EUEN share over the pre-period 2005-9. Since this variable is calculated prior to 2011-14 it removes any potential mechanical correlation with contemporaneous outcomes. The magnitudes and patterns are very similar, suggesting that bias is minimal.

Figure 13 and **Figure 14** show effects on wages and employment. Wages are defined by the log wage of full-time workers, while employment is calculated as a change in a dummy equal to 1 if a worker is employed full-time.²⁵ Unlike the previous two figures, these both suggest null effects. A null effect on employment means that while EUEN migrants did crowd Germans out from firms, they didn't crowd them out from employment. A null effect on wages suggests that the reallocation effect roughly balanced out the within-firm wage decrease that we documented in the firm-level analysis in **Section 6**.

Figure C13 and **Figure C8** show effects on mobility across occupations, industries and local labor markets. The dependent variables in these regressions are dummy variables equal to 1 when worker i 's occupation, industry, and local labor market in 2014 differs from the one they were employed in in 2010. While estimates are fairly imprecise, the coefficients are close to zero in the bottom deciles, suggesting that mobility across occupations, markets or industries were not a primary margin of adjustment. This suggests that the reallocation primarily occurred across firms within occupations, industries, or local labor markets.

The previous results could be biased if markets with higher exposure to EUEN inflows 2011-14 as measured by the local labor market-level shift-share z_r were experiencing unobserved shocks to labor demand relative to less exposed markets. To address this concern, we

²⁵The variable is equal to 0 if the worker is employed part-time or if the worker is unemployed

run a continuous “triple difference” version of the sequence of regressions in **Equation 7**:

$$\Delta y_{it} = \alpha_{dt} + \gamma_{1d} z_{r(i,2010)} + \gamma_{2d} z_{r(i,2010)} Post_t + \beta_{dt} X_i + \epsilon_{it} \quad (8)$$

where $t \in \{2014, 2009\}$ and $\Delta y_{it} = y_{it} - y_{it-4}$ are 4-year long-differences and $Post_t = 1\{t = 2014\}$ is an indicator for the post-period. The coefficients $\gamma_{d,2}$ capture the change in the relationship between z_r and Δy_i in the 2011-14 period. The component of the correlation that is persistent across both periods is captured by γ_{d1} . **C11** and **C12** plot the coefficient estimates $\hat{\gamma}_{d2}$ and associated 95% confidence intervals for each decile for regressions where the outcome is worker i 's change in firm wage premia (top panel **C11**), change in firm EUEN share 2011-14 (bottom panel **C11**), change in log wage (top panel **C12**) and change in full-time employment status (bottom panel **C12**). Coefficient estimates are quantitatively very close to their counterparts estimated by **Equation 7**, suggesting that these observed effects aren't explained by persistent shocks in exposed labor markets predating the 2011 policy change.

As a final robustness check, we investigate whether results are robust to alternative definitions of local labor markets. **Figure C13** plots coefficients from **Equation 7** for regressions using shocks at the the district level alongside equivalent regressions using two broader local labor market definitions: as local labor market (200 levels) or commuting zones (50 levels). While confidence intervals are somewhat wider in some deciles, point estimates are similar and overall the three sets of estimates track each other closely.

8 Conclusion

In this paper, we have argued that the sorting of workers across firms and inter-firm mobility play a role in mediating the market-level wage impacts of immigration-induced supply shocks. When migrant workers are highly segregated across firms and concentrated in low wage firms, the effect on average native-born worker's wages is attenuated by two forces. First, the

high level of segregation reduces the spill-over of negative wage effects that occur from direct within-firm competition. Second, native-born workers who *are* exposed within their firms may reallocate towards higher-paying firms. We demonstrated this mechanism both theoretically in a model of worker sorting across heterogeneous firms and empirically using German matched employer-employee data. Germans who stayed at firms experiencing larger quasi-exogenous migrant inflows experienced lower wage growth. However, exposed firms also saw net German outflows, and workers in segments of the labor market with high exposure moved to firms with lower migrant shares and higher wages.

Our results have implications for the study of the economics of immigration. First, our results underline the importance of firm heterogeneity and imperfect competition in the study of immigration. In many perfectly competitive models of the labor market where firms do not set wages and workers are paid their marginal product, the distribution of workers across firms is irrelevant. Firm wage dispersion is key to the mechanism we document, and imperfect competition is widely believed to be the one of the factors underpinning wage dispersion. Second, our results caution against extrapolating evidence on the firm-level effects to conclusions about broader market-level effects. The reallocation effects we document that a simple aggregation may not be accurate, especially for broad immigration shocks.

In terms of policy implications, our results highlight the importance of inter-firm mobility as a way in which the economy absorbs labor supply shocks. Policies that increase workers' information about jobs (Jäger et al., 2023), lower the costs of job switching, or lower hiring costs (Angrist and Kugler, 2003) may help markets absorb migrant labor supply shocks without negative wage effects.

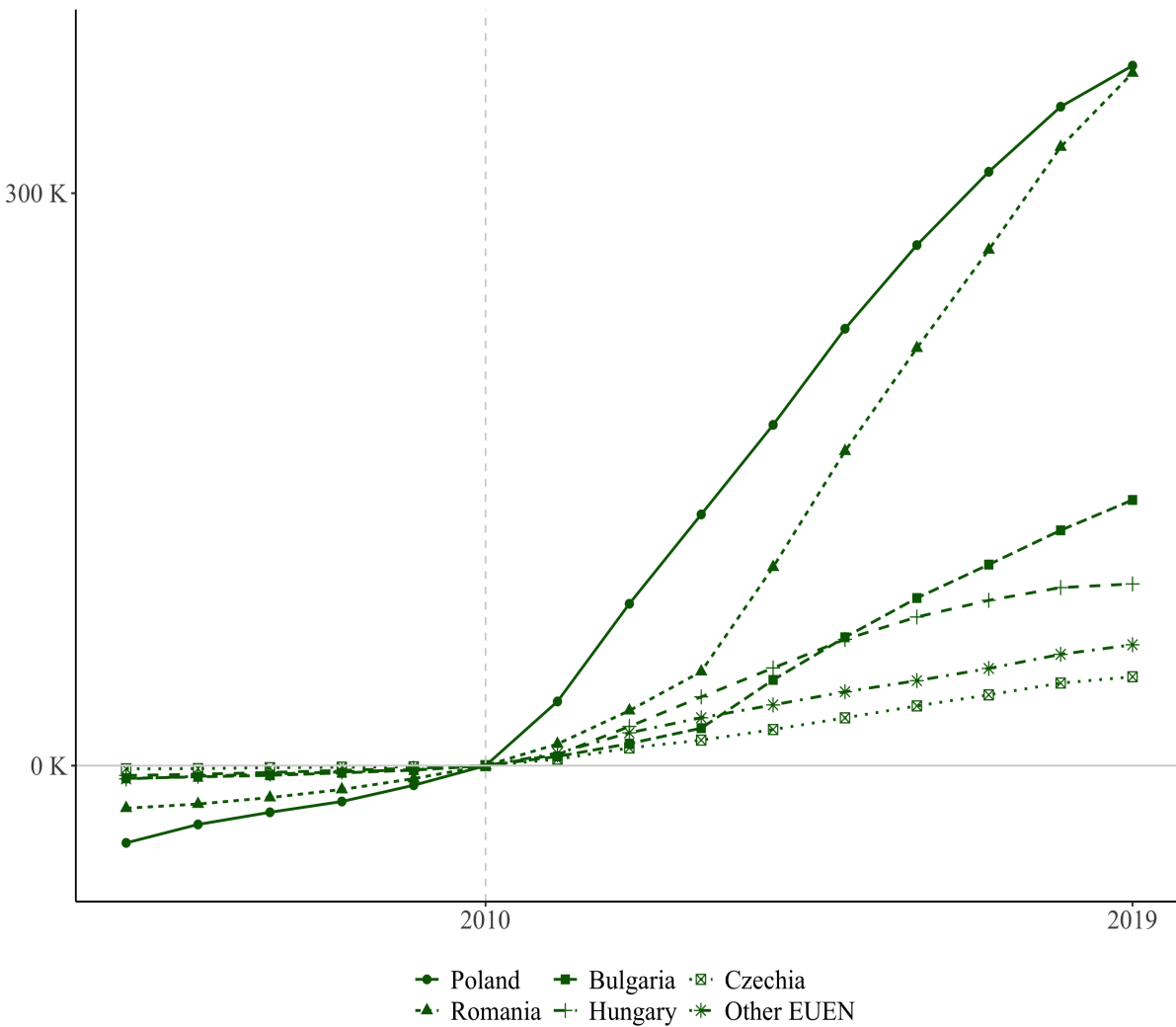
At first blush, our results appear to suggest a grim trade-off between the economic assimilation of migrant workers and the labor market outcomes of the native-born. However, this may be a false choice when other policy instruments are available. While our results suggest a silver lining to the segregation of migrant workers in low-wage firms, policies such as the

minimum wage or sectoral bargaining could improve outcomes of both groups of workers by restricting the exercise of employer monopsony power in the low wage labor market. Our results suggest rethinking policies that prevent immigrants from entering labor markets where they have access to networks, such as the residence obligations that Germany imposes on refugees.

This paper suggests several promising avenues for future research. One is to study the interaction of the immigration wave with Germany's federal minimum wage law, passed in 2015. Another is to extend our theoretical model to a full-blown structural-empirical model (Lamadon et al., 2022, Sharma, 2022) which would allow the estimation of unobserved amenities, differential rent-sharing, incorporation of data on employer concentration, and the simulation of policy counterfactuals.

9 Figures and Tables

Figure 1: Employment Inflows to Germany from EU Enlargement Countries



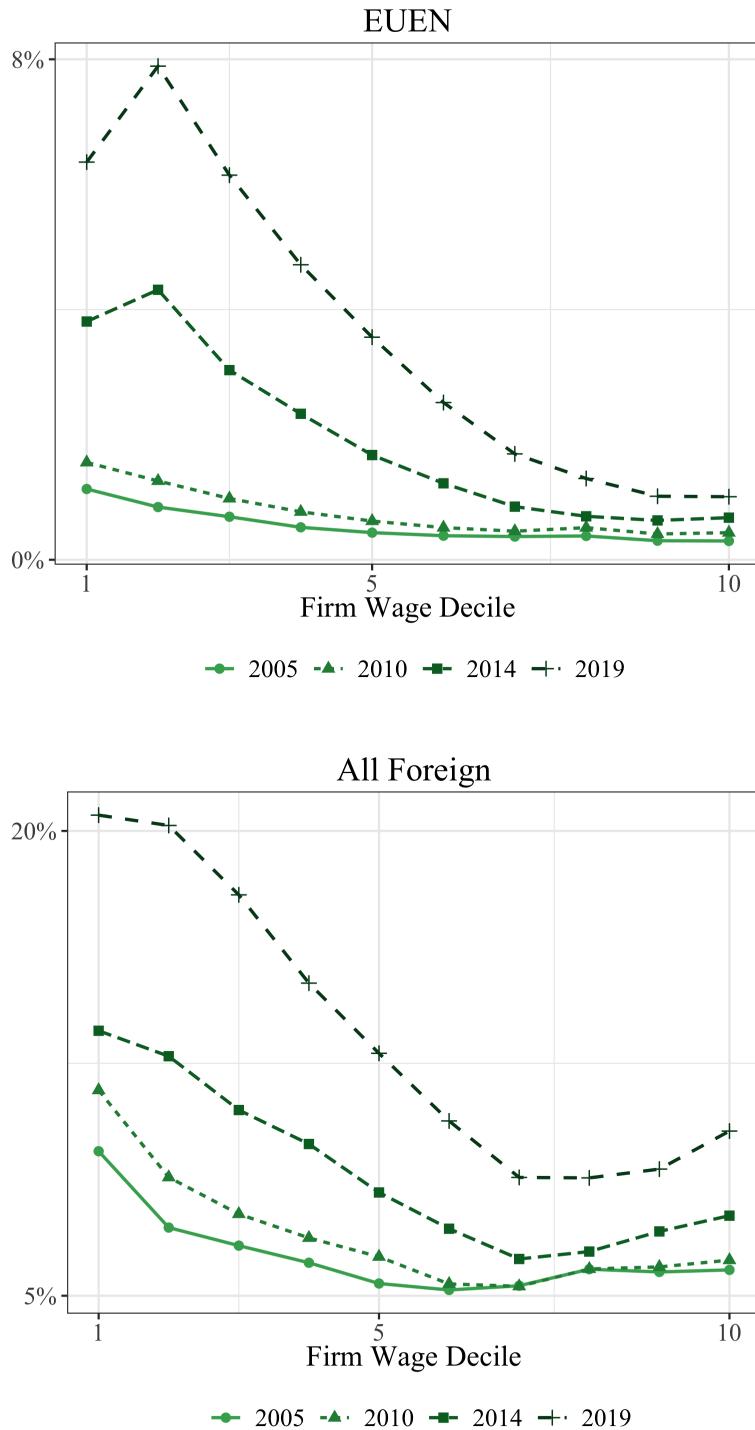
This figure depicts the net change in the number of workers employed in Germany since 2010 for each of the EU Enlargement countries. The “Other EUEN” category includes workers from Estonia, Latvia, Lithuania, Slovakia and Slovenia. Data are from a 100% sample of German Social Security Records.

Table 1: Summary of Worker Statistics

| | EUEN | | Non-EUEN foreign | | German | |
|-------------------------|----------|---------|------------------|---------|----------|---------|
| | Pre 2010 | 2010-14 | Pre 2010 | 2010-14 | Pre 2010 | 2010-14 |
| Share | | | | | | |
| Female | 58.5 | 39.9 | 41.6 | 44.9 | 48.8 | 49.4 |
| Education | | | | | | |
| Low educ | 13.6 | 23.4 | 22.3 | 29.2 | 4.4 | 21.2 |
| Mid educ | 65.2 | 59 | 62.5 | 43.4 | 76.3 | 60.6 |
| High educ | 21.3 | 17.5 | 15.2 | 27.4 | 19.3 | 18.2 |
| Age | | | | | | |
| 18-29 | 6.3 | 30.8 | 9.6 | 44.1 | 12.4 | 65.3 |
| 30-49 | 64.8 | 56.1 | 57.5 | 44.9 | 45.1 | 19.7 |
| 50+ | 28.9 | 13.1 | 32.9 | 11 | 42.6 | 15 |
| Employment | | | | | | |
| Full-time | 61.6 | 64.3 | 62.2 | 49.7 | 66.1 | 54.7 |
| Occupation | | | | | | |
| Unskilled | 33.8 | 54.9 | 32.3 | 39.2 | 15.2 | 28.3 |
| Qualified | 48.9 | 38.5 | 52.5 | 43.1 | 59.3 | 56.9 |
| Specialist | 7.5 | 2.5 | 7.1 | 5.8 | 13.1 | 6.6 |
| Expert | 9.8 | 4.1 | 8.2 | 12 | 12.4 | 8.2 |
| Mean Firm Size | | | | | | |
| Unskilled | 70.1 | 44.4 | 110.7 | 90.1 | 79.3 | 100.4 |
| Qualified | 393.5 | 125.9 | 603.8 | 286.7 | 566.7 | 345.3 |
| High-skilled | 201.1 | 44.3 | 268.3 | 191.7 | 251.7 | 179.3 |
| Median Firm Size | | | | | | |
| Unskilled | 6 | 5 | 11 | 7 | 6 | 7 |
| Qualified | 32 | 18 | 54 | 21 | 56 | 31 |
| High-skilled | 3 | 1 | 5 | 3 | 7 | 3 |

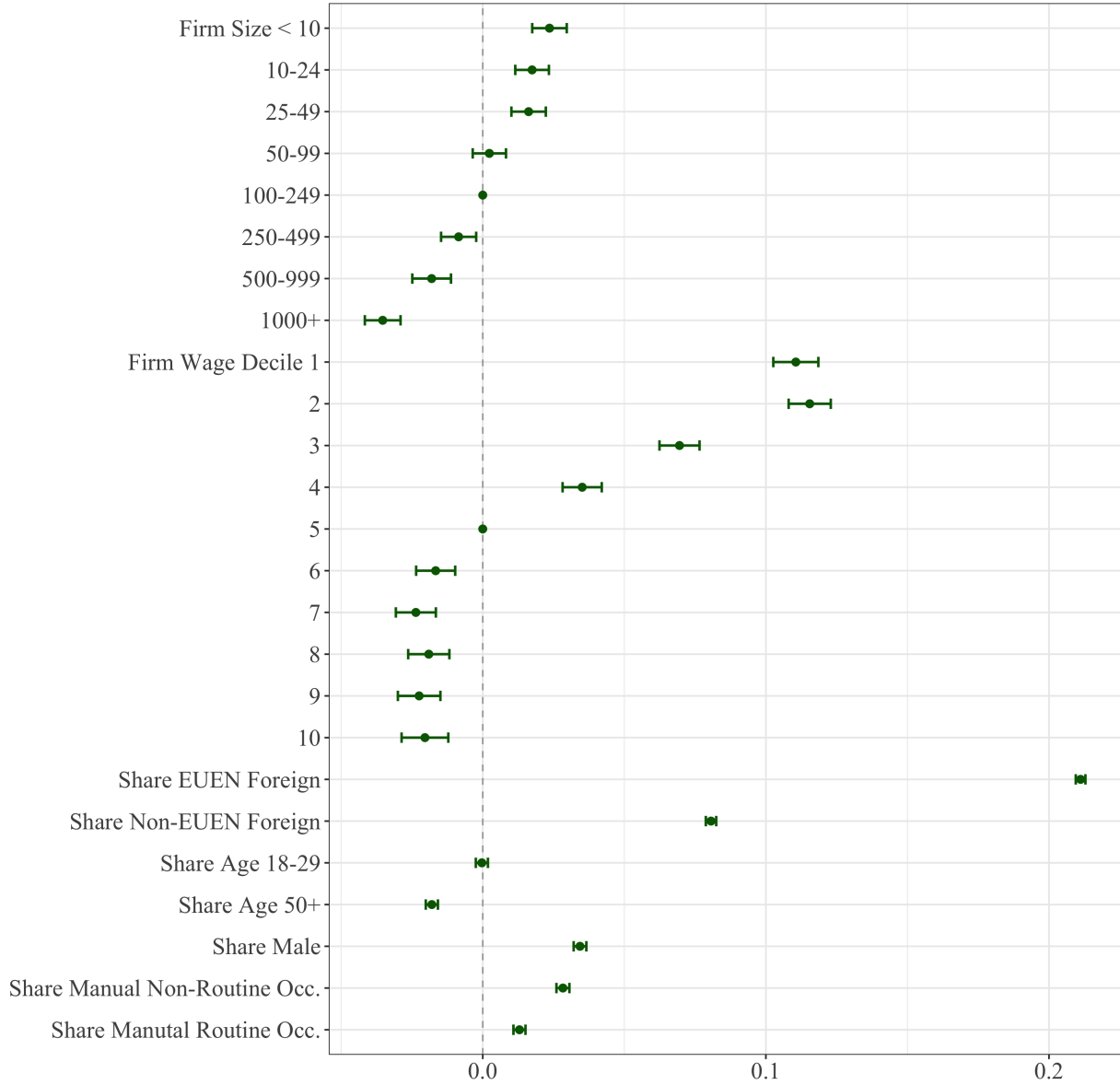
This table reports summary statistics on the demographic and labor market characteristics of workers employed in Germany in 2014. EUEN refers to EU Enlargement Nationals (workers from Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia), and Non-EUEN Foreign refers to foreign-born workers from all other countries of origin. “Pre-2010” and “2010-14” refers to the period in which workers are first observed in Germany. Low Education refers to workers with a High School degree or less, Mid refers to workers with vocational training, and High refers to workers with a University degree or more. Occupation classifications are based on the first digit of the German Classification of Occupations 2010. Firm Size is calculated for each worker’s main employer on June 30th, 2014. Based on data from the Sample of Integrated Employer Employee Data (Schmidtlein, Seth, and Vom Berge, 2020).

Figure 2: Migrant Firm Wage Sorting 2005-19



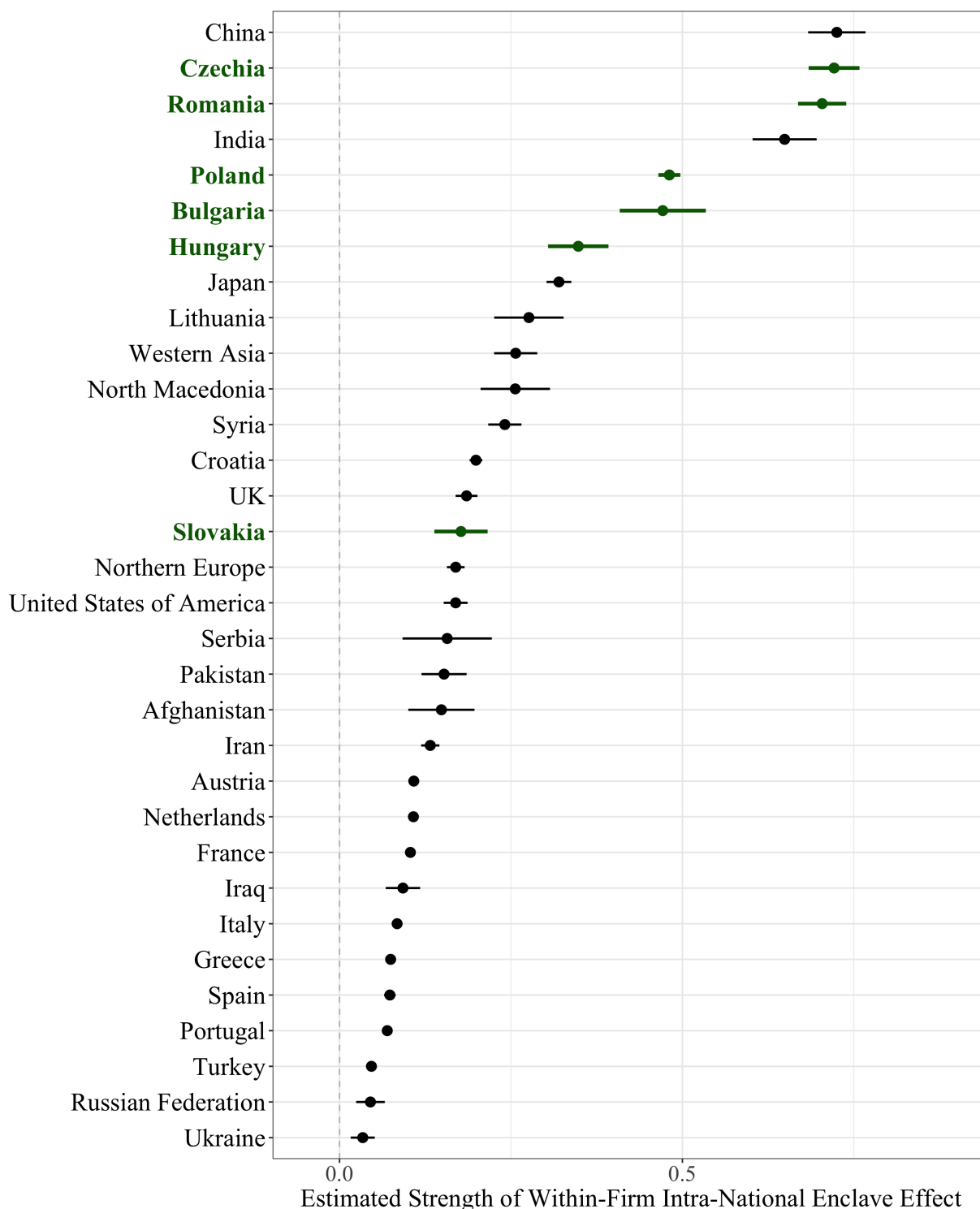
This figure plots the share of workers who are foreign citizens within each decile of the firm wage distribution in 2005, 2010, 2014 and 2019. The top panel plots the employment share for workers from the EU enlargement nations of Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia. The bottom panel plots the employment share for foreign workers from all countries. Firm wage deciles are calculated by taking the mean log wage among full-time employees. Deciles are weighted by employment so that every decile contains 10% of workers. Data come from a 100% sample of German social security records.

Figure 3: Descriptive Regression: EUEN Inflow 2014.



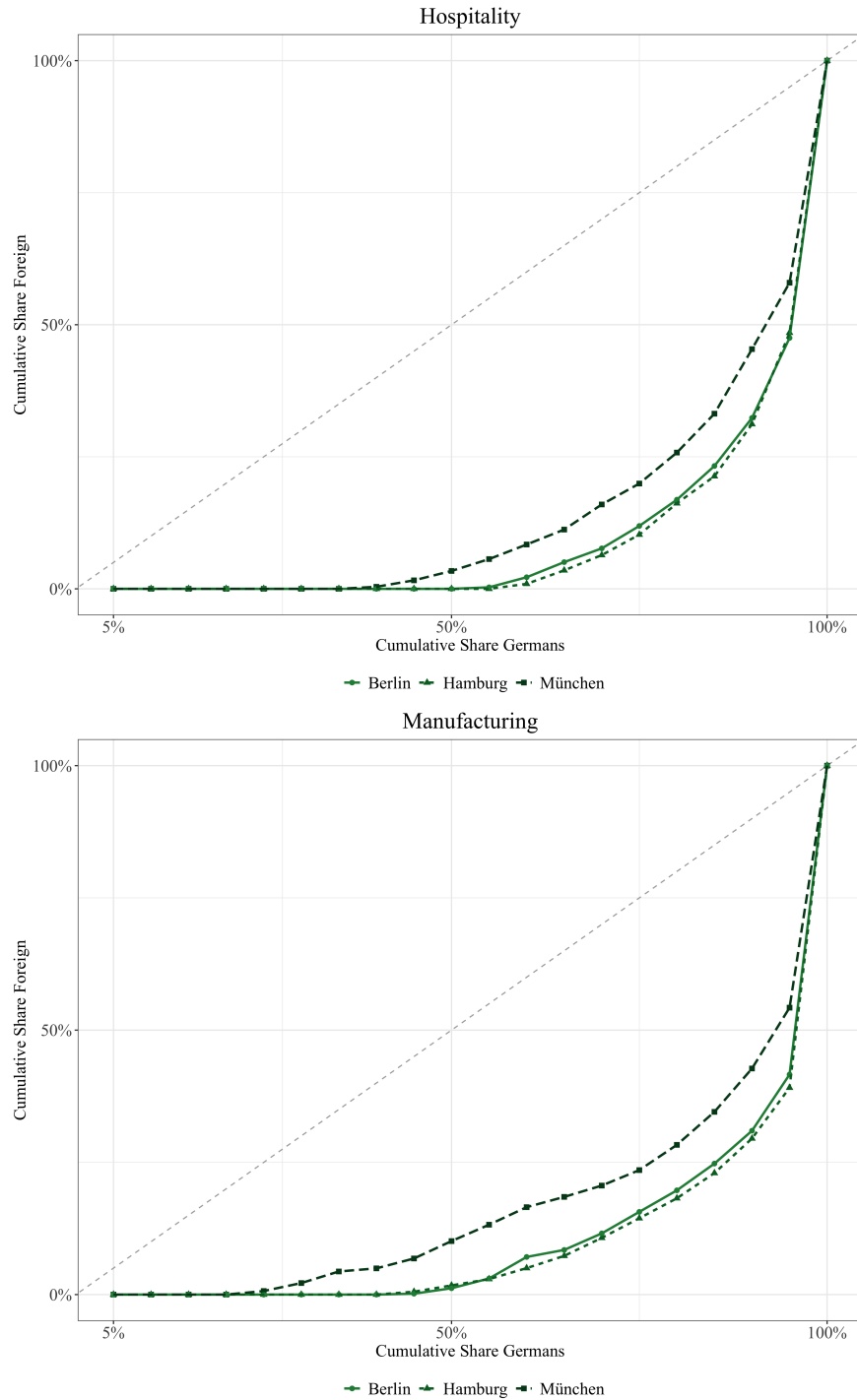
The figure plots coefficients and 95% confidence intervals from the regression in **Equation 4**. The dependent variable is $M_{j,2014}^{EUEN,New} / \bar{L}_{j,2005-9}$ where $M_{j,2014}^{EUEN,New}$ is the number of EUEN migrants from the 2010-14 cohort employed at firm j in 2014 and $\bar{L}_{j,2005-9}$ is the mean firm size of firm j between 2005-9. All continuous covariates are calculated by pooling the period 2005-9. Share EUEN Foreign is the share of workers from the EU Enlargement Nations (Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia), Share Non-EUEN Foreign is the share of foreign-born workers from other countries. Share Manual (Non-)Routine Occ is the share of workers employed in a manual (non-)routine task-intensive occupation, according to the classification of Dengler, Matthes, and Paulus (2014). Both the dependent variable and the continuous covariates X_j were normalized by their standard deviations. The other variables are indicators, with the dummies for firm size 100-249 and the middle firm wage decile omitted. In addition to the regressors depicted, a set of commuting-zone and industry fixed effects were partialled out. Confidence intervals were constructed using heteroskedasticity-robust standard errors.

Figure 4: Strength of Within-Firm Intranational Migrant Flows by Country



This figure plots coefficients and 95% confidence intervals from the regression in **Equation 2** for the 30 largest countries by foreign population share in Germany in 2014, as well as the EU Enlargement Countries (which are bold and colored dark green). The dependent variable is the ratio $M_{jc,2011-14}^{New}/L_{j,2011-14}$, where $M_{jc,2011-14}^{New}$ is the number of worker-years worked by recent migrants from country c in firm j over the period 2011-14, and $L_{j,2011-14}$ is the total number of worker-years worked at firm j over the period 2011-14. Recent migrants refers to migrants who are first observed in German administrative data after 2010. The dependent variable is the same ratio calculated over the period 2005-9 for all migrants. The regression also includes a set of firm fixed effects and country-fixed effects. Standard errors are two-way clustered at the firm and country level.

Figure 5: Segregation Curves Within Industry-Commuting Zone



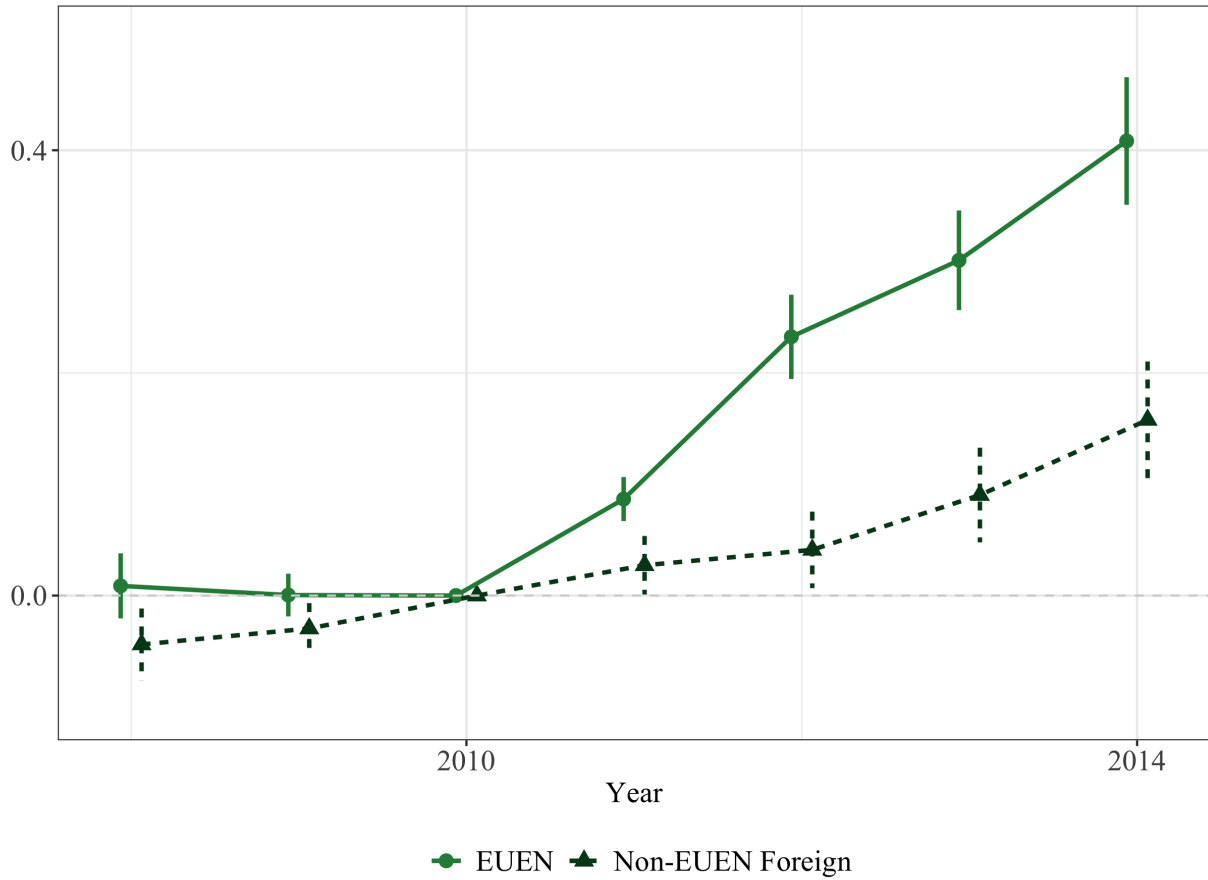
This figure plots the segregation curves for the hospitality and manufacturing industries in Berlin, Hamburg and Munich in 2014. The horizontal axis is the cumulative share of Germans, ordered by the share of their coworkers who are from the EU Enlargement Nations (EUN) of Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia. The vertical axis is the cumulative share of EUN foreign workers. The green lines are the segregation curves. The dashed grey line is the 45 degree line. Data come from a 100% sample of German social security records.

Table 2: Segregation Indices

| Year | Group | Unadj. | Adj. | CZ | Ind CZ |
|------|------------------|--------|------|------|--------|
| 2014 | EUEN | 74.6 | 56.5 | 53.0 | 39.5 |
| | EUEN (Recent) | 84.7 | 70.9 | 68.6 | 54.9 |
| | Foreign | 55.5 | 43.0 | 35.8 | 27.2 |
| | Foreign (Recent) | 72.0 | 56.3 | 53.0 | 39.5 |
| 2019 | EUEN | 71.7 | 58.2 | 55.7 | 42.0 |
| | EUEN (Recent) | 77.2 | 65.0 | 63.1 | 48.8 |
| | Foreign | 53.5 | 43.9 | 38.3 | 28.5 |
| | Foreign (Recent) | 62.5 | 51.6 | 48.2 | 35.7 |

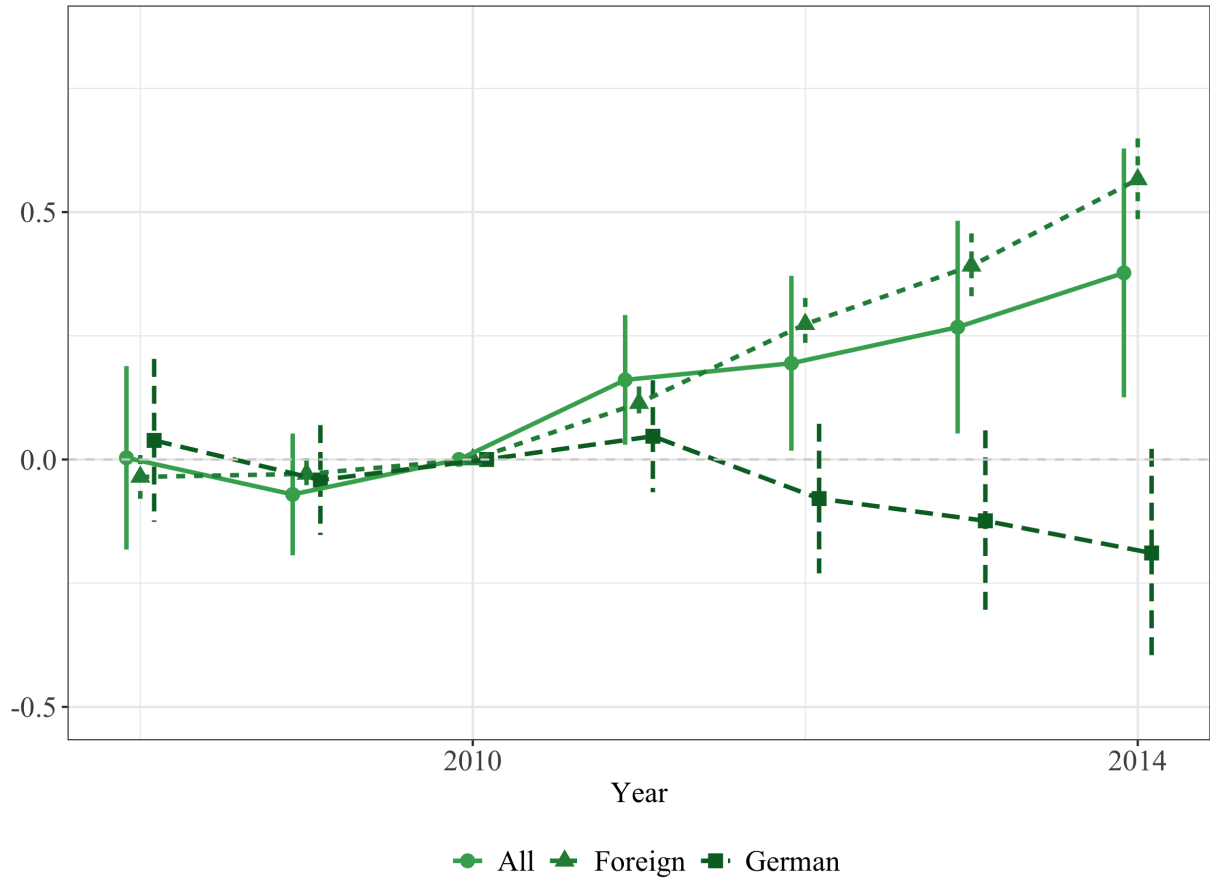
This table displays reports unconditional and conditional segregation indices measuring the level of segregation between different groups of migrants and native-born workers in Germany in 2014 and 2019. ID refers to the [Duncan and Duncan \(1955\)](#) Index of Dissimilarity. The column labeled “Unadj.” reports the unadjusted index, equal to $ID_{\text{Uncond}} = \sum_j |\frac{M_j}{L_j} - \frac{M}{L}| \times 100$, where M_j is the number of foreign workers from the group in firm j and L_j is total employment at firm j . The column labeled “Adj.” reports adjusted values of the index, where the adjustment consists of subtracting an unconditional simulated index. The columns labeled “CZ” and “Ind CZ” adjust for Commuting Zone and the intersection of Industry and Commuting Zone. See details of the simulation in the text. EUEN refers to the EU Enlargement Nations of Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia. Firms with only one worker are excluded from the analysis. Recent refers to migrant workers who first immigrated after 2010. Data come from a 100% sample of German social security records.

Figure 6: Firm-level Event Study: EUEN and Non-EUEN Foreign Net Inflows



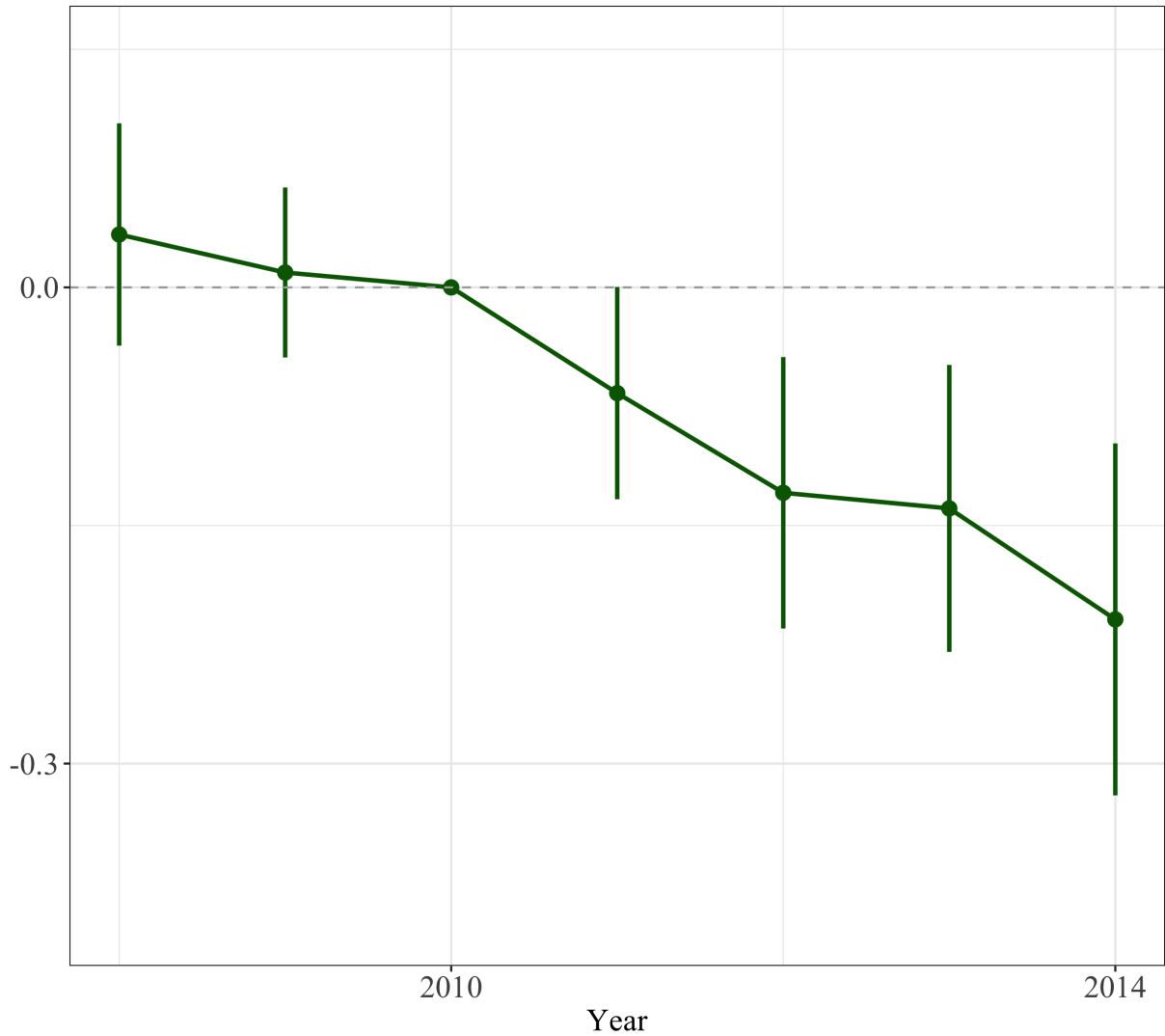
This figure plots coefficients from the event-study regression in **Equation 4**. The outcome is equal to the net employment inflow to firm j by foreign-born workers, normalized by firm size in 2010 ($y_{jt} = \Delta M_{jt}/L_{j,2010}$). The model includes a firm fixed effect and a year fixed effect. The values of the coefficients in 2010 are normalized to zero. Models for EU Enlargement Nationals (EUEN) and Non-EUEN foreign workers are plotted separately. Standard errors are clustered by firm.

Figure 7: Firm-level Event Study: Employment



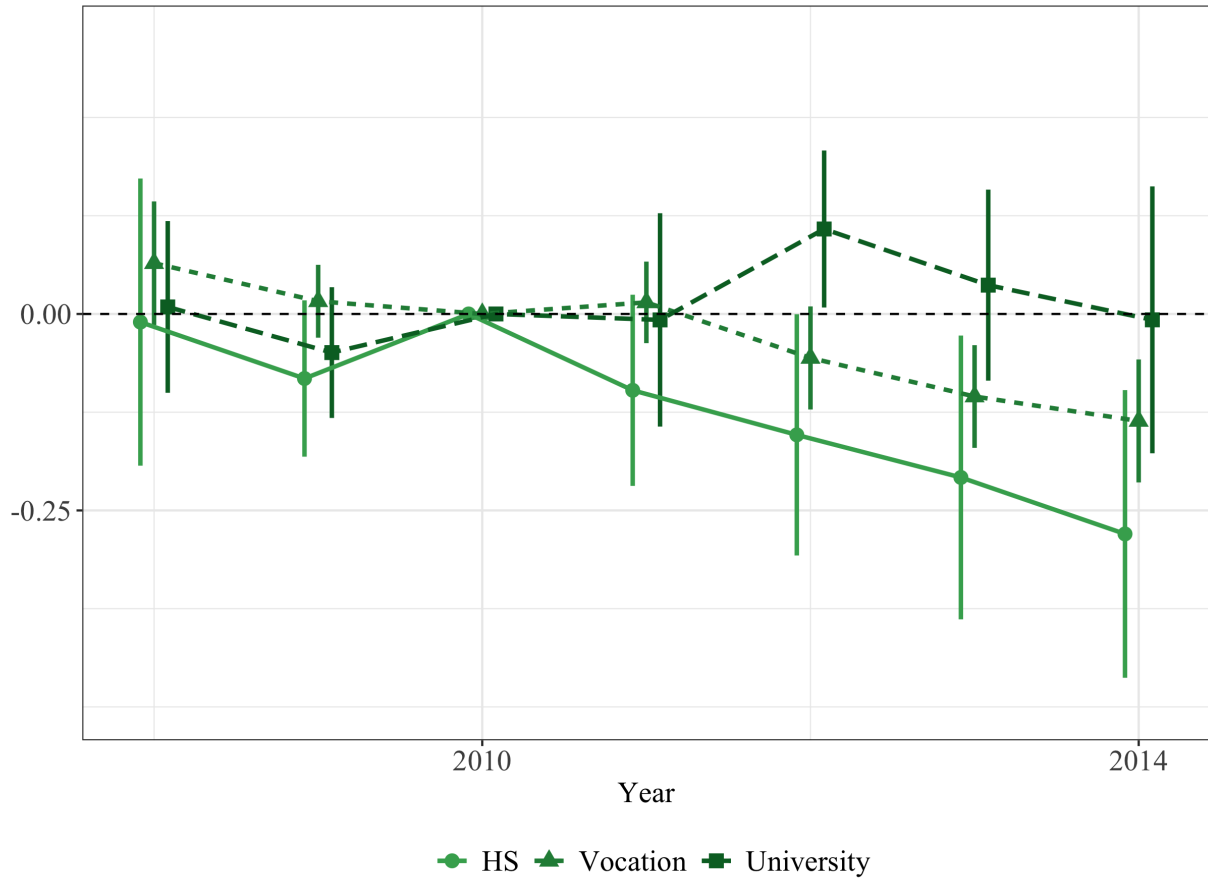
This figure plots coefficients from the event-study regression in **Equation 4**. The outcome is equal to the net employment inflow to firm j normalized by firm size in 2010 ($y_{jt} = L_{jt} - L_{j,2010} / L_{j,2010}$). The employment effect is further decomposed into the contribution from foreign workers and German workers. The model includes a firm fixed effect and a year fixed effect. The values of the coefficients in 2010 are normalized to zero. Standard errors are clustered by firm.

Figure 8: Firm-level Event Study: Log Wage of German Stayers



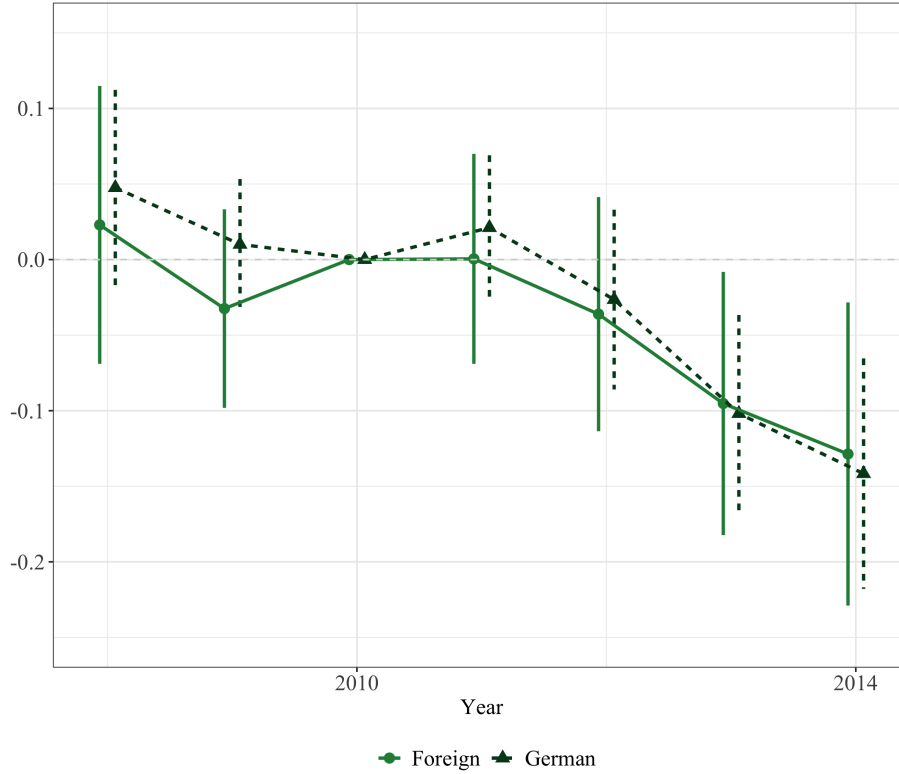
This figure plots coefficients from the event-study regression in [Equation 4](#). The outcome is equal to the log wages of German “firm stayers”, workers who remained employed at firm j over the entire period 2008-14. The model includes a firm fixed effect and a year fixed effect. The values of the coefficients in 2010 are normalized to zero. Standard errors are clustered by firm.

Figure 9: Firm-level Event Study: Log Wage of German Stayers by Level Education

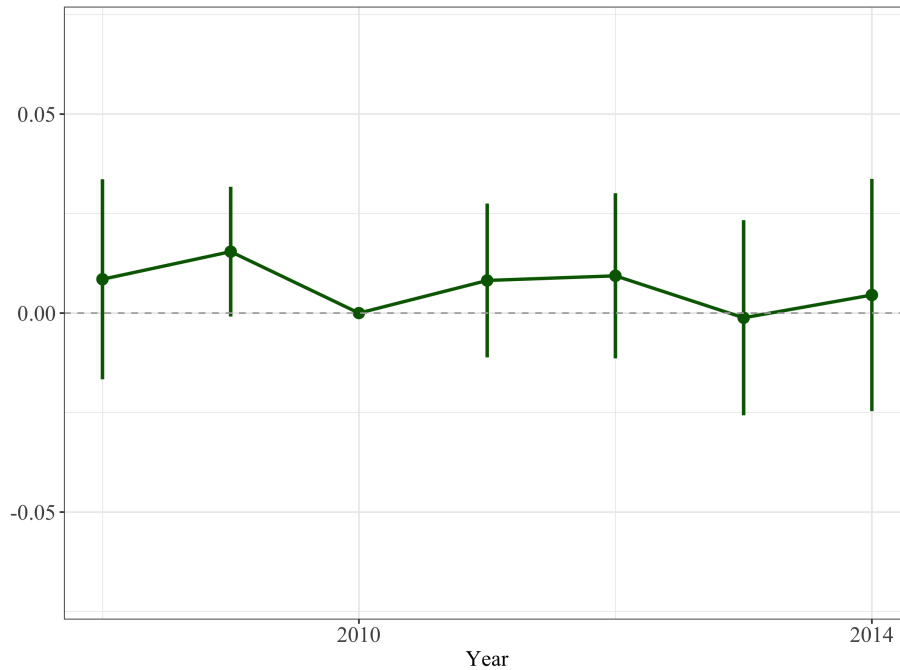


This figure plots coefficients from the event-study regression in **Equation 4**. The outcome is equal to the log wages of German “firm stayers”, workers who remained employed at firm j over the entire period 2008-14. Values are shown for three separate regressions, each fit for a different education level. “HS” refers to workers with a high school education or less. The education level of each workers is based on the value recorded in 2010. The model includes a firm fixed effect and a year fixed effect. The values of the coefficients in 2010 are normalized to zero. Standard errors are clustered by firm.

Figure 10: Firm-Level Event Study: Log Wage of German and Foreign Firm Stayers



(a) German and Foreign Stayers



(b) Relative Wage German/Foreign Wage Stayers

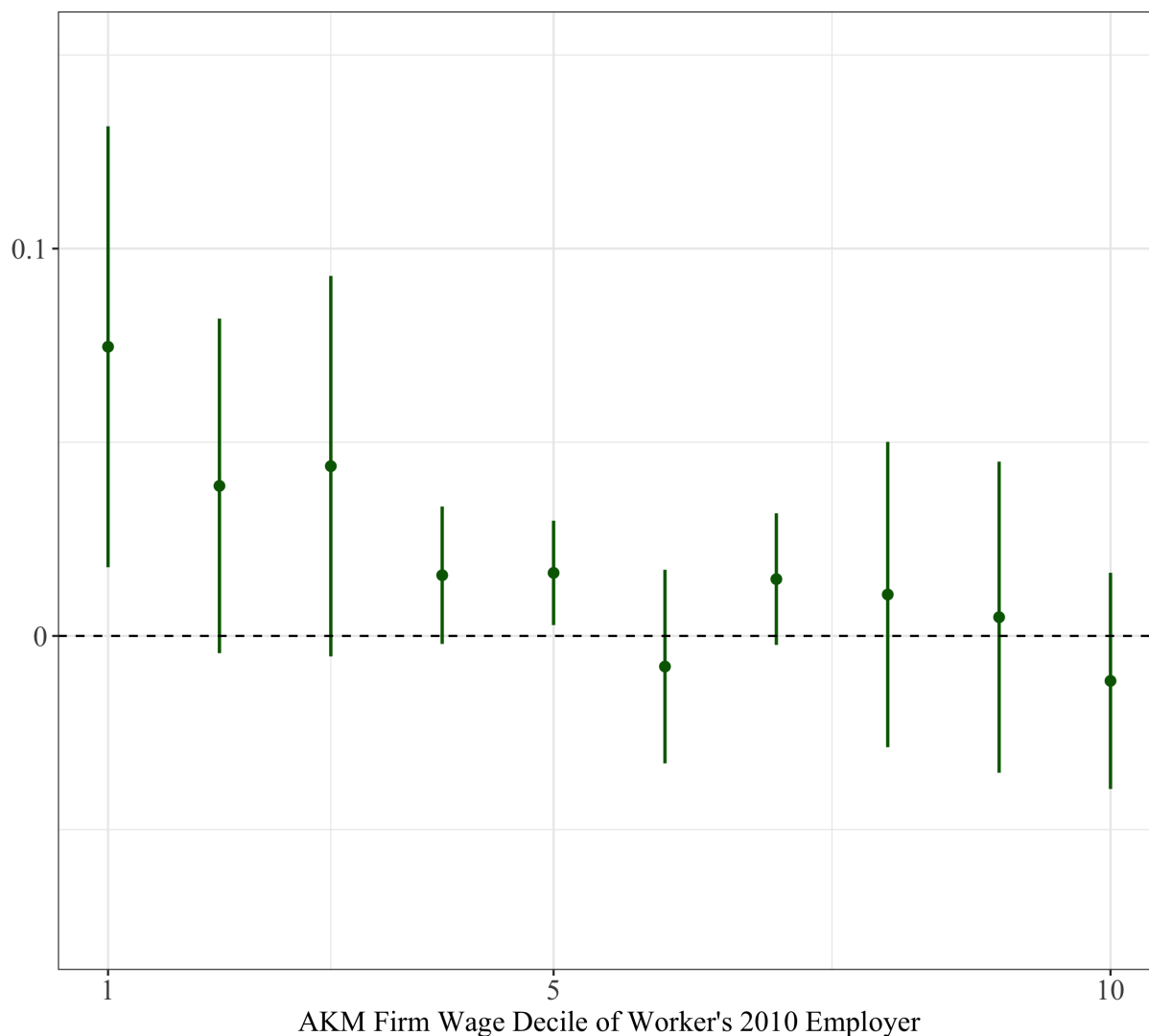
This figure plots coefficients from the event-study regression in **Equation 4**. The top panel plots coefficients from two regressions where the outcomes are the log wages of German and Foreign firm stayer wages, respectively. The bottom panel depicts the log of the relative wage $\log(w_{Nj}/w_{Mj})$, i.e., the log of the mean wage among native firm stayers divided by the mean foreign wage among firm stayers.

Table 3: Effects of Firm-Level Migrant Inflow on Incumbent Workers

| | (1) | (2) | (3) |
|------------------------------------|-------------------|-------------------|-------------------|
| Dependent Variable | | | |
| Chg. AKM Firm Wage Premium | 0.459 (0.136) | 0.48 (0.142) | 0.421 (0.138) |
| Chg. Log Commute | 0.18 (0.059) | 0.183 (0.05) | 0.204 (0.063) |
| Chg. Log Wage | 0.162 (0.05) | 0.27 (0.049) | 0.166 (0.048) |
| Chg. Firm Foreign Share | -0.246 (0.067) | -0.219 (0.063) | -0.214 (0.06) |
| Chg. Firm EUEN Foreign Share | -0.195 (0.058) | -0.185 (0.046) | -0.183 (0.055) |
| Log(1 + Days Non-Employed) | -0.05 (0.038) | -0.08 (0.045) | -0.07 (0.041) |
| Net Foreign Inflow (2010 Employer) | 0.554 (0.131) | 0.522 (0.129) | 0.507 (0.142) |
| Controls | | | |
| Worker Controls | ✓ | | ✓ |
| Firm Controls | | ✓ | ✓ |

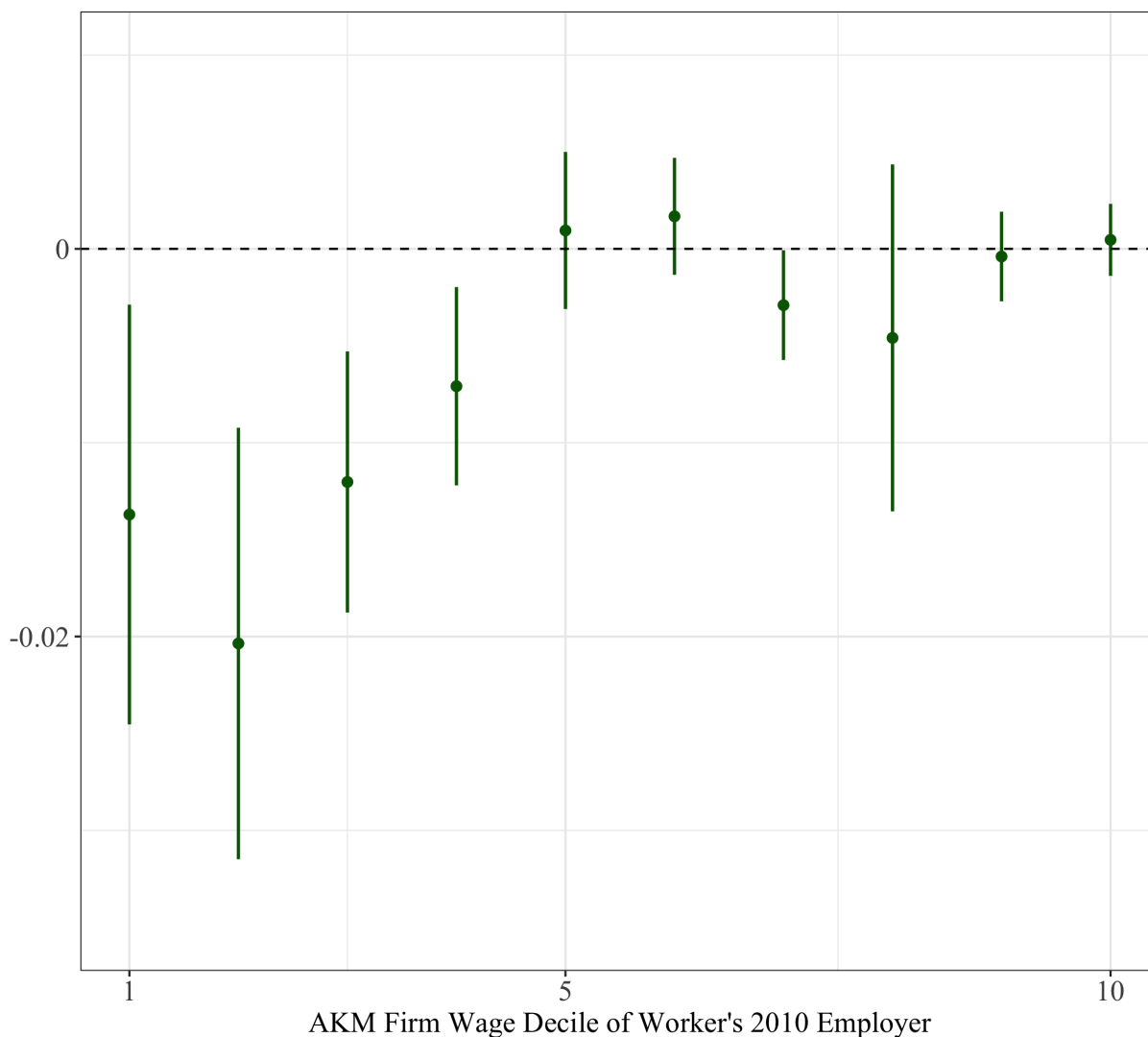
This table displays coefficients and associated standard errors from regressions described in [Equation 5](#). These are regressions of the form $\Delta y_i = \alpha + \gamma z_{j(i,2010)} + X_i' \beta + \epsilon_i$ where i indexes workers, j indexes firms (so that $j(i, 2010)$ refers to workers i 's employer in 2010), $\Delta y_i := y_{i,2014} - y_{i,2010}$ refers to the change in worker i 's outcome between 2010 and 2014, z_j is the shift-share of firm j , and X_i is a vector of controls. Worker controls include polynomials in age, experience, and tenure (calculated in 2010), as well as dummies for education (3 levels) and gender. Firm controls include industry (13 levels), commuting zone (50 levels), and firm size ventile fixed effects, corresponding to the sector, location, and size of i 's 2010 employer. The regression is run on a sample of all German workers for whom the variable $z_{j(i,2010)}$ is defined and non-zero (see [Section 6](#) for details). Each coefficient comes from a separate regression. Standard errors are clustered at the firm level, where firm corresponds to the worker's' employer in 2010.

Figure 11: Worker Market IV: Change in AKM of Current Employer 2010-14.



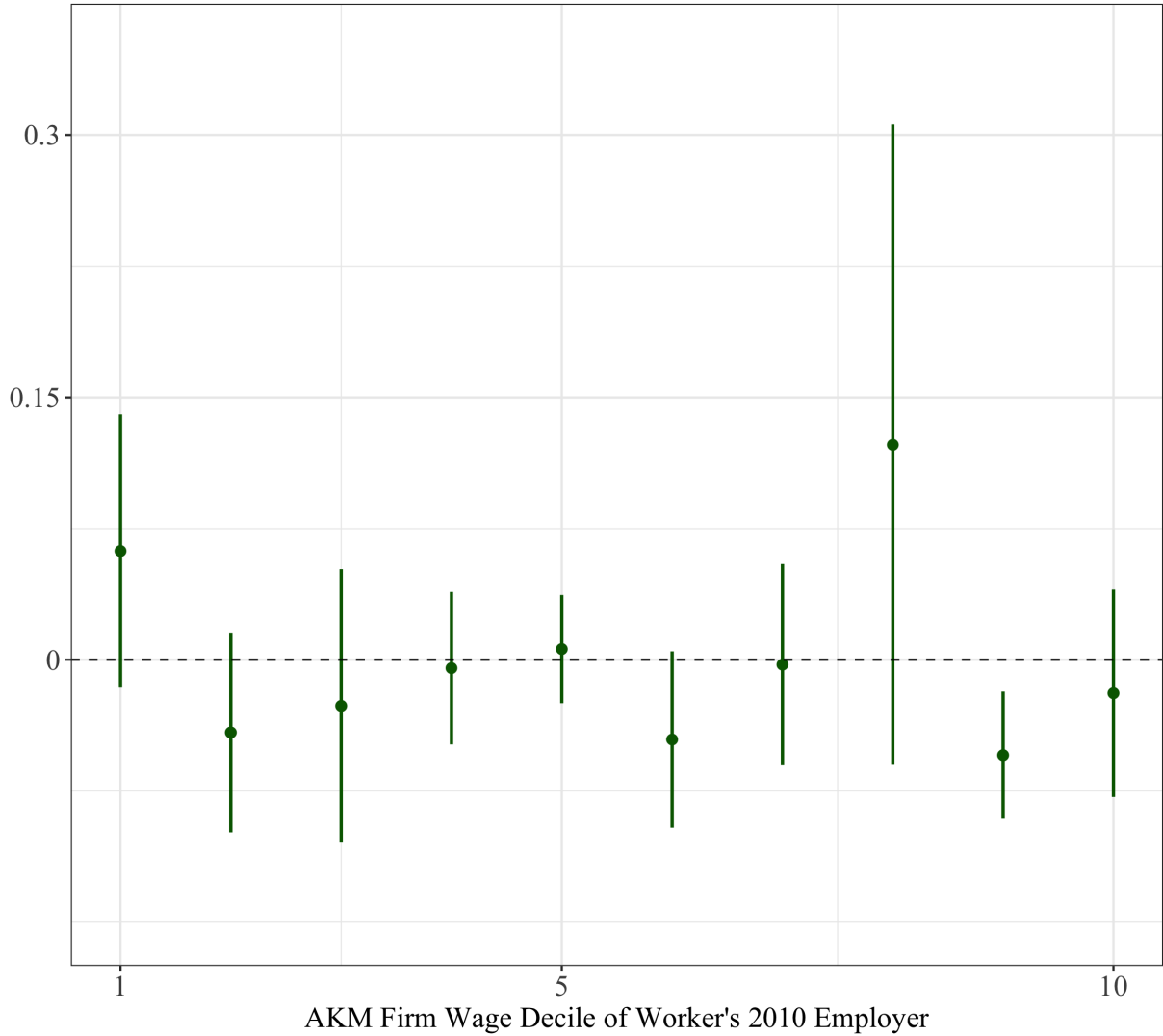
This figure plots coefficient estimates and 95% confidence intervals for the parameter γ_a from the sequence of regressions described in **Equation 7**. The dependent variable is the difference between the AKM firm effect of the worker's 2014 employer and their 2010 employer. The regressions are run at the worker level and stratified by the decile of the worker's 2010 employer's AKM firm effect, which are on the horizontal axis. The coefficient plotted is the coefficient on the shift-share measuring the local labor market-level exposure to EUEN migrant inflows. All coefficients were scaled so that they represent the effect of a 5 percentage point increase in the shift-share. Local labor markets are measured by districts (*kreise*) of which there are 401 in Germany. Standard errors are clustered at the district level.

Figure 12: Worker Market IV: Change in EUEN Share of Current Employer 2010-14.



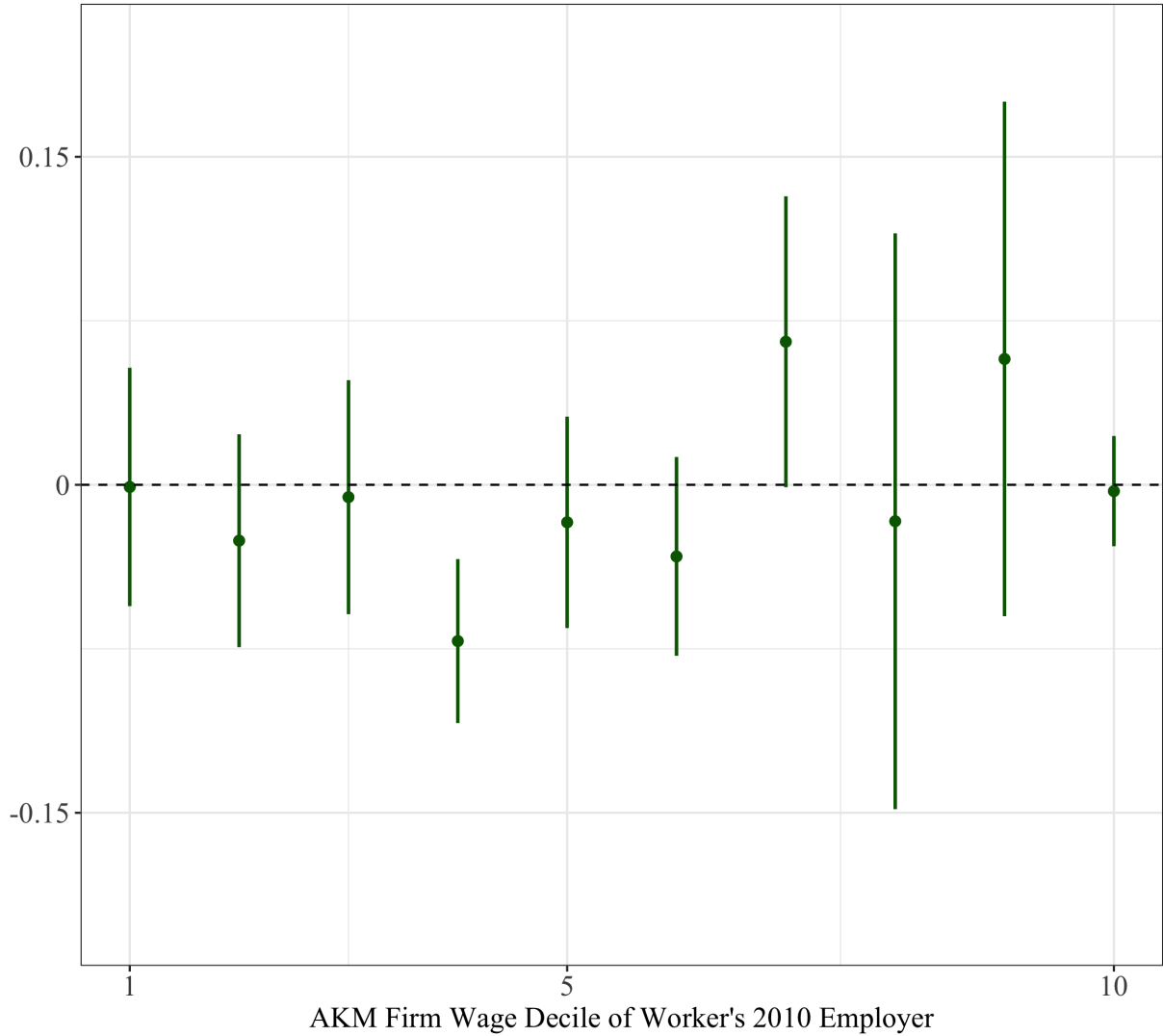
This figure plots coefficient estimates and 95% confidence intervals for the parameter γ_a from the sequence of regressions described in **Equation 7**. The dependent variable is the difference between the EUEN foreign share of the worker's 2014 employer and their 2010 employer. EUEN refers to the EU enlargement nations of Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia. EUEN share is calculated over the period 2011-14. The regressions are run at the worker level and stratified by the decile of the worker's 2010 employer's AKM firm effect, which are on the horizontal axis. The coefficient plotted is the coefficient on the shift-share measuring the local labor market-level exposure to EUEN migrant inflows. All coefficients were scaled so that they represent the effect of a 5 percentage point increase in the shift-share. Local labor markets are measured by districts (*kreise*) of which there are 401 in Germany. Standard errors are clustered at the district level.

Figure 13: Worker Market IV: Change in Log Wage.



This figure plots coefficient estimates and 95% confidence intervals for the parameter γ_d from the sequence of regressions described in **Equation 7**. The dependent variable is the change in each worker's wages between 2010 and 2014. The regressions are run at the worker level and stratified by the decile of the worker's 2010 employer's AKM firm effect, which are on the horizontal axis. The coefficient plotted is the coefficient on the shift-share measuring the local labor market-level exposure to EUEN migrant inflows. All coefficients were scaled so that they represent the effect of a 5 percentage point increase in the shift-share. Local labor markets are measured by districts (*kreise*) of which there are 401 in Germany. Standard errors are clustered at the district level.

Figure 14: Worker Market IV: Change in Employment Status.



This figure plots coefficient estimates and 95% confidence intervals for the parameter γ_a from the sequence of regressions described in **Equation 7**. The dependent variable is the change in a dummy equal to one if the worker is employed full time and zero otherwise. The regressions are run at the worker level and stratified by the decile of the worker's 2010 employer's AKM firm effect, which are on the horizontal axis. The coefficient plotted is the coefficient on the shift-share measuring the local labor market-level exposure to EUEN migrant inflows. All coefficients were scaled so that they represent the effect of a 5 percentage point increase in the shift-share. Local labor markets are measured by districts (*kreise*) of which there are 401 in Germany. Standard errors are clustered at the district level.

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A Data Appendix

A.1 AKM Firm Effect Imputation

We obtain AKM firm effects calculated by Lochner, Seth, and Wolter (2023) during the period 2003-10 and 2010-17. For firms who have no AKM firm effect, we follow Dustmann, Lindner, Schönberg, Umkehrer, and vom Berge (2022) and impute their value using information on firm size, share of full-time workers, and industry. Specifically, we fit models

$$\hat{\psi}_j = \alpha_{Ind(j)} + \alpha_{FirmSize(j)} + \beta \text{ShareFT}_j + \varepsilon_j$$

where $\alpha_{Ind(j)}$ are fixed effects for industry at the 5-digit level, $\alpha_{FirmSize(j)}$ are dummies for a set of firm size bins²⁶, and ShareFT_j is the share of workers who are employed full-time at firm j . All values are calculated by taking an average over the period (e.g., for the 2003-10 AKM firm effects, the firm's average firm size over the period 2003-10 is used).

B Model Appendix

B.1 Micro-Foundation of Labour Supply

In the model, we assumed migrant labour supply curves facing the firm of the form

$$\ln M_j = \ln M + \beta \ln w_j + \log a_{Mj}.$$

In this appendix, we provide a micro-foundation based on a discrete choice model where workers have limited information about jobs. The coefficients a_{Mj} in the model represent a combination of the average migrant's preference for the non-wage amenities of firm j , as well as their information about job opportunities at firm j .

²⁶The firm size bins are 0-4, 5-9, 10-24, 25-49, 50-99, 100-149, 150-249, 250-499, 500-999, 1000+

In section A.1 we set up the limited information model, which features both random consideration sets and idiosyncratic tastes. In section A.2 we prove that the limited information model is equivalent to a model with only random taste shocks. In Section A.3 we show that a_{Mj} is a weighted average of parameters summarizing migrants' tastes and information with weights depending on the ethnic composition of the labour market. The results in this section build closely on arguments from [Goeree \(2008\)](#) and [Abaluck and Adams-Prassl \(2021\)](#).

B.1.1 A Limited Information Firm Choice Model

Workers do not observe all jobs in a market, they observe only a random subset of jobs $S \in \mathcal{S}$. Denoting the event that worker i observes job j by A_{ij} , the probability of an immigrant from country c_i observing j is $P(A_{ij} = 1|c_i)$. Assuming a single-index structure $A_{ij} = 1\{c_{ij}\gamma + \eta_{ij}\}$ where η_{ij} are independent across j , the probability of an immigrant from country c_i being aware of a given set of jobs S is

$$P(S|c_i) = \prod_{l \in S} P(A_{il} = 1|c_i) \cdot \prod_{k \notin S} P(A_{ik} = 0|c_i).$$

Each worker then chooses with firm to work at among those they are aware of by solving

$$\max_{j \in S} \beta \ln w_j + b_{cj} + \epsilon_{ij}$$

where b_{cj} represent the average preference of migrants from country c for the non-wage amenities of firm j , and $\epsilon_{ij} \sim T1EV$ is an idiosyncratic taste shock. Denoting the event that worker i supplies labour to firm j by Y_{ij}^* conditional on observing it, and let Y_{ij} denote the unconditional equivalent. By standard arguments,

$$P(Y_{ij}^*|c_i, S) = \frac{\exp(\beta \ln w_j + \ln b_{cj})}{\sum_{k \in S} \exp(\beta \ln w_k + \ln b_{ck})}$$

and

$$P(Y_{ij}|c_i) = \sum_{S \in \mathcal{S}} P(S|c_i)P(Y_{ij}^*|c_i, S).$$

Workers from country c are therefore more likely to be observed working in firms that pay high wages w_j , that provide highly valued non-wage amenities b_{cj} , and that they are more likely to be aware of.

B.1.2 Equivalence to Full Information Model

We now show that the model described above is equivalent to a full information model. Specifically, we show that there exists ψ_j such that the model above is equivalent to a full information model where i 's utility from working at j is given by

$$U_{ij} = \beta \ln w_i + \ln b_{c_{ij}} + \psi_j + \epsilon_j.$$

To simplify notation, we suppress dependence on country of origin c_i . We will show that equivalence holds for

$$\psi_j = \ln \left(\frac{P(A_j) \sum_{k \neq j} \exp(\beta \ln w_k + \ln b_k + \psi_k)}{(1 - P(A_j)) \exp(\beta \ln w_j + \ln b_j) + \sum_{k \neq j} \exp(\beta \ln w_k + \ln b_k + \psi_k)} \right). \quad (9)$$

We proceed by induction. To begin, assume there are two firms indexed 0 and 1. Firm 0 is observed with certainty while firm 1 is observed with probability $P(A_{i1})$. Then the probability that firm 1 is chosen in the limited information model is

$$P(Y_{i1} = 1) = P(A_{i1})P(Y_{i1}^* = 1)$$

where

$$P(Y_{i1}^* = 1) = \frac{\exp(\beta \ln w_1 + \ln b_1)}{\exp(\beta \ln w_0 + \ln b_0) + \exp(\beta \ln w_1 + \ln b_1)}.$$

In the complete information model where $\psi_0 = 1$ and

$$\psi_1 = \ln \left(\frac{P(A_1) \exp(\beta \ln w_0 + \ln b_0)}{(1 - P(A_1)) \exp(\beta \ln w_1 + \ln b_1) + \exp(\beta \ln w_0 + \ln b_0)} \right),$$

the probability that firm 1 is chosen is

$$\begin{aligned} P(Y_{i1}^* = 1) &= \frac{\exp(\beta \ln w_1 + \ln b_1 + \psi_1)}{\exp(\beta \ln w_0 + \ln b_0) + \exp(\beta \ln w_1 + \ln b_1 + \psi_1)} \\ &= P(A_1) \frac{\exp(\beta \ln w_1 + \ln b_1)}{\exp(\beta \ln w_0 + \ln b_0) + \exp(\beta \ln w_1 + \ln b_1)} \end{aligned}$$

which shows that the two models are equivalent for the case with two firms. Now assume that the result holds for firms $j \in \{0, \dots, J-1\}$:

$$P(Y_{ij} = 1) = \frac{\exp(\beta \ln w_j + b_j + \psi_j)}{\sum_{k=1}^{J-1} \exp(\beta \ln w_k + \ln b_k + \psi_k)} = P(A_j) P(Y_{ij}^* = 1).$$

Adding firm J as an alternative to the full-alternative model gives

$$P(Y_{iJ}^* = 1) = \frac{\exp(\beta \ln w_J + \ln b_J)}{\exp(\beta \ln w_J + \ln b_J) + \sum_{k=0}^{J-1} \exp(\beta \ln w_k + \ln b_k + \psi_k)}$$

Finally, we confirm that the models are equivalent when setting ψ_J according to (9):

$$\begin{aligned} P(A_j) P(Y_{iJ}^* = 1) &= \frac{\exp(\beta \ln w_J + \ln b_J + \psi_J)}{\exp(\beta \ln w_J + \ln b_J + \psi_J) + \sum_{k=0}^{J-1} \exp(\beta \ln w_k + \ln b_k + \psi_k)} \\ &= \frac{\exp(\beta \ln w_J + \ln b_J) \exp(\psi_J)}{\exp(\beta \ln w_J + \ln b_J) \exp(\psi_J) + \sum_{k=0}^{J-1} \exp(\beta \ln w_k + \ln b_k + \psi_k)} \\ &= P(A_j) \frac{\exp(\beta \ln w_j + b_j + \psi_j)}{\sum_{k=1}^{J-1} \exp(\beta \ln w_k + \ln b_k + \psi_k)}. \end{aligned}$$

B.1.3 Effect of A Change in Market-Level Ethnic Composition

Since migrants' preferences and information about jobs vary according to their country of origin, a change in the ethnic composition of a labour market will affect some firms more

than others. In this section, we derive expressions for the change in labour supply to each firm for a generic immigration shock.

$$M_{jt} = M_t a_{M_{jt}} w_j^\beta = w_j^\beta M_t \left[\sum_c \left(\frac{M_{ct}}{M_t} \right)^{a_{M_{cj}}} \right]$$

Take logs

$$\log M_{jt} = \beta \ln w_j + \log M_t + \log \left[\sum_c \left(\frac{M_{ct}}{M_t} \right)^{a_{M_{cj}}} \right]$$

Take derivative with respect to M_{ct}/M_t :

$$\frac{\partial \log M_{jt}}{\partial M_{ct}/M_t} = \frac{a_{M_{jc}}}{a_{M_j}}$$

then the total derivative of labour supply to a firm from a shock to labour supply is

$$d \log M_{jt} = d \log M_t + \sum_c \frac{a_{M_{jc}}}{a_{M_j}} \cdot d \frac{M_{ct}}{M_t}$$

B.2 Model Derivations

In this section we consider a more general case of the model considered in [Section 5](#) and provide a detailed derivation of Proposition 1. The model is extended to accommodate imperfect substitution between native-born and migrant workers, heterogeneous labor supply elasticities and productivity of native and migrant-born labor, and an imperfectly competitive product market. The model we consider is closely related to the models in [Card, Cardoso, Heining, and Kline \(2018\)](#), [Lindner, Muraközy, Reizer, and Schreiner \(2022\)](#) and [Lamadon, Mogstad, and Setzler \(2022\)](#). While the model is fair standard, the results we prove are (to the best of our knowledge) new.²⁷

²⁷In an early draft of [Card, Cardoso, Heining, and Kline \(2018\)](#) (available at https://eml.berkeley.edu/~pkline/papers/CCHK_NBER_slides.pdf), the authors suggest that a future area of research would be to study the effects “supply shocks to individual firms” in this class of models, noting that these correspond to

As in the baseline model, firm $j \in \{1, \dots, J\}$ faces native and migrant labor supply curves

$$N_j = N\lambda_N \cdot w_{Nj}^{\beta_N} a_{Nj} \qquad M_j = M\lambda_M \cdot w_{Mj}^{\beta_M} a_{Mj} \qquad (10)$$

where w_{Nj} and w_{Mj} are posted wages and $\lambda_G = (\sum_k w_{Gk}^{\beta_G} a_{Gk})^{-1}$ for $G \in \{N, M\}$ is an index. As shown in [Section B.1](#), these labor supply functions can be micro-founded by a discrete choice model where workers with limited information about jobs and heterogeneous preferences over firm non-wage attributes select which firm to work at. The parameters a_{Nj} , a_{Mj} reflect a combination of the information and preferences of the average native-born and migrant worker, respectively. Firm j combines migrant and native-born labor to produce Y_j units of a differentiated good according to the production function

$$Y_j = A_j \cdot [\theta_N N_j^\rho + \theta_M M_j^\rho]^{(1-\eta)/\rho}$$

which it sells in an imperfectly competitive product market where it faces the inverse demand curve

$$P_j = P_{j0} \cdot Y_j^{-1/\varepsilon}.$$

The elasticity of substitution between native-born and migrant labor is $\frac{1}{1-\rho}$ for $\rho \in [1, \infty)$, the product demand elasticity is ε , θ_N and θ_M govern the relative productivity of native and migrant labor, and $1 - \eta$ is the degree of returns to scale. The model considered in [Section 5](#) corresponds to the case $\varepsilon \rightarrow \infty$, $\rho = 1$, $\beta_N = \beta_M = \beta$, and $\theta_N = \theta_M = 1$.

Firms set wages w_{Nj} , w_{Mj} to maximize revenue minus the cost of labor taking subject to product demand and labor supply, treating λ_M and λ_N as fixed.²⁸ Firm first-order conditions

the “converse of [the] rent sharing literature” that estimates the pass-through of shocks to firm value-added to wages. The results in this section fill this gap, and we go beyond supply shocks to individuals firms and consider arbitrary distributions of supply shocks across firms.

²⁸The assumption that firms treated λ_N and λ_M as fixed—in the parlance of [Lamadon, Mogstad, and Setzler \(2022\)](#) term, firms are “strategically small”—rules out strategic wage-setting whereby firms with a large market share consider the spill-over effects of their own wages on over-all market-level wages. Relaxing this assumption in future analyses of immigration is a fruitful avenue for future research. Papers considering this form of labor market power include [Berger, Herkenhoff, and Mongey \(2022\)](#), [Chan, Kroft, and Mourifie](#)

imply that

$$w_{Nj} = \log \psi_{Nj} + (\rho - 1) \log N_j + \phi \log[\theta_N N_j^\rho + \theta_M M_j^\rho] \quad (11)$$

$$w_{Mj} = \log \psi_{Mj} + (\rho - 1) \log M_j + \phi \log[\theta_N N_j^\rho + \theta_M M_j^\rho] \quad (12)$$

where

$$\begin{aligned} \phi &:= \frac{\eta - 1}{\rho \varepsilon} + \frac{1 - \eta - \rho}{\rho} \\ \psi_{Nj} &= \theta_N \left(\frac{\beta_N}{\beta_N + 1} \right) \cdot \left(\frac{\varepsilon - 1}{\varepsilon} \right) (1 - \eta) \cdot P_{j0} A_j^{1-1/\varepsilon} \\ \psi_{Mj} &= \theta_M \left(\frac{\beta_M}{\beta_M + 1} \right) \cdot \left(\frac{\varepsilon - 1}{\varepsilon} \right) (1 - \eta) \cdot P_{j0} A_j^{1-1/\varepsilon}. \end{aligned}$$

Our goal is to derive the total effect of an arbitrary migrant supply shock (dM_1, \dots, dM_J) on average native-born log wages:

$$d \log \bar{w}_N = \sum_k \sum_j \left(\frac{\partial}{\partial M_k} \sum_j s_{Nj} \log w_{Nj} \right) d \log M_k,$$

where

$$\log \bar{w}_N = \sum_j \left(\frac{N_j}{N} \right) \log w_{Nj} = \sum_j s_{Nj} \log w_{Nj}.$$

In particular, we are interested in the following decomposition:

$$d \log \bar{w}_N = \underbrace{\sum_k \sum_j s_{Nj} \cdot \frac{\partial \log w_{Nj}}{\partial \log M_k} \cdot d \log M_k}_{\text{Competition}} + \underbrace{\sum_k \sum_j \frac{\partial s_{Nj}}{\partial \log w_{Nk}} \cdot \log M_k \cdot d \log w_{Nj}}_{\text{Mobility}}.$$

Competition is the effect on wages holding the distribution of natives across firms fixed, while mobility is the effect on native re-allocation across firms holding wages fixed. Throughout the analysis, we treat migrant labor supply to each firm as fixed aside from the shocks under [\(2023\)](#) and [Sharma \(2022\)](#).

consideration. Specifically, we assume $\frac{\partial \log M_j}{\partial \log M_k} = 0$ for $j \neq k$, ruling out second-order knock-on effects on firm-level migrant labor supply.

The effect of a migrant labor supply shock to firm k on native-born wages at firm j is

$$\frac{\partial \log w_{Nj}}{\partial \log M_k} = \begin{cases} \alpha_1(q_{Nj}) \cdot \frac{\partial \lambda_N}{\partial \log M_j} + \rho\phi \cdot \alpha_2(q_{Mj}) \cdot q_{Mj} & \text{if } k = j \\ \alpha_2(q_{Mj}) \cdot \frac{\partial \log \lambda_N}{\partial \log M_k} & \text{if } k \neq j \end{cases}$$

where

$$\alpha_1(q) = \left(\frac{\rho - 1 + \rho\phi q}{1 - \beta_N(\rho - 1 + \rho\phi q)} \right) \quad \alpha_2(q) = \left(\frac{1}{1 - \beta_N(\rho - 1 + \rho\phi(1 - q))} \right) \quad (13)$$

and

$$q_{Nj} = \frac{\theta_N N_j^\rho}{\theta_N N_j^\rho + \theta_M M_j^\rho} \quad q_{Mj} = \frac{\theta_M M_j^\rho}{\theta_N N_j^\rho + \theta_M M_j^\rho}.$$

To derive the above equation, we differentiate the wage equation (11) to get

$$\frac{\partial \log w_{Nj}}{\partial \log M_k} = (\rho - 1) \cdot \frac{\partial \log N_j}{\log w_{Mk}} + \phi \left(\frac{1}{\theta_N N_j^\rho + \theta_M M_j^\rho} \right) \cdot \left[\rho q_{Nj} \frac{\partial \log N_j}{\log M_k} + \rho q_{Mj} \frac{\partial \log M_j}{\partial \log M_k} \right]. \quad (14)$$

We then differentiate the log of the native labor supply equation from (10)

$$\frac{\partial \log N_j}{\partial M_k} = \frac{\partial \log \lambda_N}{\partial \log M_k} + \beta_N \frac{\partial \log w_{Nj}}{\partial \log M_k},$$

substitute it into (14), and impose $\frac{\partial \log M_j}{\partial \log M_k} = 1\{j = k\}$, which can be rearranged to obtain (13). The semi-elasticity of native employment shares with respect to migrant shock at firm k is

$$\frac{\partial s_{Nj}}{\partial \log M_k} = s_{Nj} \frac{\partial \log s_{Nj}}{\partial \log M_k} = s_{Nj} \frac{\partial \log N_j}{\partial \log M_k} = s_{Nj} \frac{\partial \log \lambda_N}{\partial \log M_k} + \beta_N s_{Nj} \frac{\partial \log w_{Nj}}{\partial \log M_k},$$

where the first equality converts semi-elasticity to elasticity, and the second equality holds because $N_j = N s_{Nj}$. The Competition component is equal to:

$$\begin{aligned}
& \sum_k \sum_j s_{Nj} \frac{\partial \log w_{Nj}}{\partial \log M_k} d \log M_k \\
&= \sum_k s_{Nk} \left[\alpha_1(q_{Nk}) \cdot \frac{\partial \log \lambda_N}{\partial \log M_k} \cdot + \rho \phi \cdot \alpha_2(q_{Mk}) \cdot q_{Mk} \right] d \log M_k \\
&+ \sum_k \sum_{j \neq k} s_{Nj} \left[\alpha_2(q_{Mj}) \cdot \frac{\partial \log \lambda_N}{\partial \log M_k} \right] d \log M_k \\
&= \rho \phi \sum_k s_{Nk} \alpha_2(q_{Mk}) q_{Mk} d \log M_k + \sum_j s_{Nj} \alpha_1(q_{Nj}) \sum_k \frac{\partial \log \lambda_N}{\partial \log M_k} d \log M_k \\
&= \rho \phi \sum_k s_{Nk} \tilde{q}_{Mk} d \log M_k + \bar{\alpha}_1(q_N) d \log \lambda_N.
\end{aligned}$$

where $\tilde{q} := \alpha_2(q)q$ and $\bar{\alpha}_1(q_N) := \sum_j s_{Nj} \alpha_1(q_{Nj})$. The Mobility component is equal to:

$$\begin{aligned}
& \sum_k \sum_j \frac{\partial s_{Nj}}{\partial \log w_{Nk}} \cdot \log w_{Nj} \cdot d \log M_k \\
&= \sum_k \sum_j \left[s_{Nj} \frac{\partial \log \lambda_N}{\partial \log M_k} + \beta_N s_{Nj} \frac{\partial \log w_{Nj}}{\partial \log M_k} \right] \cdot \log w_{Nj} \cdot d \log M_k \\
&= \sum_k \left[(1 + \beta_N(q_{Nk})) \frac{\partial \log \lambda_N}{\partial \log M_k} s_{Nk} + \beta_N \rho \phi \cdot \alpha_2(q_{Mk}) q_{Mk} s_{Nk} \right] \log w_{Nk} d \log M_k \\
&+ \sum_k \sum_{j \neq k} \left[(1 + \beta_N(q_{Nj})) \frac{\partial \log \lambda_N}{\partial \log M_k} s_{Nj} \right] \log w_{Nj} d \log M_k \\
&= \beta_N \rho \phi \sum_k s_{Nk} \log w_{Nk} \alpha_2(q_{Mk}) q_{Mk} d \log M_k \\
&+ \sum_j s_{Nj} (1 + \beta_N(q_{Nj})) \log w_{Nj} \sum_k \frac{\partial \log \lambda_N}{\partial \log M_k} d \log M_k \\
&= \beta_N \rho \phi \sum_k s_{Nk} \log w_{Nk} \tilde{q}_{Mk} d \log M_k + \overline{(1 + \beta_N(q_N)) \log w_N} d \log \lambda_N,
\end{aligned}$$

where $\overline{(1 + \beta_N(q_N)) \log w_N} = \sum_j s_{Nj} (1 + \beta_N(q_{Nj})) \log w_{Nj}$. Focusing on the first term in the last line above, we recognize it as the inner product of the vectors $\log w_N = (\log w_{N1}, \dots, \log w_{NJ})$ and $q_M d \log M = (\tilde{q}_{M1}, \dots, d \log M_J)$ with weights $s_N = (s_{N1}, \dots, s_{NJ})$. Considering $\log w_N$

and $q_M d \log M$ to be random vectors and s_N a set of probability weights, it can also be viewed as the expectation of the product of the two random variables. We then use the fact that $E[XY] = E[X]E[Y] + Cov(X, Y)$ to re-write

$$\sum_k s_{Nk} \log w_{Nk} \tilde{q}_{Mk} d \log M_k = E[\log w_{Nk}] E[\tilde{q}_{Mk} d \log M_k] + Cov(\log w_{Nk}, \tilde{q}_{Mk} d \log M_k).$$

Using this substitution, we can write the sum of the Competition and Mobility components as

$$d \log \bar{w}_N = \alpha_0 + \kappa d \log \lambda_N + \rho \phi \sum_k s_{Nk} \tilde{q}_{Mk} d \log M_k + \beta_N \rho \phi \cdot Cov(\log w_N, \tilde{q}_M). \quad (15)$$

where α_0 and κ are constants. This constitutes the statement of our main result for the general model. In order to derive the main result in **Section 5**, we impose $\rho = 1$, $\epsilon \rightarrow \infty$, $\beta_N = \beta_M$, and $\theta_M = \theta_M = 1$. In this simplified model, we can express the log wage at firm j by

$$\log w_j = \alpha + \left(\frac{1}{1 + \eta\beta} \right) \log \psi_j - \left(\frac{\eta}{1 + \eta\beta} \right) \log (1 - \bar{m} a_{Mj} + (1 - \bar{m}) a_{Nj})$$

where $\bar{m} := \frac{M\lambda_M}{M\lambda_M + N\lambda_N}$. Imposing the parameters of the simplified model and substituting the above expression into **Equation 15** yields **Equation 3**:

$$\begin{aligned} d \log \bar{w}_N &= \alpha_0 + \kappa d \log \lambda_N \\ &\quad - \eta \sum_k s_{Nk} \tilde{m}_k d \log M_k \\ &\quad - \left(\frac{\eta\beta}{1 + \eta\beta} \right) Cov(\psi_j, \tilde{m}_j d \log M_k) + \eta \left(\frac{\eta\beta}{1 + \eta\beta} \right) Cov(\bar{a}_j, \tilde{m}_j d \log M_k), \end{aligned}$$

where \tilde{m}_j and \bar{a}_j are defined as in **Section 5**.

B.3 Extension: Uniform Wage Setting (Amior and Manning, 2023)

In this section, we consider version of the model presented in [Section B.2](#) where firms are migrants have lower labor supply elasticities than native-born workers ($\beta_N > \beta_M$) and firms are unable to wage discriminate and must set a uniform wage $w_j = w_{Nj} = w_{Mj}$. This assumption, which is inspired by [Amior and Stuhler \(2022\)](#) and [Amior and Manning \(2023\)](#), leads to a *monopsonistic spill-over* whereby the lower labor supply elasticity of migrants leads to a lower wage markdown for native-born workers. To facilitate exposition, we simplify the firm production function to be linear: $Y_j = A_j \cdot L_j$.

When wage discrimination is allowed, firms set w_{Nj} and w_{Mj} so that marginal cost equals the marginal product of labor

$$MCL_N(w_{Nj}) = MPL_j \qquad MCL_M(w_{Mj}) = MPL_j,$$

which results in the familiar Lerner index markdown for wages:

$$w_{Nj} = \left(\frac{\beta_N}{1 + \beta_N} \right) \cdot A_j \qquad w_{Mj} = \left(\frac{\beta_M}{1 + \beta_M} \right) \cdot A_j.$$

This case is depicted in the top panel of [Figure C14](#) below. With two wages, the firm can set a wage corresponding to the point where the marginal cost curve for each type of labor intersects the marginal productivity of labor.

When the firm is restricted to set uniform wages, wages are set according to

$$\phi = \frac{w_j}{MPL_j} = \left(\frac{\bar{\beta}}{1 + \bar{\beta}} \right)$$

where

$$\bar{\beta} = m_j \beta_M + (1 - m_j) \beta_N.$$

The firm sets wages using the same markdown formula, but now the markdown is a weighted

average of the native and migrant labor supply elasticities, with the weight proportional to the migrant share. Note however that in this model, the migrant share itself depends on the wage:

$$m_j = \frac{M_j}{L_j} = \frac{1}{1 + \frac{N}{M} \cdot \frac{a_{Nj}}{a_{Mj}} \cdot w_j^{\beta_N - \beta_M}}.$$

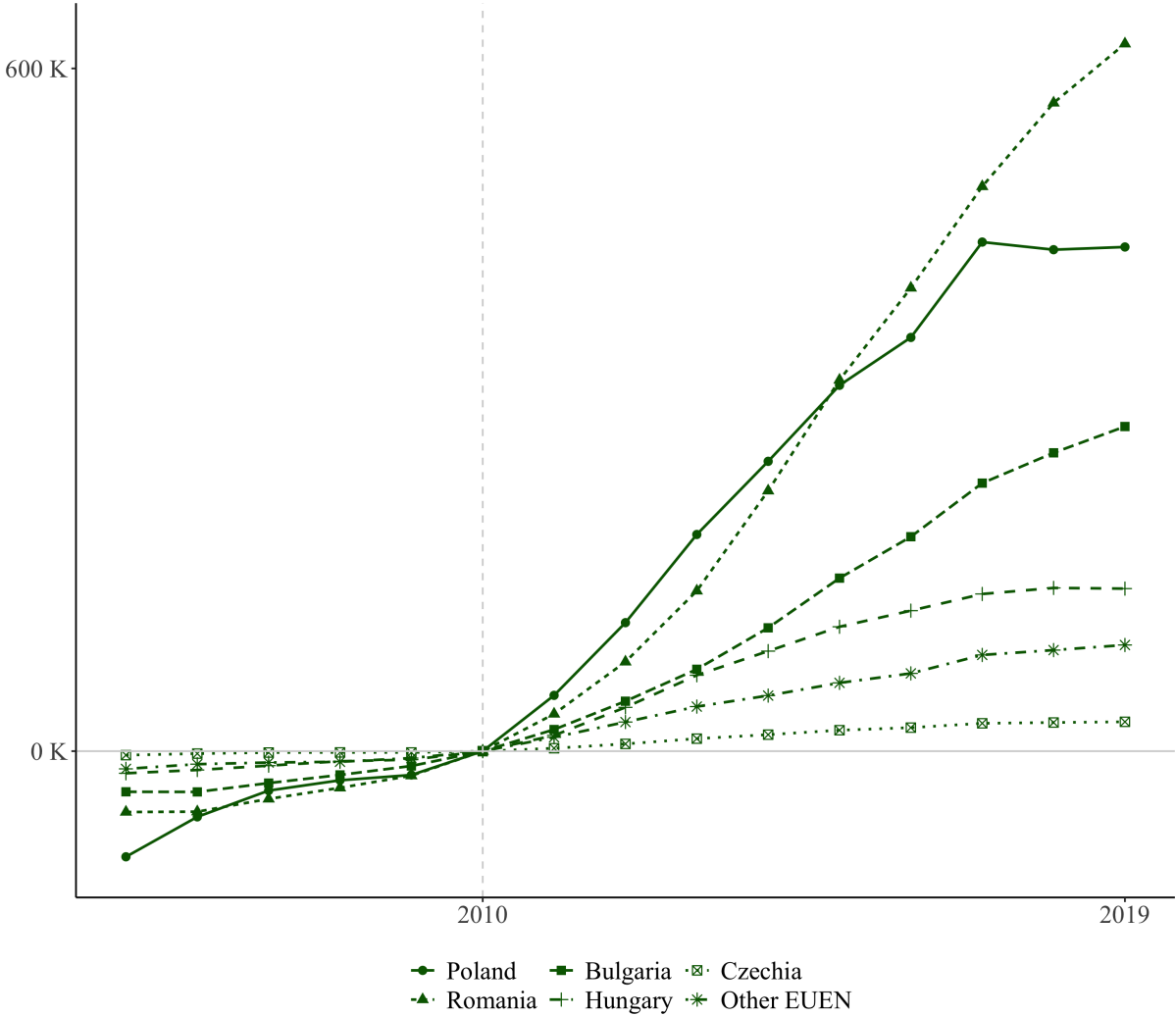
The firm therefore faces a trade-off. As it decreases the wage, it employs a greater share of migrants, and it is able to extract a larger profit by marking down the wage lower below marginal product. At very low values of the wage $w_j \approx 0$, the marginal cost of labor is approximately parallel to $MCL_M(w_j)$ from the perfect wage discrimination case. At very high wages, the migrant share approaches zero and the marginal cost of labor is approximately parallel to $MCL_N(w_j)$. For intermediate values, the marginal cost of labor *bends* from one curve to the other. The optimal wage is the point at which this new “bent” $MCL(w_j)$ intersects the marginal product of labor. This is depicted in the bottom panel of **Figure C14**.

In this model, an increase in migrant labor supply concentrated in a small subset of low-wage firms causes native-born workers to reallocate to other firms. Compared to the model in **Section 5**, however, in this model, reallocation of native-born workers increases wages at the target firm by lowering the migrant share. This is in contrast to the previous model, where native workers’ labor supply depresses wages at the target firm (by increasing labor supply). This model therefore exhibits stronger incentive to reallocate.

In **Amior and Stuhler (2022)** and **Amior and Manning (2023)**, monopsony power in the form of lower β_M (or, equivalently, a lower migrant outside option) unambiguously amplifies the negative wage effects of immigration. In a model with heterogeneous firms, however lower β_M has a more ambiguous effect. Migrant workers will be more concentrated in low wage firms, which reduces competition, and increases the positive effect of increases in the native-born worker share on wages at target firms, therefore amplifying the mobility channel.

C Additional Figures and Tables

Figure C1: Net Population Inflow Since 2010 by Country (EUE).



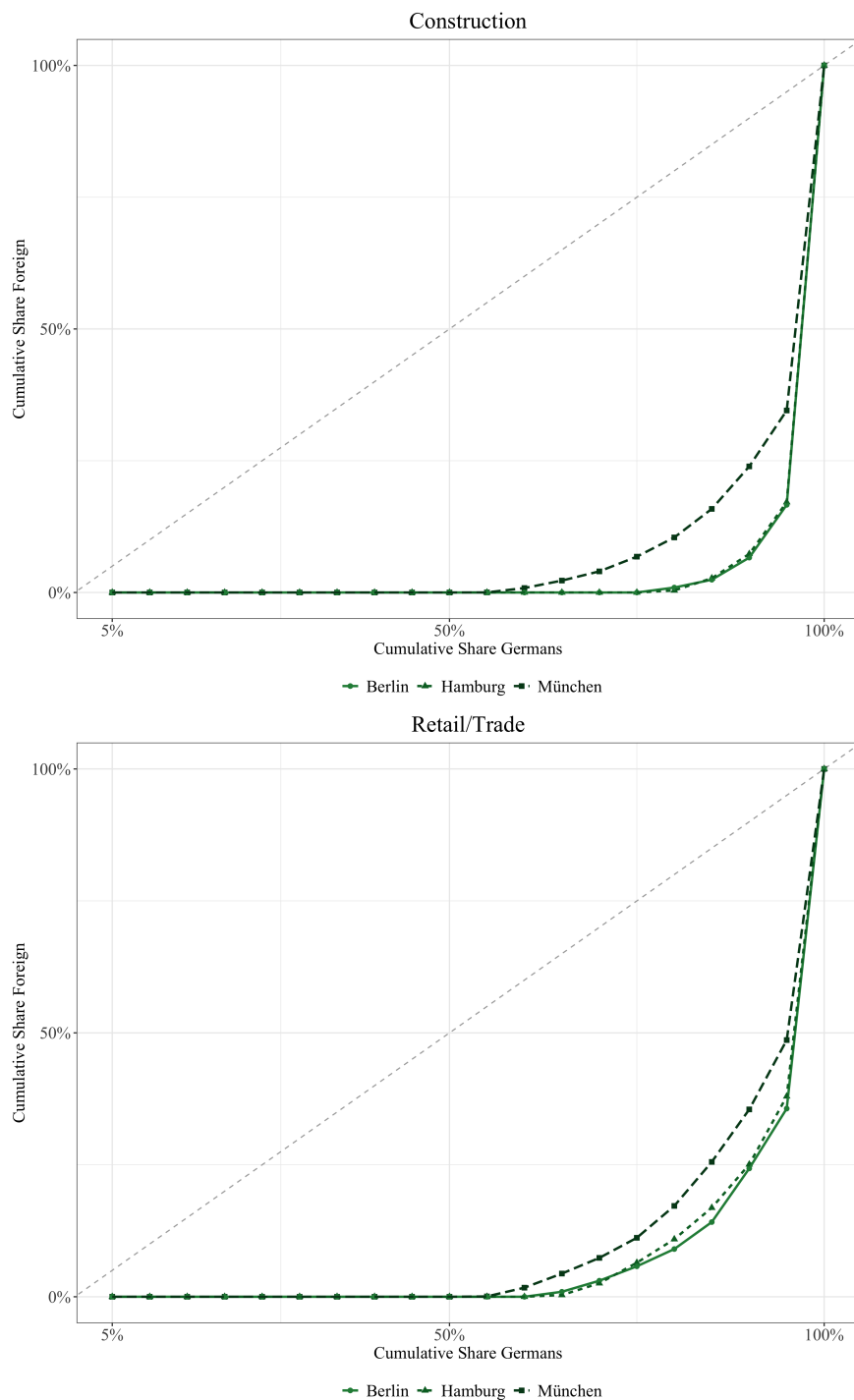
This figure depicts the net change in the number of individuals living in Germany since 2010 for each of the EU Enlargement countries. The “Other EUE” category includes individuals from Estonia, Latvia, Lithuania, Slovakia and Slovenia. Data are from the German Federal Statistical Office (DeStatis).

Table C1: Immigration to Germany 2005-19

| | 2005 | | 2010 | | 2014 | | 2019 | |
|----------------------------|------|------|------|------|------|------|------|------|
| | N | % | N | % | N | % | N | % |
| Panel A: Workers | | | | | | | | |
| EUEN | 0.1 | 0.5 | 0.2 | 0.8 | 0.6 | 2 | 1.3 | 3.7 |
| Non-EUEN Foreign | 1.7 | 5.8 | 1.9 | 6.3 | 2.4 | 7.3 | 3.6 | 10 |
| German | 27.9 | 93.7 | 29.4 | 92.9 | 30.5 | 90.7 | 31.1 | 86.4 |
| All workers | 29.8 | 100 | 31.6 | 100 | 33.6 | 100 | 36.1 | 100 |
| Panel B: Population | | | | | | | | |
| EUEN | 0.5 | 0.7 | 0.7 | 1 | 1.5 | 1.9 | 2.4 | 2.9 |
| Non-EUEN Foreign | 6.1 | 7.5 | 5.9 | 7.3 | 6.6 | 8.2 | 8.8 | 10.6 |
| German | 75.6 | 91.8 | 74.9 | 91.7 | 73.0 | 90 | 71.9 | 86.5 |
| All | 82.4 | 100 | 81.7 | 100 | 81.1 | 100 | 83.1 | 100 |

This table reports the levels and shares of total employment and population in Germany in the years 2005, 2010, 2014, and 2019 for different groups. EUEN refers to workers and individuals from the EU Enlargement Nations (Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia). Non-EUEN Foreign refers to foreign-born workers and individuals who are not EUEN. *N* counts the number of workers or individuals in millions, % calculates the share within each year. Panel A is calculated from data drawn from a 100% sample of German Social Security Records. Panel B is calculated from data from the German Federal Statistical Office (DeStatis).

Figure C2: Segregation Curves Within Industry-Commuting Zone



This figure plots segregation curves for the construction and retail industries in Berlin, Hamburg and Munich in 2014. The horizontal axis is the cumulative share of Germans, ordered by the share of their coworkers who are from the EU Enlargement Nations (EUN) of Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia. The vertical axis is the cumulative share of EUN foreign workers. The green lines are the segregation curves. The dashed grey line is the 45 degree line. Data come from a 100% sample of German social security records.

Figure C3: Migrant Firm Wage Sorting 2005-19 by AKM Firm Effect

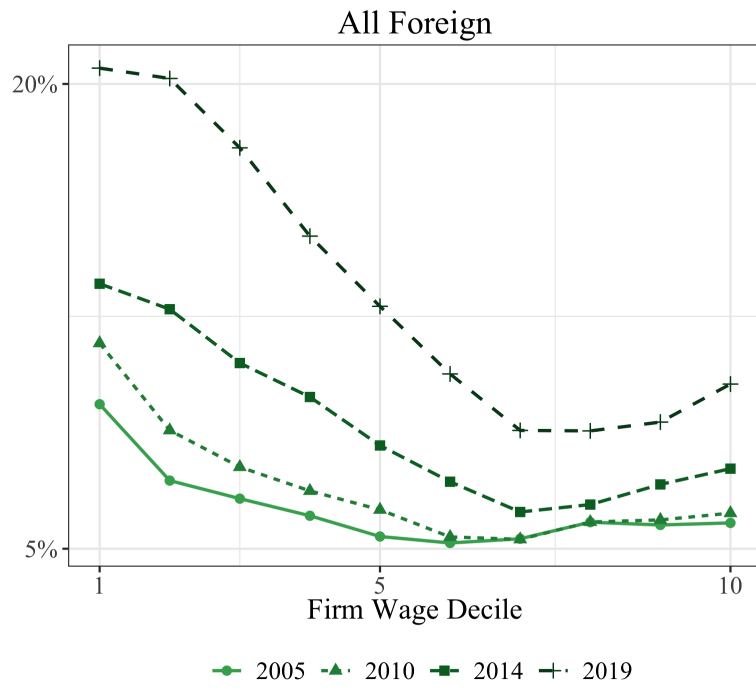
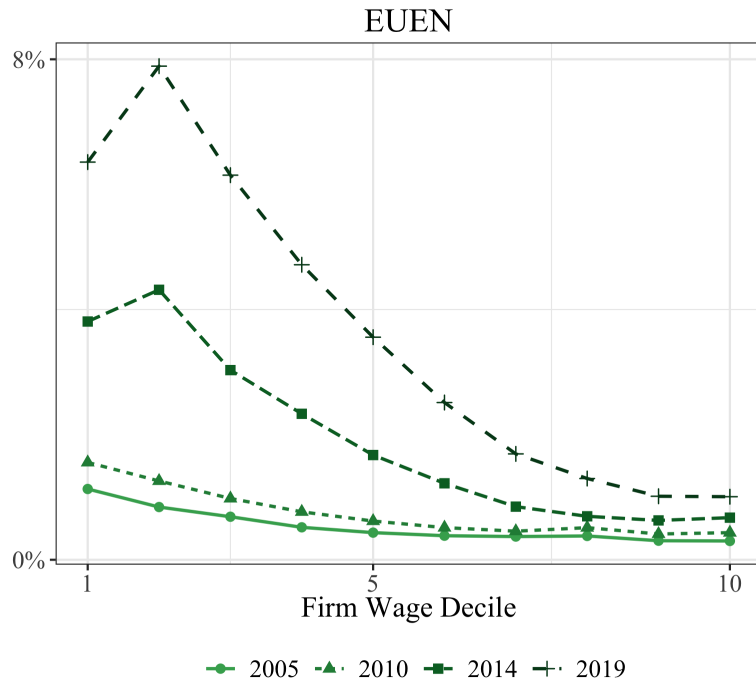
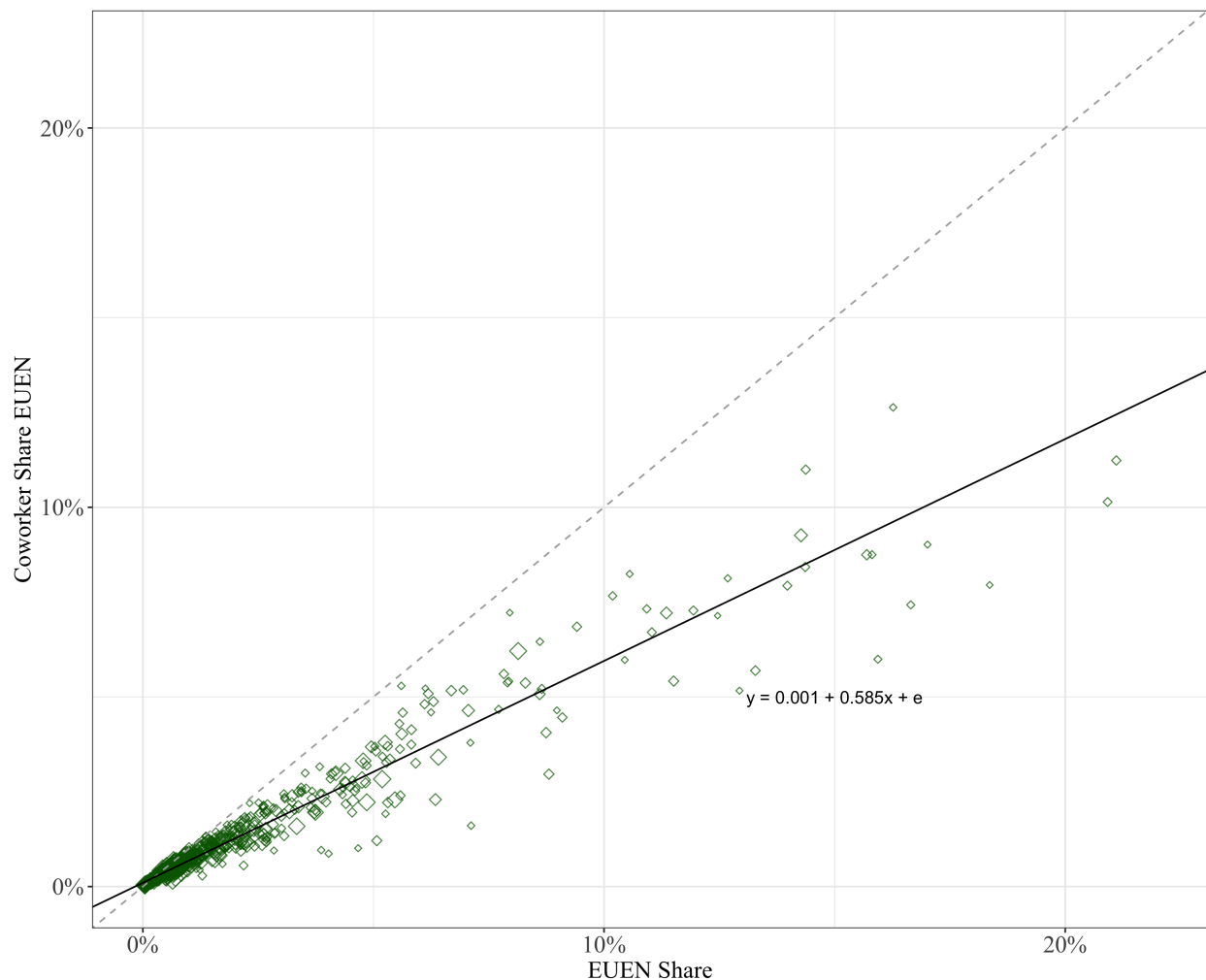


Figure C4: Market-Level Foreign Share and Average German Exposure to Foreigners (2014)



This figure is a scatter plot depicting the relationship between the share of the average German’s coworkers who are EUEN foreigners and the overall EUEN foreign share within markets defined by Industry-Commuting Zone (CZ) cells in 2014. EUEN refers to workers and individuals from the EU Enlargement Nations (Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia). Each diamond represents a market. Coworker Share EUEN is calculated by calculating the share of EUEN coworkers of each German worker and then taking a weighted average within the market. EUEN Share is calculated by dividing the number of EUEN Foreign workers in a market by the total employment in the market. The size of each diamond is proportional to its total employment. The grey dashed line is the 45-degree line. The solid black line is the line of best fit from running an employment-weighted bivariate regression. The text $y = 0.001 + 0.585x + e$ gives the intercept and slope from the regression. Data are from a 100% sample of German Social Security Records.

Table C4: Comparison of Worker Characteristics in Custom Sample to Representative Sample

| | Firm IV Sample | Non-IV Sample |
|------------|----------------|---------------|
| Female | 47.9 | 47.5 |
| German | 89.2 | 91.4 |
| Age | | |
| 18-29 | 19.4 | 20 |
| 30-49 | 52.9 | 51.6 |
| 50+ | 27.7 | 28.4 |
| Education | | |
| HS | 14.3 | 12.7 |
| Vocational | 68.5 | 74.3 |
| University | 17.2 | 13 |
| Skill | | |
| Unskilled | 16.1 | 15.4 |
| Qualified | 58.6 | 65 |
| Specialist | 10.1 | 9.1 |
| Expert | 15.2 | 10.5 |
| Full-Time | 68 | 64.4 |

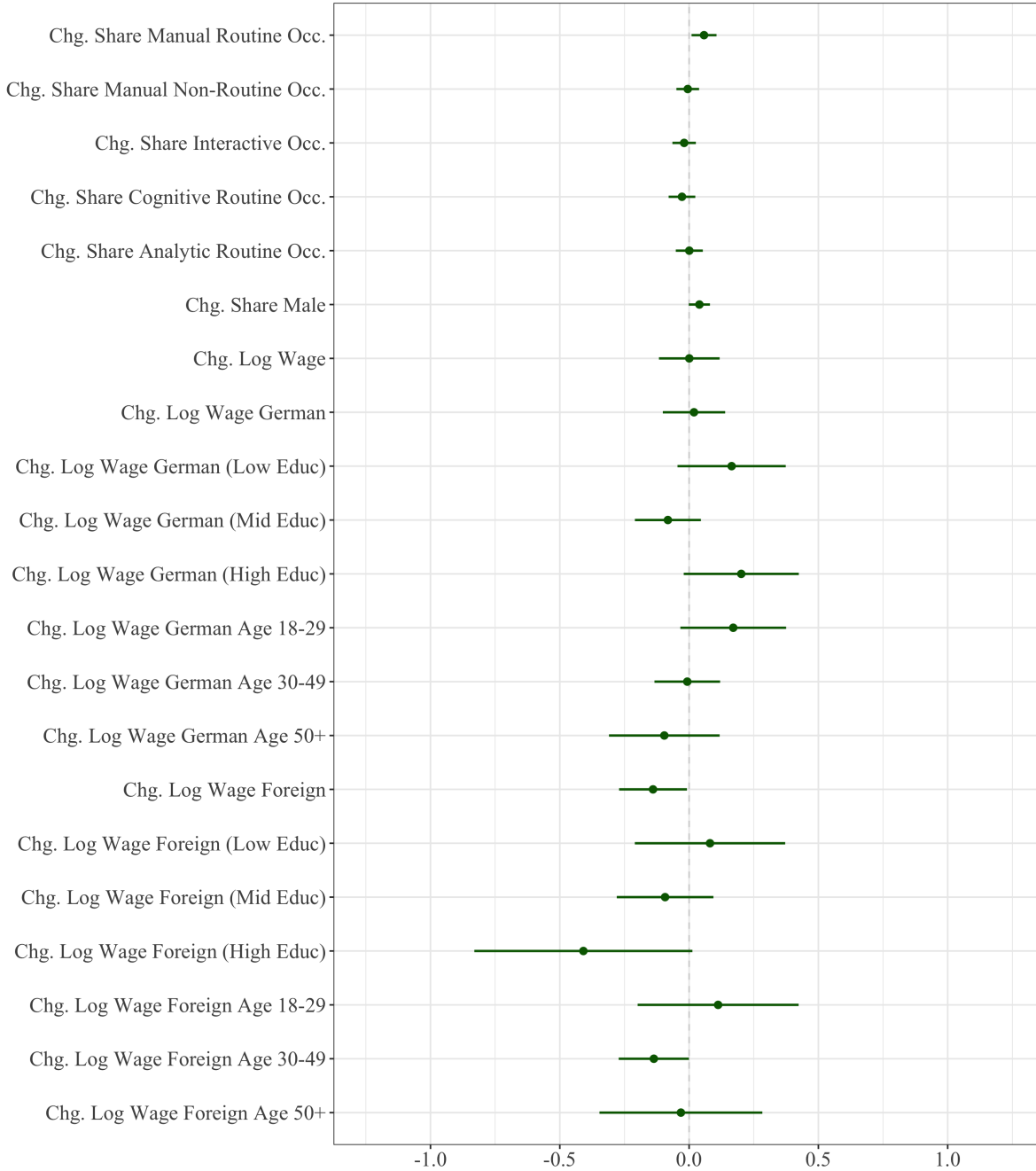
This table compares the characteristics of workers in our custom sample of workers to a representative sample. The custom sample is described in [Section 2.2](#) and the representative sample is described in [Section 2.3](#). HS refers to workers with a high school education or less. Both samples are drawn over the year 2005-19 and estimates are pooled across all years. Data drawn from German Social Security Records.

Table C4: Bartik Decomposition

| Country | β | α | γ | π | G |
|-----------|---------|----------|----------|-------|------|
| Bulgaria | -0.52 | 0.07 | -0.07 | 0.14 | 1.21 |
| Czechia | -0.13 | 0.09 | -0.02 | 0.18 | 0.43 |
| Hungary | -0.18 | 0.10 | -0.03 | 0.17 | 1.35 |
| Latvia | 0.68 | 0.01 | 0.20 | 0.29 | 1.39 |
| Lithuania | -0.36 | 0.02 | -0.09 | 0.25 | 0.97 |
| Poland | -0.48 | 0.38 | -0.10 | 0.20 | 0.63 |
| Romania | -0.38 | 0.26 | -0.09 | 0.24 | 1.29 |
| Slovakia | -0.26 | 0.07 | -0.09 | 0.34 | 0.69 |

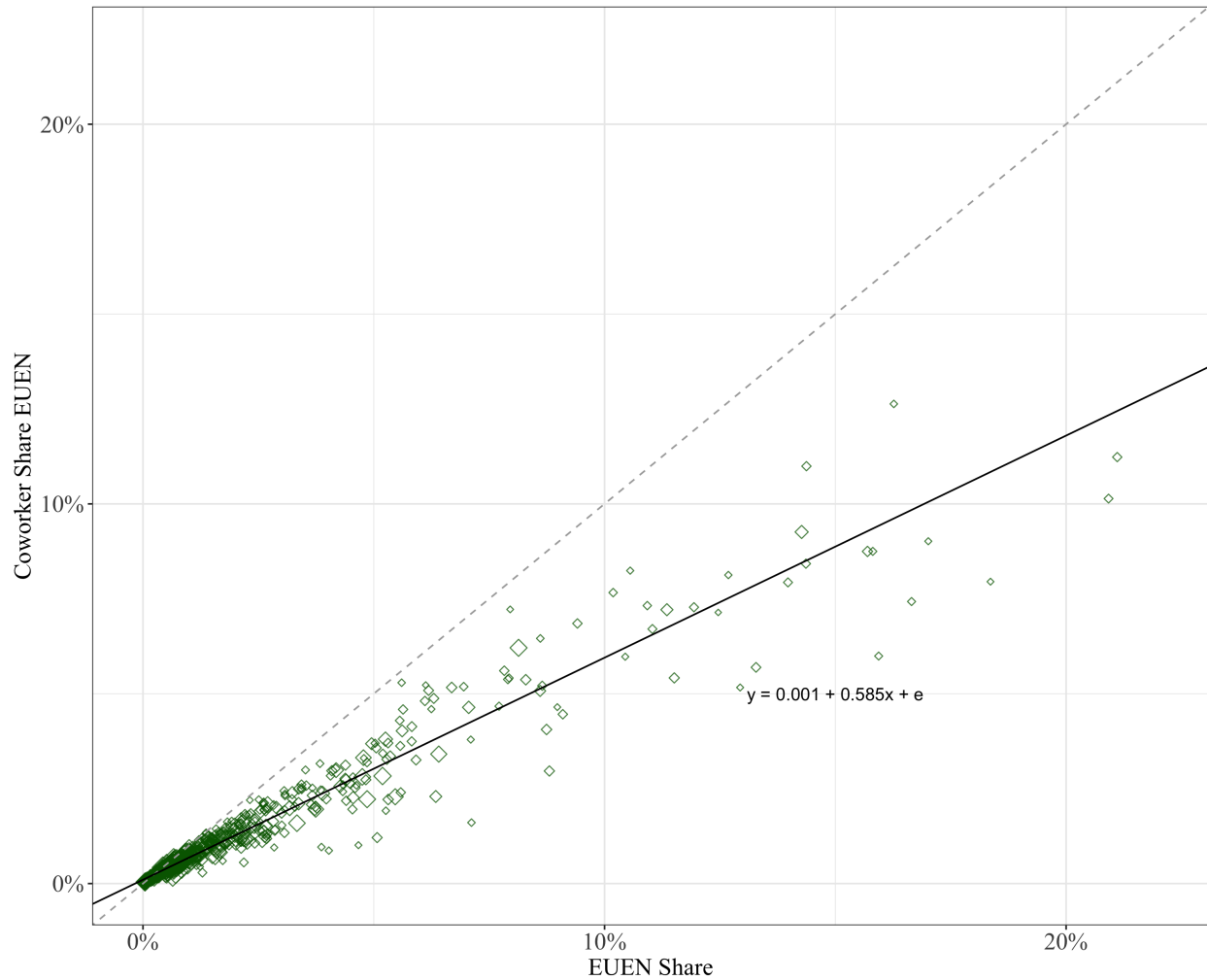
This table contains parameters of the Bartik Decomposition of Goldsmith-Pinkham, Sorkin, and Swift (2020). β is the second-stage coefficient, α are the “Rotemberg Weights”, γ are reduced-form coefficients, π are first-stage coefficients, and G are national growth rates calculated over the period 2010-14.

Figure C5: Firm Shift-Share Balance Test: Changes 2008-10



This figure depicts coefficients $\hat{\beta}$ and associated 95% confidence intervals from a set of regressions of the form $\Delta y_j = \alpha + \beta z_j + \epsilon_j$ where $\Delta y_j = y_{j,2010} - y_{j,2008}$ is the change in outcome y for firm j between 2008 and 2010. z_j is firm j 's predicted inflow of migrants from the EU Enlargement Nations of Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia over the period 2011-14, as predicted from a shift-share using the firm's ethnic composition during the period 2005-7 as shares (see [Section 6.1](#) for details). All dependent variables y_j are normalized by their standard deviation in 2008 for comparability, so e.g. a coefficient of 0.5 implies that a unit increase in z_j is associated with a half a standard deviation increase in y_j between 2008-10. Regressions are weighted by firm employment in 2010. Confidence intervals are calculated using heteroskedasticity robust standard errors. Data are from a custom sample of German Social Security Records.

Figure C6: Market-Level Foreign Share and Average German Exposure to Foreigners (2019)



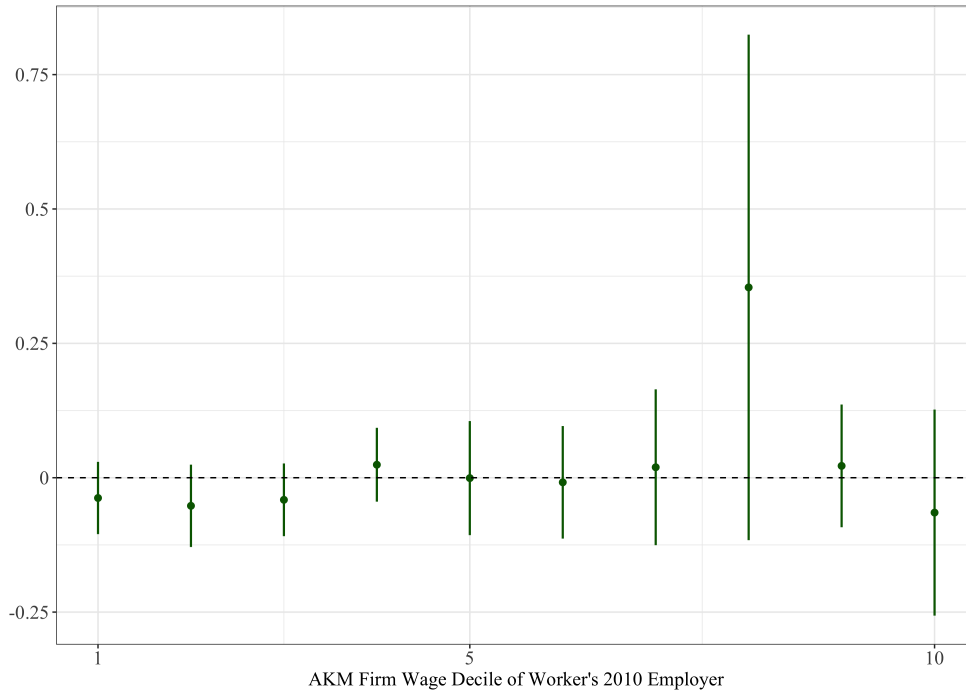
This figure is a scatter plot depicting the relationship between the share of the average German’s coworkers who are EUEN foreigners and the overall EUEN foreign share within markets defined by Industry-Commuting Zone (CZ) cells in 2019. EUEN refers to workers and individuals from the EU Enlargement Nations (Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia). Each diamond represents a market. Coworker Share EUEN is calculated by calculating the share of EUEN coworkers of each German worker and then taking a weighted average within the market. EUEN Share is calculated by dividing the number of EUEN Foreign workers in a market by the total employment in the market. The size of each diamond is proportional to its total employment. The grey dashed line is the 45-degree line. The solid black line is the line of best fit from running an employment-weighted bivariate regression. The text $y = 0.001 + 0.585x + e$ gives the intercept and slope from the regression. Data are from a 100% sample of German Social Security Records.

Table C6: Effects of Firm-Level Migrant Inflow on Incumbent Workers

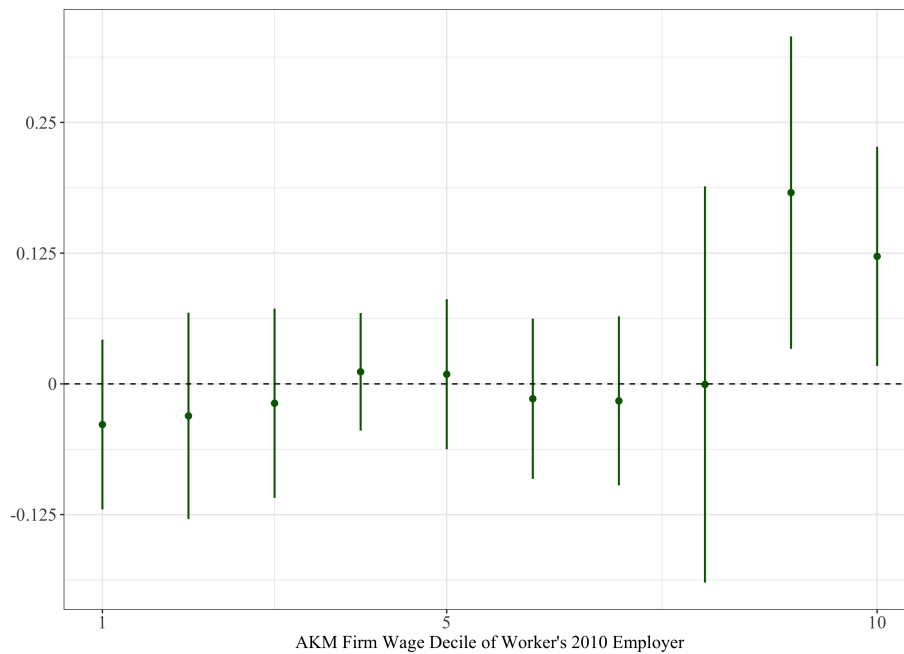
| | (1) | (2) | (3) |
|------------------------------------|-------------------|-------------------|-------------------|
| Dependent Variable | | | |
| Chg. AKM Firm Wage Premium | 0.482 (0.213) | 0.52 (0.233) | 0.447 (0.16) |
| Chg. Log Commute | 0.186 (0.056) | 0.191 (0.051) | 0.203 (0.072) |
| Chg. Log Wage | 0.189 (0.049) | 0.30 (0.048) | 0.195 (0.043) |
| Chg. Firm Foreign Share | -0.253 (0.078) | -0.225 (0.072) | -0.219 (0.066) |
| Chg. Firm EUEN Foreign Share | -0.204 (0.065) | -0.193 (0.052) | -0.195 (0.065) |
| Log(1 + Days Non-Employed) | -0.063 (0.032) | -0.102 (0.04) | -0.092 (0.038) |
| Net Foreign Inflow (2010 Employer) | 0.53 (0.139) | 0.502 (0.141) | 0.487 (0.154) |
| Controls | | | |
| Worker Controls | ✓ | | ✓ |
| Firm Controls | | ✓ | ✓ |

This table displays coefficient estimates $\hat{\gamma}_2$ and associated standard errors from regressions described in **Equation ??**. These are regressions of the form $\Delta y_{i,t} = \alpha_t + \gamma_1 z_{j(i,2010)} + \gamma_2 z_{j(i,2010)} Post_t + X_i' \beta + \epsilon_{i,t}$ where i indexes workers, j indexes firms (so that $j(i, 2010)$ refers to workers i 's employer in 2010), $t \in \{2014, 2009\}$ index years, and $Post_t = 1\{t = 2014\}$. $\Delta y_{i,t} := y_{i,t} - y_{i,t-4}$ are 4-year long differences, z_j is the shift-share of firm j , and X_i is a vector of controls. Worker controls include polynomials in age, experience, and tenure (calculated in 2010), as well as dummies for education (3 levels) and gender. Firm controls include industry (13 levels), commuting zone (50 levels), and firm size ventile fixed effects, corresponding to the sector, location, and size of i 's 2010 employer. The regression is run on a sample of all German workers for whom the variable $z_{j(i,2010)}$ is defined and non-zero (see **Section 6** for details). Each coefficient comes from a separate regression. Standard errors are clustered at the firm level, where firm corresponds to the worker's employer in 2010.

Figure C7: Effect of Market-Level Shock on Worker Sorting Across Jobs (Occupation/Skill)



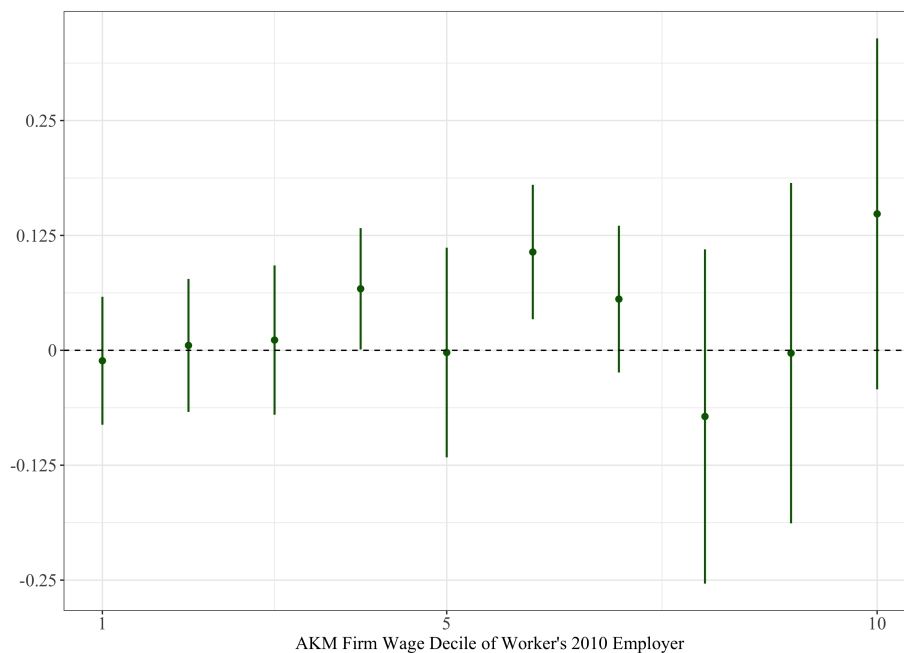
(a) Change Occupation



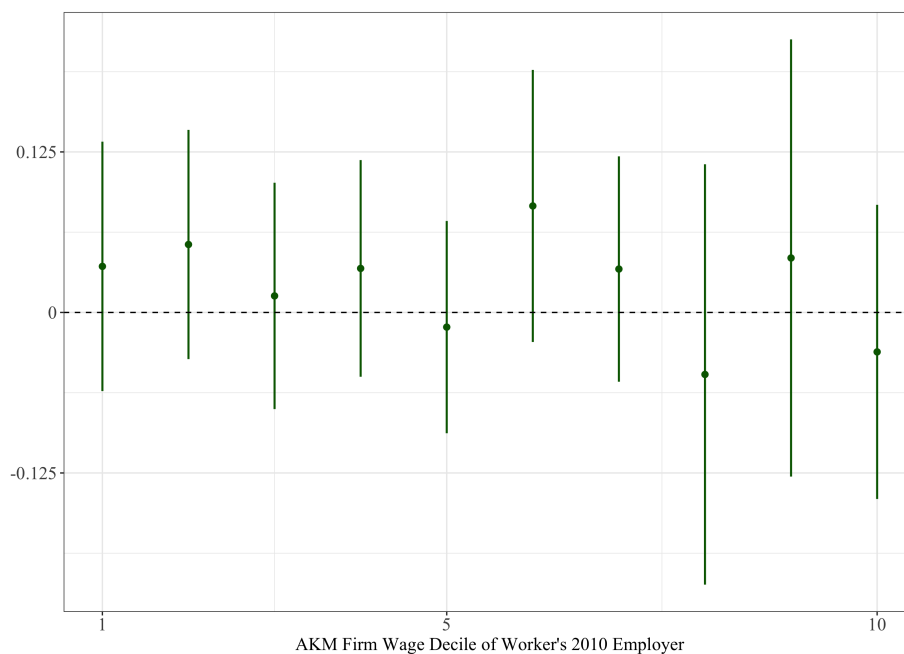
(b) Change Skill Level

This figure plots coefficient estimates and 95% confidence intervals for the parameter γ_d from the sequence of regressions described in [Equation 7](#). The dependent variable in the top panel is a dummy equal to 1 if the worker changed occupation (6 levels) between 2010 and 2014, and the bottom panel is equal to 1 if the worker changed skill level (5 levels). The regressions are run at the worker level and stratified by the decile of the worker's 2010 employer's AKM firm effect, which are on the horizontal axis. The coefficient plotted is the coefficient on the shift-share measuring the local labor market-level exposure to EUEN migrant inflows. All coefficients were scaled so that they represent the effect of a 5 percentage point increase in the shift-share. Local labor markets are measured by districts (*kreise*) of which there are 401 in Germany. Standard errors are clustered at the district level.

Figure C8: Effect of Market-Level Shock on Worker Sorting Across Industry/District



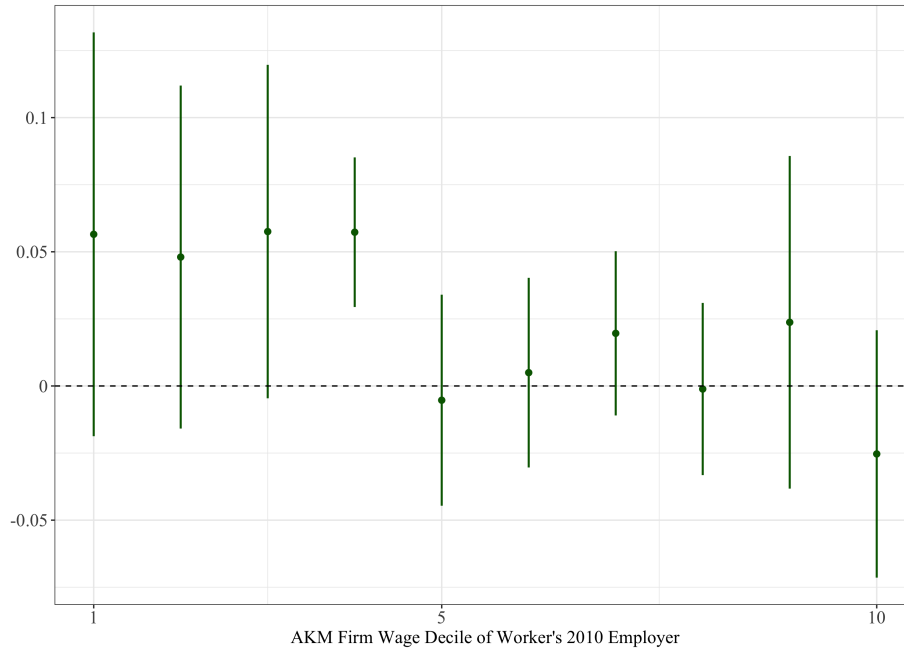
(a) Change Industry



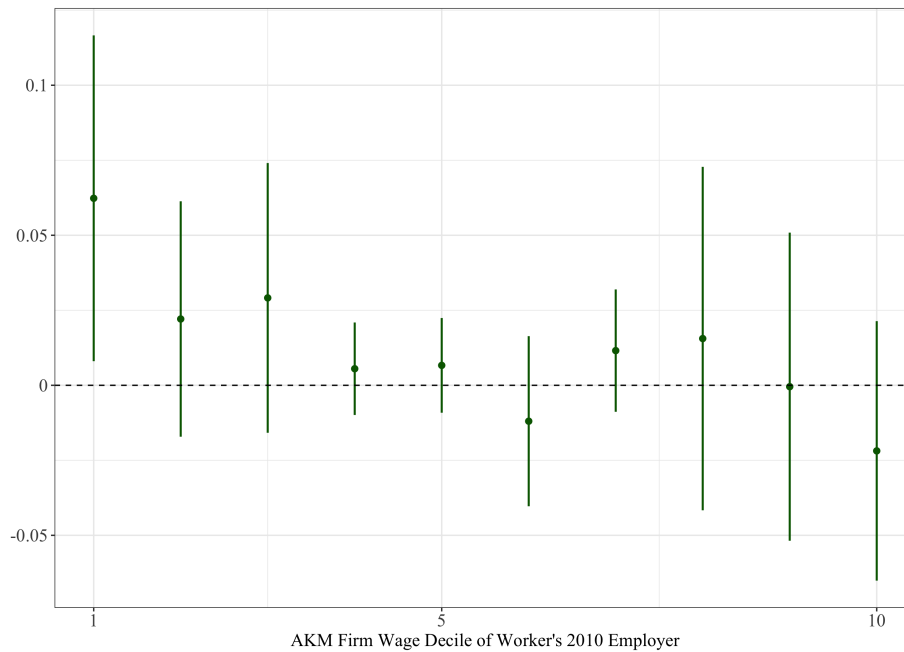
(b) Change District

This figure plots coefficient estimates and 95% confidence intervals for the parameter γ_d from the sequence of regressions described in [Equation 7](#). The dependent variable in the top panel is a dummy equal to 1 if the worker changed industry of employment (17 levels) between 2010 and 2014, and the bottom panel is equal to 1 if the worker changed district of employment (401 levels). The regressions are run at the worker level and stratified by the decile of the worker's 2010 employer's AKM firm effect, which are on the horizontal axis. The coefficient plotted is the coefficient on the shift-share measuring the local labor market-level exposure to EUEN migrant inflows. All coefficients were scaled so that they represent the effect of a 5 percentage point increase in the shift-share. Local labor markets are measured by districts (*kreise*) of which there are 401 in Germany. Standard errors are clustered at the district level.

Figure C9: Effect of Market-Level Shock on Worker Sorting Across Firms: Alternative Firm Wage Measures



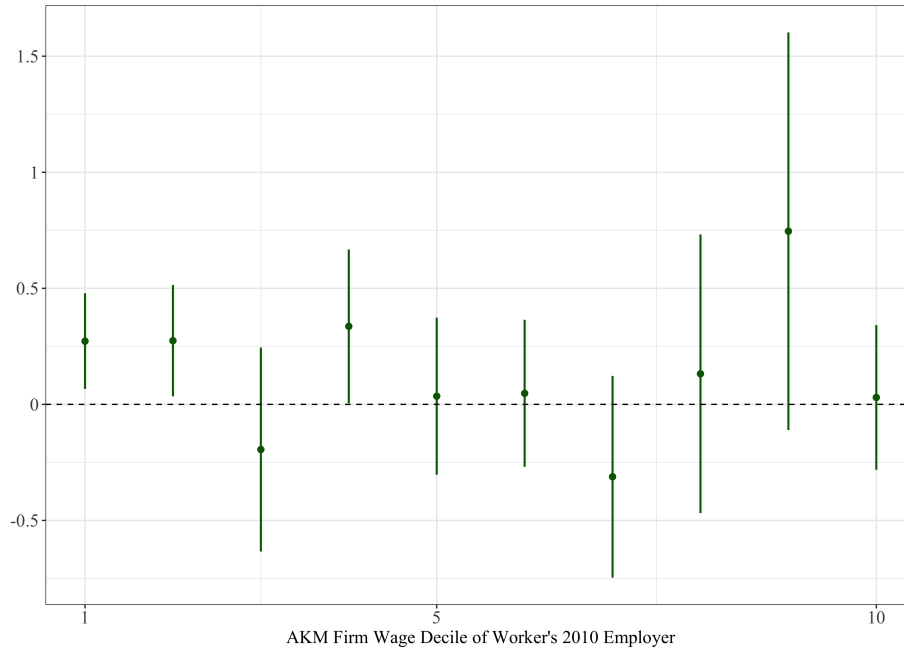
(a) Change Average Full-Time Wage (2010-14) of Current Employer



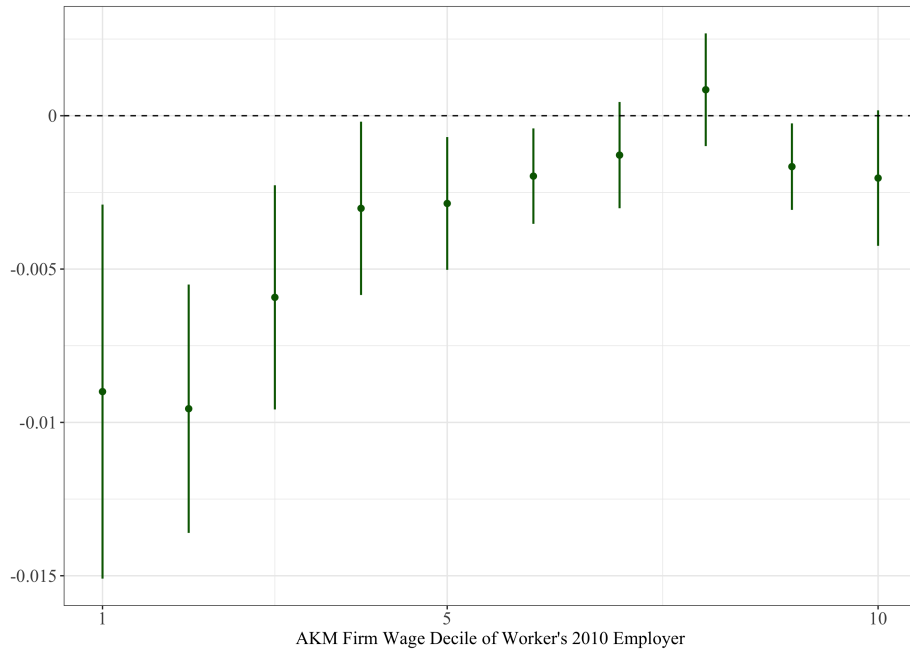
(b) Change Imputed AKM Wage Premia of Current Employer

This figure plots coefficient estimates and 95% confidence intervals for the parameter γ_d from the sequence of regressions described in [Equation 7](#). The dependent variable in the top panel is the difference between the log wage of full-time workers—calculated over the period 2010-14—of the workers 2014 employer minus that of their 2010 employer. The bottom panel is the AKM Firm Effect including imputed values for firms for which no AKM effect exists in our data (see text for details). The regressions are run at the worker level and stratified by the decile of the worker's 2010 employer's AKM firm effect, which are on the horizontal axis. The coefficient plotted is the coefficient on the shift-share measuring the local labor market-level exposure to EUEN migrant inflows. All coefficients were scaled so that they represent the effect of a 5 percentage point increase in the shift-share. Local labor markets are measured by districts (*kreis*) of which there are 401 in Germany. Standard errors are clustered at the district level.

Figure C10: Effect of Market-Level Shock on Worker-Firm Sorting: Alternative Measures



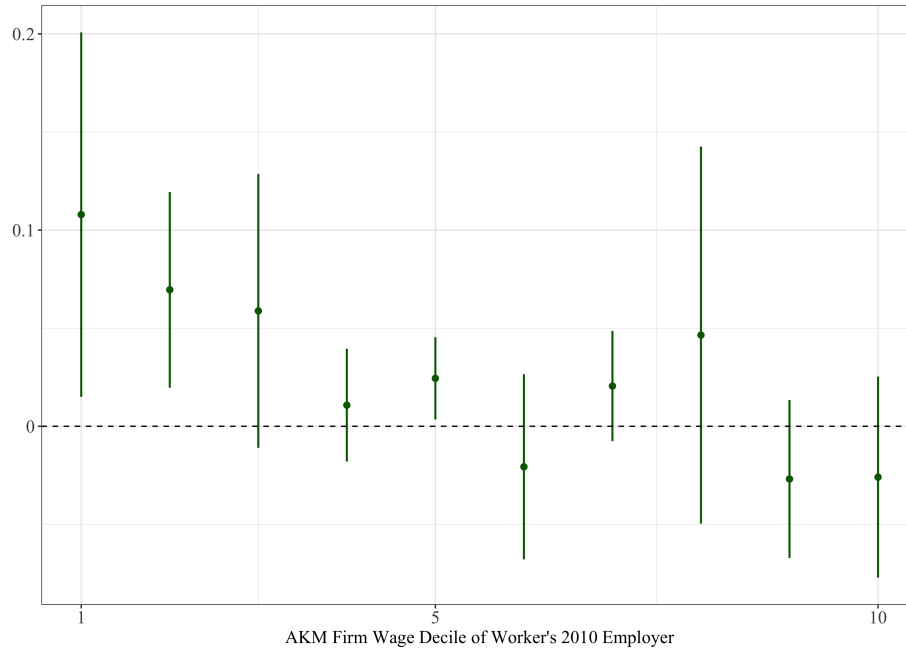
(a) Change Log Firm Size (2010-14) of Current Employer



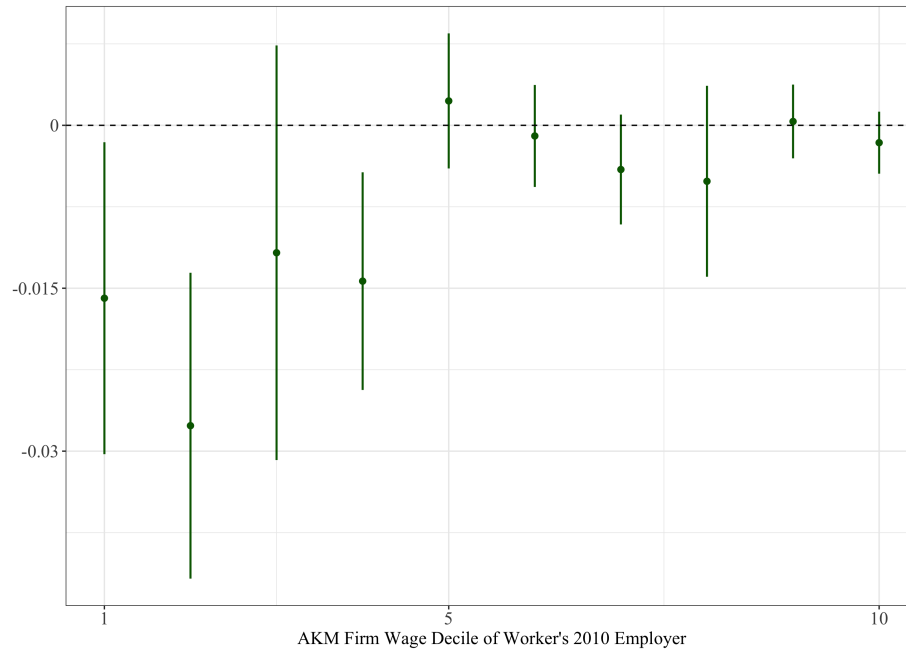
(b) Change Imputed AKM Wage Premia of Current Employer

This figure plots coefficient estimates and 95% confidence intervals for the parameter γ_d from the sequence of regressions described in [Equation 7](#). The dependent variable in the top panel is the difference between the log wage of full-time workers—calculated over the period 2010-14—of the workers 2014 employer minus that of their 2010 employer. The bottom panel is the AKM Firm Effect including imputed values for firms for which no AKM effect exists in our data (see text for details). The regressions are run at the worker level and stratified by the decile of the worker’s 2010 employer’s AKM firm effect, which are on the horizontal axis. The coefficient plotted is the coefficient on the shift-share measuring the local labor market-level exposure to EUEN migrant inflows. All coefficients were scaled so that they represent the effect of a 5 percentage point increase in the shift-share. Local labor markets are measured by districts (*kreise*) of which there are 401 in Germany. Standard errors are clustered at the district level.

Figure C11: Effect of Market-Level Shock on Worker-Firm Sorting: Triple Difference



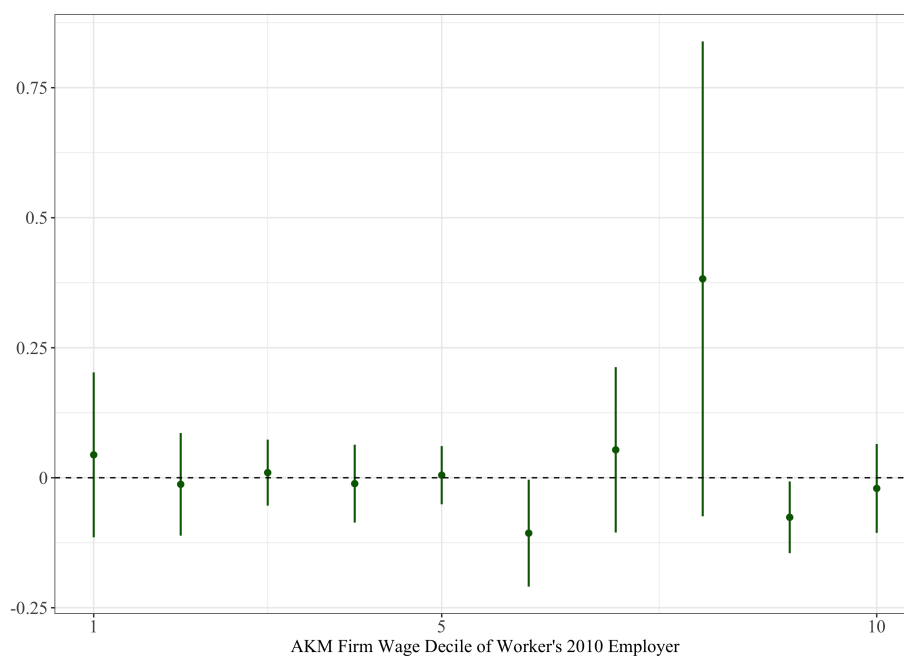
(a) Change AKM Firm Wage Premia (2010-14) of Current Employer



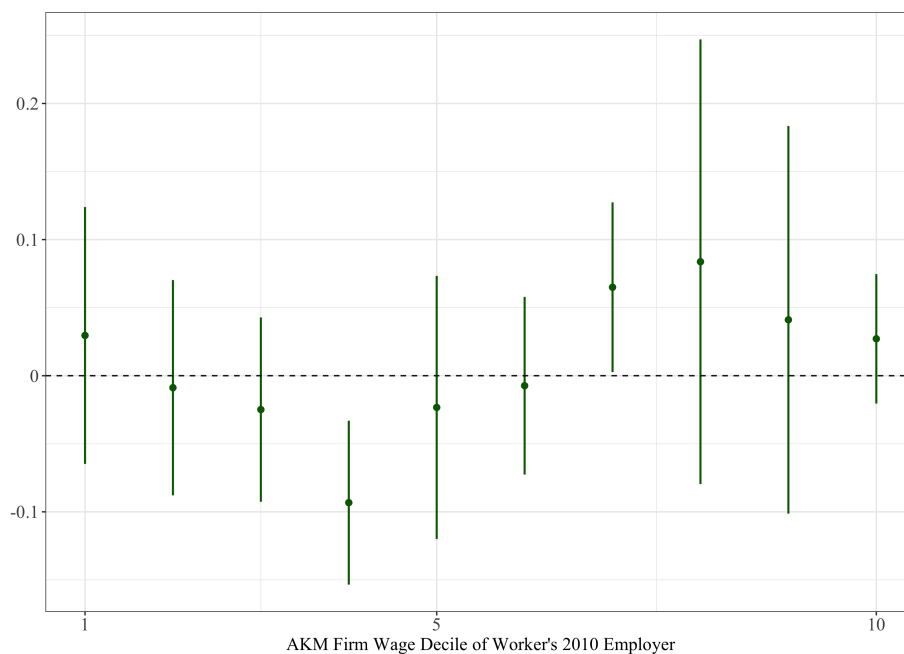
(b) Change EUEN Share (2010-14) of Current Employer

This figure plots coefficient estimates and 95% confidence intervals for the parameter γ_{d2} from the sequence of regressions described in **Equation 8**. The dependent variable in the top panel is the difference between the mean log firm size—calculated over the period 2010-14—of the worker’s 2014 employer minus that of their 2010 employer. The bottom panel is the difference between the EUEN foreign share of the worker’s 2014 employer and their 2010 employer. EUEN share is calculated over the pre-policy period 2005-9. The regressions are run at the worker level and stratified by the decile of the worker’s 2010 employer’s AKM firm effect, which are on the horizontal axis. The coefficient plotted is the coefficient on the shift-share measuring the local labor market-level exposure to EUEN migrant inflows. All coefficients were scaled so that they represent the effect of a 5 percentage point increase in the shift-share. Local labor markets are measured by districts (*kreis*) of which there are 401 in Germany. Standard errors are clustered at the district level.

Figure C12: Effect of Market-Level Shock on Wages and Employment: Triple Difference



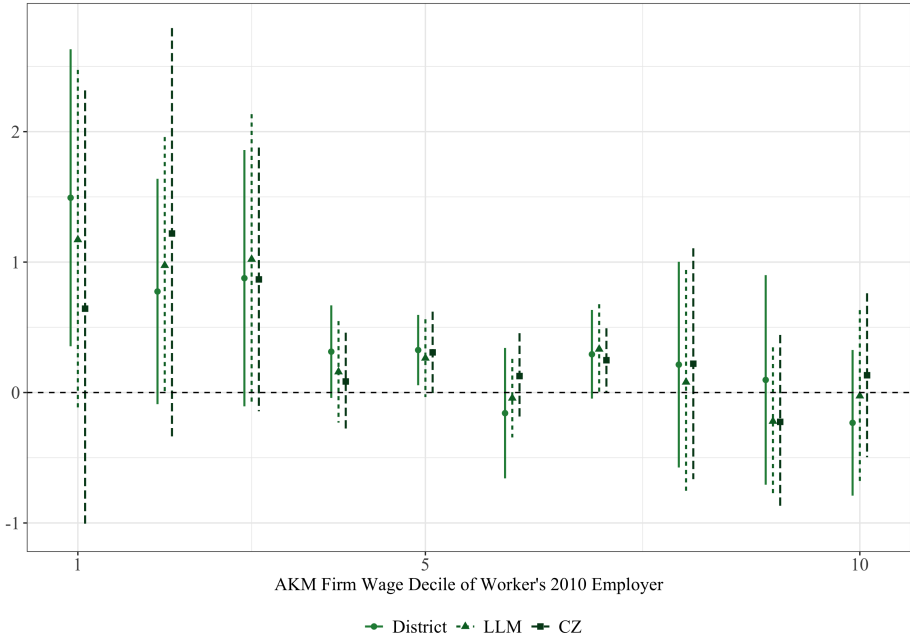
(a) Change Log Wage



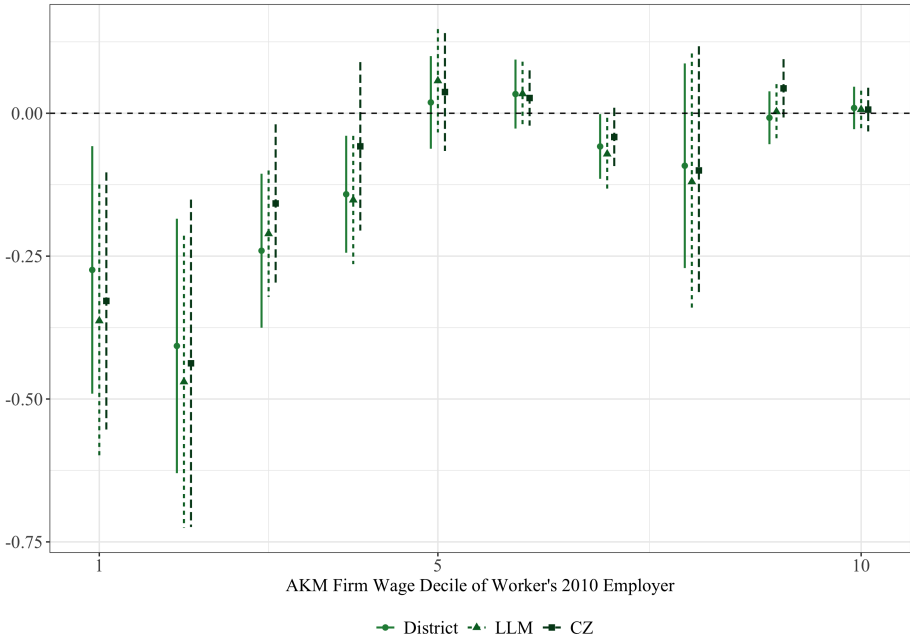
(b) Change Full-Time Employment Status

This figure plots coefficient estimates and 95% confidence intervals for the parameter γ_{d2} from the sequence of regressions described in **Equation 8**. The dependent variable in the top panel is the difference between the mean log firm size—calculated over the period 2010–14—of the worker’s 2014 employer minus that of their 2010 employer. The bottom panel is the difference between the EUEN foreign share of the worker’s 2014 employer and their 2010 employer. EUEN share is calculated over the pre-policy period 2005–9. The regressions are run at the worker level and stratified by the decile of the worker’s 2010 employer’s AKM firm effect, which are on the horizontal axis. The coefficient plotted is the coefficient on the shift-share measuring the local labor market-level exposure to EUEN migrant inflows. All coefficients were scaled so that they represent the effect of a 5 percentage point increase in the shift-share. Local labor markets are measured by districts (*kreis*) of which there are 401 in Germany. Standard errors are clustered at the district level.

Figure C13: Effect of Market-Level Shock on Firm Sorting: Alternative Market Definitions



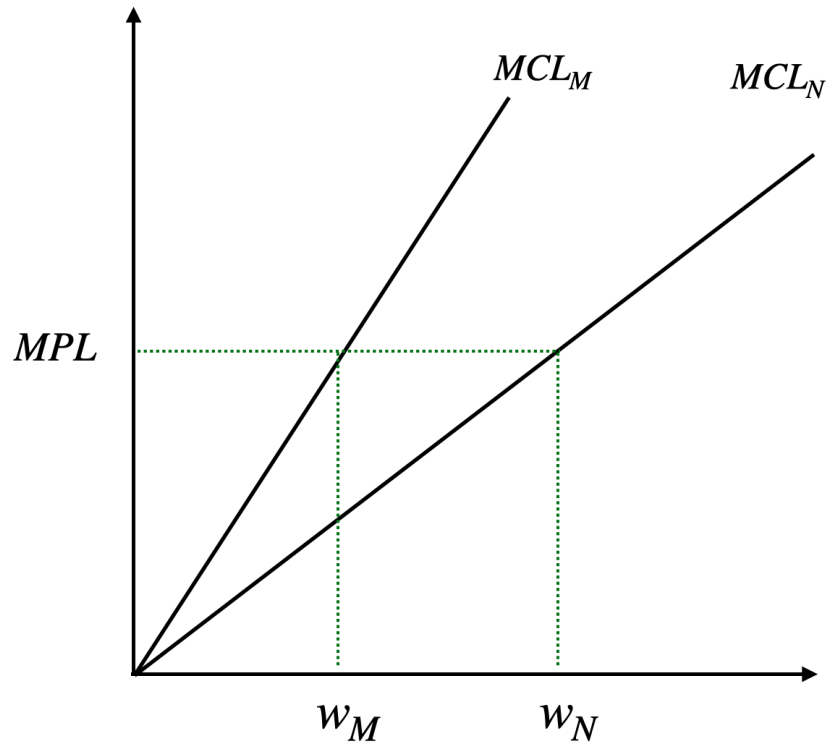
(a) Change AKM Firm Wage Premium



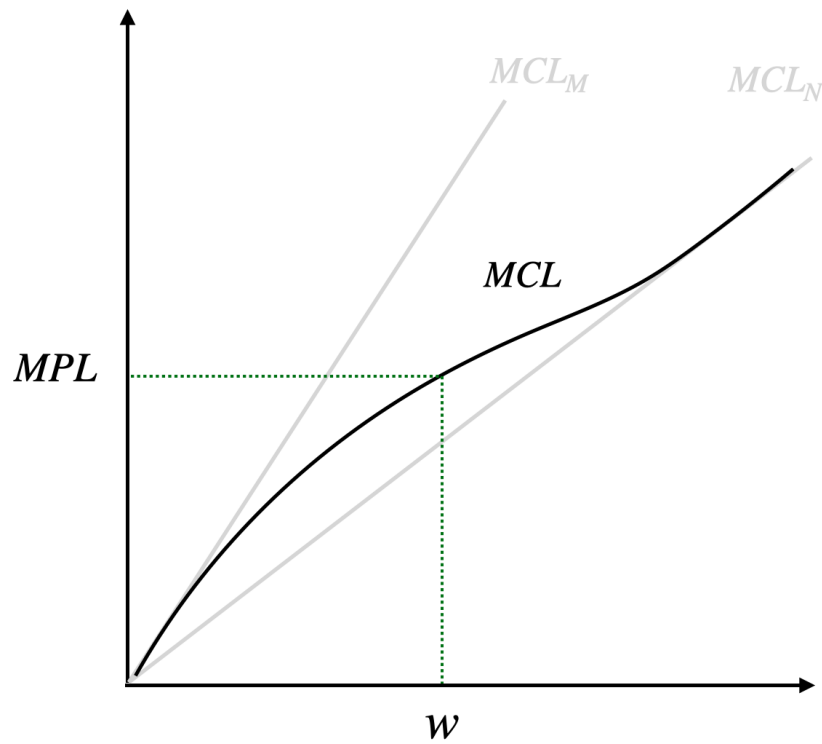
(b) Change Firm EUEN Foreign Share

This figure plots coefficient estimates and 95% confidence intervals for the parameter γ_d from the sequence of regressions described in **Equation 7**. The figure plots estimates from separate regressions using alternative market definitions: district (401 levels), Local Labor Market (222 levels), and Commuting Zone (50 levels).

Figure C14: Firm-Wage Setting



(a) Wage Discrimination



(b) Uniform Wage-Setting