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Abstract

We are the first to provide empirical evidence on differences in the individual costs of job loss for migrants compared to natives in Germany. Using linked employer-employee data for the period 1996-2017, we compute each displaced worker's earnings, wage, and employment loss after a mass layoff in comparison to a matched, nondisplaced, control worker. We find that migrants face substantially higher earnings losses than natives due to both higher wage and employment losses. Differences in individual characteristics and differential sorting across industries and occupations can fully explain the gap in wage losses but not the employment gap after displacement. Laid-off migrants are both less likely to become re-employed and work fewer days than laid-off natives. In terms of channels, we show that i) migrants sort into worse establishments and ii) migrants' slightly lower geographic mobility across federal states may explain part of their lower re-employment success; iii) our results suggest that competition from other migrants, rather than natives, negatively contributes to migrants' costs of job loss.

Zusammenfassung

Wir sind die ersten, die empirische Belege für Unterschiede in den individuellen Kosten des Arbeitsplatzverlustes für Migranten im Vergleich zu Einheimischen in Deutschland liefern. Unter Verwendung von verknüpften Arbeitgeber-Arbeitnehmer-Daten für den Zeitraum 1996-2017 berechnen wir die Verdienst-, Lohn- und Beschäftigungsverluste jedes entlassenen Arbeitnehmers nach einer Massenentlassung im Vergleich zu einem nicht-entlassenen Kontrollarbeiter. Wir stellen fest, dass Migranten aufgrund höherer Lohn- und Beschäftigungsverluste wesentlich höhere Einkommensverluste hinnehmen müssen als Einheimische. Unterschiede in den individuellen Merkmalen und die unterschiedliche Selektion nach Branchen und Berufen können den Unterschied bei den Lohnverlusten vollständig erklären, nicht aber die Unterschiede bei der Beschäftigung nach der Entlassung. Entlassene Migranten haben sowohl eine geringere Wahrscheinlichkeit, wieder eingestellt zu werden, als auch weniger Arbeitstage als entlassene Einheimische. In Bezug auf diverse Kanäle zeigen wir, dass i) Migranten sich in schlechtere Betriebe sortieren und ii) die etwas geringere geografische Mobilität von Migranten zwischen den Bundesländern einen Teil ihres geringeren Wiederbeschäftigungserfolgs erklären kann; iii) unsere Ergebnisse deuten darauf hin, dass die Konkurrenz durch andere Migranten und nicht durch Einheimische negativ zu den Kosten des Arbeitsplatzverlustes von Migranten beiträgt.

JEL

J61, J63, J20, J65, J71, J64

Keywords

Employment, Job Loss, Layoffs, Migrants, Wages

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1 Introduction

A large body of literature has investigated workers' long-term costs of job loss (e.g., Jacobson/LaLonde/Sullivan (1993), Couch/Placzek (2010), von Wachter/Song/Manchester (2011), Schmieder/von Wachter/Heining (2020)). Most of these studies pay little attention to heterogeneities in costs of job loss, with almost no evidence on migrant workers. However, for several reasons, the experience of losing one's job may differ dramatically between migrant and native workers: Migrants are at high risk of losing their job during recessions, including the recession caused by the COVID-19 pandemic (e.g., Borjas/Cassidy (2020), Freeman et al. (1973), Fairlie/Couch/Xu (2020), Montenovo et al. (2020)), migrants may face discrimination (Bertrand/Mullainathan (2004)), migrants' entry wages when changing employers are typically lower than natives' (Borjas (1995)), and their networks may be worse (Glitz (2017), Gërxhani/Kosyakova (2020)). To better understand whether job loss reinforces inequalities between migrants and natives, it is crucial to investigate differences in their response to job displacement in more detail.

Understanding these differences is of high economic and political relevance, in particular because immigration in many OECD countries has increased substantially in recent decades. One prominent example is Germany: While in 2005, 18 percent of the German population reported that they or at least one of their parents were born without German citizenship, this share had increased to 26 percent by 2019 (Destatis (2020)). Given that Germany, along with many other OECD countries, is facing skilled worker shortages as a result of demographic change, there is increased attention towards migrants' labor market integration. Successful labor market integration is crucial for migrants to contribute to the fiscal system (Dustmann/Frattini (2014)) and – due to path dependence – for the next generations' labor market outcomes[1]. It is therefore surprising that no study to date has analyzed how quickly migrants, compared to natives, reintegrate into the labor market after displacement.

In this paper, we use rich administrative employer-employee data from Germany provided by the Institute for Employment Research (IAB), which span more than 20 years (1996-2017), to compare the labor market outcomes of displaced migrants and natives. These data cover the universe of employees covered by social security in Germany, and they are directly filed by employers, making them both representative and highly reliable. We use the rich set of individual characteristics recorded in the data to follow the growing literature on heterogeneity in the costs of job loss by worker type (see, e.g., Blien/Dauth/Roth (2020) for differences by occupational routine intensity and Illing/Schmieder/Trenkle (2021) and Meekes/Hassink (2020) for differences by gender).

[1] See, e.g., Solon (1999) for a survey. Furthermore, there exists a large body of literature comparing the economic outcomes of migrants, migrants' children, and natives. See, for instance, Dustmann/Frattini/Lanzara (2012), Algan et al. (2010), Dustmann (2008), Casey/Dustmann (2008), Casey (2010), Gang/Zimmermann (2000), or Riphahn (2003).

Our main empirical approach builds on the seminal paper by Jacobson/LaLonde/Sullivan (1993), who compare the labor market outcomes of displaced to nondisplaced workers before and after job loss. The intuition behind this approach is that job loss is unexpected for long-tenured workers, and these are therefore highly comparable to workers with similar characteristics who are not displaced in the same year.

The key challenge of our study is to make migrants (individuals with non-German citizenship) comparable to natives. Migrants have, on average, different individual characteristics than natives. Migrants in our sample are, e.g., less educated (11.2 vs. 12.3 years), younger (37.9 vs. 39.4 years), and earn lower wages (89.2 EUR vs. 102.3 EUR) in the year before displacement. We thus proceed in two steps. First, we focus on workers who lose their job involuntarily due to a mass layoff and match displaced to nondisplaced workers using propensity score matching, separately for migrants and natives. This allows us to measure the costs of job loss by migration status and compare migrants and natives in a very similar situation. Second, we use a reweighting scheme first proposed by DiNardo/Fortin/Lemieux (1996) and first applied to the context of job loss by Illing/Schmieder/Trenkle (2021) to control for migrants' and natives' different individual characteristics and differential sorting across industries and occupations before displacement.

Descriptively, we find that both migrants and natives face large average earnings losses after displacement, with substantially larger losses for migrants (12,000 EUR vs. 16,000 EUR in the year after losing their job, compared to earnings two years earlier). The results from our event study regression model, where we control for worker and year fixed effects, confirm that the decline in migrants' earnings in the year of the layoff is 35 percentage points larger than that of natives[2]). Our results moreover show that migrants do not catch up with natives even five years after displacement. Once we reweight migrants to natives using individual characteristics, industry, and occupation, this gap in earnings immediately after displacement shrinks to 14 percentage points.

We then decompose earnings losses into wage and employment losses. We find that while observable characteristics fully explain the gap in wage losses (conditional on finding a job), the gap in employment losses persists even after reweighting. Differences in age, education, or occupational distribution can thus explain why migrants earn lower wages after job loss, but they cannot explain why migrants are less likely to take up new employment. In particular, we find that migrants are approximately 5 percentage points less likely to be employed in the year after job loss. This gap shrinks to approximately 2 percentage points five years later. We observe a similar pattern for days worked per year: Migrants work approximately 25 fewer

[2] If we include spells with zero earnings (and thus account for workers in unemployment or workers temporarily unobserved due to, e.g., self-employment), this difference increases to 80 percentage points, meaning that the effects on migrants are 1.8 times the effects on natives. We construct a panel where we keep workers in the sample if they disappear from the social security data in a given year and appear again in a future year. If they fully disappear from the data, we include them up to the last year they are observed in the data.

days per year in the year after displacement; five years later, the difference is still statistically significant but reduced to approximately 10 days.

We explore three channels to better understand the potential causes behind the migrant-native gap in earnings losses. First, we investigate whether, conditional on employment, migrants sort into different types of establishments. We show that after displacement, migrants work in establishments with lower average wages, lower establishment fixed effects[3] (Abowd/Kramarz/Margolis (1999)), and a higher share of marginally employed and migrant workers. Consistent with our findings on wage losses, these differences are much weaker once we reweight migrants to natives. Nevertheless, they suggest that we can attribute part of migrants' worse labor market outcomes after layoff to differences in establishment sorting.

Second, we analyze whether migrants' and natives' mobility patterns (conditional on finding a new job) differ. In line with Huttunen/Møen/Salvanes (2018), we find that both migrants and natives expand their regional mobility – both in terms of changing workplace location and commuting – after job loss. Our results suggest that migrants are slightly more likely to commute after job loss (a 2 percentage point difference compared to natives) and slightly less likely to move workplaces to a new federal state (a 3 percentage point difference). Migrants may thus face higher mobility constraints than natives (e.g., because of housing market tightness), and their lower geographic mobility may partly explain their larger earnings losses.

Third, we explore the importance of local labor market concentration, proxied by three measures: i) the change in local unemployment rates around time of displacement, ii) city residency, and iii) the share of same-nationality working age population in a worker's workplace county. We believe that these three proxies are relevant because prior literature has shown that i) migrants' wage assimilation is particularly slow in periods of high unemployment (Bratsberg/Barth/Raaum (2006)), ii) displaced workers' unemployment duration is particularly high if they live in cities (Haller/Heuermann (2019)), and iii) within-network competition may be harmful to migrants (e.g., Albert/Glitz/Llull (2020), Beaman (2012)).

To assess the importance of local labor market concentration, we follow Schmieder/von Wachter/Heining (2020) and conduct a matched difference-in-differences (DID) analysis. We thus construct an individual-level variable measuring the difference in earnings before and after job loss between each displaced and nondisplaced worker pair. For our sample of displaced workers, we then regress this measure on the three concentration proxies and a number of worker- and establishment-level controls. Our results suggest that displaced workers, irrespective of nationality, face greater earnings losses if local unemployment rates at the time

[3] Based on Abowd/Kramarz/Margolis (1999), a large literature finds that persistent wage differentials exist across firms within the same labor market (e.g., Card/Heining/Kline (2013), Song et al. (2019), Bonhomme/Lamadon/Manresa (2019)).

of displacement increase more. Moreover, earnings losses are greater if displaced workers live in a city at the time of displacement, and this effect is approximately twice as high for migrants. In addition, migrants working in counties with a higher share of the same-nationality population in the year before displacement face substantially higher costs of job loss. These findings suggest, in line with Caldwell/Danieli (2021), that a greater concentration of similar workers at the time of displacement is a crucial factor driving displaced workers' earnings losses. Migrants in particular seem to compete with workers of the same origin for the same types of jobs.

This paper contributes to the literature on the individual costs of job loss by adding evidence on migrant workers. Many studies have documented large and persistent earnings losses for displaced workers (see, e.g., Jacobson/LaLonde/Sullivan (1993), Couch/Placzek (2010), von Wachter/Song/Manchester (2011), Schmieder/von Wachter/Heining (2020)) but without differentiating between specific groups. While there is an emerging literature on the costs of job loss by worker type (e.g., Blien/Dauth/Roth (2020), Meekes/Hassink (2020), Helm/Kügler/Schönberg (2021), and Illing/Schmieder/Trenkle (2021)), no study to date focuses on migrant workers.[4] Against the backdrop of increasing immigration flows and interest in migrants' labor market integration, we are the first to shed more light on this issue. We establish that displaced migrants face larger earnings losses than natives and that this is mainly driven by differences in re-employment probability. While we estimate our main results for a sample of men, we show that the same patterns hold when focusing on women.

We moreover contribute to the literature investigating how sensitive migrants are to adverse economic shocks. A recent paper by Borjas/Cassidy (2020) finds that migrants particularly suffered from displacement during the COVID-19 crisis, partly because they are less likely to work in jobs that can be performed remotely. In the same spirit, other studies have shown that migrants' entry wages during recessions are lower than natives' (see, e.g., Kondo (2015), Kahn (2010), Speer (2016)) and that migrants' or black people's unemployment rate is particularly sensitive to business cycle conditions and local unemployment rates (e.g., Altonji/Blank (1999), Bratsberg/Barth/Raaum (2006), Hoynes/Miller/Schaller (2012)). The main difference from our study is that whereas most of these papers analyze aggregate outcomes, we follow individual workers' careers before and after job loss. The high-quality administrative employer-employee data from Germany thus allow us focus on the worker level and show how each worker's earnings, wage, and employment trajectory evolved up to five years before and after job loss. Our results help to understand how involuntary displacement affects migrant workers relative to native workers at the individual level.

The remainder of the paper proceeds as follows. Section 2 provides an overview of our data,

[4] A notable exception is the study by Hardoy/Schøne (2014) who focus on displacement effects from plant closings over the business cycle. In comparison to this paper, they, however, study only two outcomes: employment probability and employment duration. Moreover, they are not clear on the extent to which differences in observable characteristics drive differences in employment outcomes between migrants and natives.

including insights into our definition of job displacement, sample selection, and the propensity score matching algorithm. Section 3 describes our empirical strategy and reports descriptive evidence and our event study results. In Section 4, we explore the extent to which sorting into particular establishments after displacement, differences in geographic mobility, and local labor market concentration explain our results. Section 5 presents our robustness checks, and Section 6 concludes the paper.

2 Data and Methods

In this section, we proceed as follows: First, we describe the German linked employer-employee data that we use for our analysis. Second, we discuss how we define mass layoffs and displaced workers. Third, we explain our propensity score matching algorithm, which we use to find a unique control worker for each displaced worker.

2.1 Adminstrative Data from Germany

For our empirical analysis, we use high-quality social security data provided by the IAB. Our primary data source is a random 12.5 percent sample of the universe of workers subject to social security contributions in 1996-2017, which stems from the *Integrated Employment Biographies (IEB), version 14*.[5] Importantly, for our study, the IEB includes information on both workers' employment and unemployment spells with daily precision. We thus have access to a detailed set of labor market characteristics for each worker, including wage, employment status, and days worked. Moreover, the data contain highly reliable individual characteristics, such as nationality, age, education, industry, occupation, and workplace at the municipality level.

We use a unique establishment identifier to combine our worker-level sample with establishment data from the *Establishment History Panel (BHP)*, which provides access to information such as establishment size, average establishment wage, number of migrant workers in the establishment, and number of marginally employed workers in the establishment.

Based on the code provided by Dauth/Eppelsheimer (2020), we use these data to construct a worker-level panel as of June 30 each year. If workers leave the data and do not return until 2017, they drop out of our sample upon exit.[6] If workers only temporarily leave the data, we

[5] These data stem from administrative sources and are therefore highly reliable. Note, however, that these data do not include the self-employed, civil servants, or the informal sector. This means that we cannot observe whether more migrants than natives sort into self-employment or into the informal sector after displacement.
[6] We drop these workers because they could potentially include migrants who have moved abroad (e.g., returned to their native country) or selected into self-employment or informal sector employment. If more mi-

assign them zero earnings and missing wages for the missing spells. To ensure the validity of the data, we further conduct two imputation procedures. First, we correct implausible education entries following Fitzenberger/Osikominu/Völter (2008). Second, we impute wages censored at the contribution assessment ceiling in Germany following Gartner (2005) and Dustmann/Ludsteck/Schönberg (2009).

2.2 Job Displacement at Mass Layoffs

Next, we use the universe of German workers to identify mass layoff events in 2001-2011. To ensure that our results are comparable with state-of-the-art studies from the U.S. and other countries, we follow Hethey-Maier/Schmieder (2013) in their identification of mass layoffs. In our definition, a layoff occurs between June 30 in t=-1 and June 30 in t=0 if an establishment (i) completely closes down or (ii) reduces its workforce by at least 30 percent. To identify genuine mass layoffs, we restrict our sample to establishments with a minimum of 50 employees in the year before the layoff[7] and without major employment fluctuations in the years before. This definition follows common approaches in the U.S. literature and thus ensures the comparability of our study.

One threat to the identification of mass layoffs in administrative data are mergers, takeovers, spinoffs, and id changes. To eliminate such events from our data and thus avoid measurement error, we construct a matrix of worker flows between establishments by year following Hethey-Maier/Schmieder (2013). If more than 30 percent of displaced workers move to the same successor establishment, we exclude this establishment from our sample.

2.3 Sample of Displaced Workers

In the next step, we identify displaced workers from our random sample of workers. Closely following Schmieder/von Wachter/Heining (2020), we only consider workers subject to the following baseline restrictions at time of displacement: male workers with at least 3 years of tenure who are full-time employed in an establishment with at least 50 employees and aged 25-50.[8] These baseline restrictions allow us to compare our results to prior literature

grants than natives left social security employment for these reasons, we would otherwise overestimate our results. Note that in the data, we observe both workers' employment and unemployment spells; workers who drop out of the data are not registered with the employment agency at all. If we nevertheless keep these workers in the sample and assign them zero earnings and missing wages for all missing spells, our results do not change substantially. Regression tables are available upon request.

[7] We introduce this size restriction because in a small establishment, the employees can directly affect its profits and because the share of employment fluctuations is larger in small companies.

[8] The focus on workers with high tenure and full-time employment ensures that if workers switch jobs, they likely do so involuntarily. For high-tenure workers, job-to-job mobility in Germany is very low, as German law offers employees a high level of protection. We moreover focus on prime-age workers to ensure that workers

from the U.S. However, they come at the expense of the representativity of our sample. For example, Illing/Schmieder/Trenkle (2021) show that the costs of job loss differ substantially between men and women, and throughout this paper, we focus on men.[9] Reassuringly, however, existing literature from the U.S. (e.g., von Wachter/Song/Manchester (2011), Hildreth/Weber-Handwerker/von Wachter (2009)) shows that their results are robust to variations in establishment size, the size of the mass layoff, and restrictions on workers' tenure.

We define a worker in our sample as displaced between June 30 in $t = -1$ and $t = 0$ if (i) the establishment lays off at least 30 percent of its workforce between $t = -1$ and $t = 0$ and (ii) the worker leaves the establishment between $t = -1$ and $t = 0$ and is not employed in the displacement establishment in the following ten years. Workers in our sample are displaced in 2001-2011. Restricting our observation period to 1996-2017 thus ensures that we can follow workers for at least five years prior to and five years after displacement.

2.4 Propensity Score Matching

We cannot simply compare displaced to nondisplaced workers in our sample, since they may differ on individual characteristics, which could bias our regression coefficients. We thus follow the job loss literature, in particular Schmieder/von Wachter/Heining (2020), and apply propensity score matching to assign each displaced worker a suitable nondisplaced control worker match. We consider only displaced workers and potential controls who satisfy our baseline restrictions in a given baseline year. We then estimate a probit regression, where the outcome variable is a dummy for being displaced. In this regression, we include the following controls: establishment size in $t = -1$, log wage in $t = -3$ and $t = -4$, years of education in $t = -1$, tenure in $t = -1$, and age in $t = -1$. We only allow exact matches within cells of baseline year, 1-digit industries, and migration status. This means that we only match displaced migrants to non-displaced migrants, and displaced natives to non-displaced natives. We assign each worker a control worker with the closest propensity score (without replacement).[10]

This matching algorithm leaves us with a highly comparable control group of nondisplaced workers for migrants and natives. Table 1 presents summary statistics on the individual characteristics of displaced compared to nondisplaced workers in the year before displacement. While columns (1) and (2) show migrant workers' characteristics, columns (3) and (4) report

have already fully entered the labor market and do not yet have access to partial retirement programs. Furthermore, the outside options after job loss differ by sex (e.g., motherhood for women), which is why we exclude women from our baseline sample. All of these restrictions enable a clearer interpretation of our results.

[9] Table 20 reports our main results for a sample of women.

[10] Schmieder/von Wachter/Heining (2020) show that their results are robust to different matching specifications. In particular, they are robust to matching within counties, as well as variations in the set of matching variables.

native workers' characteristics.

Table 1: Worker Characteristics of Displaced Workers and Matched Non-Displaced Workers One Year Prior to Displacement ($t = -1$)

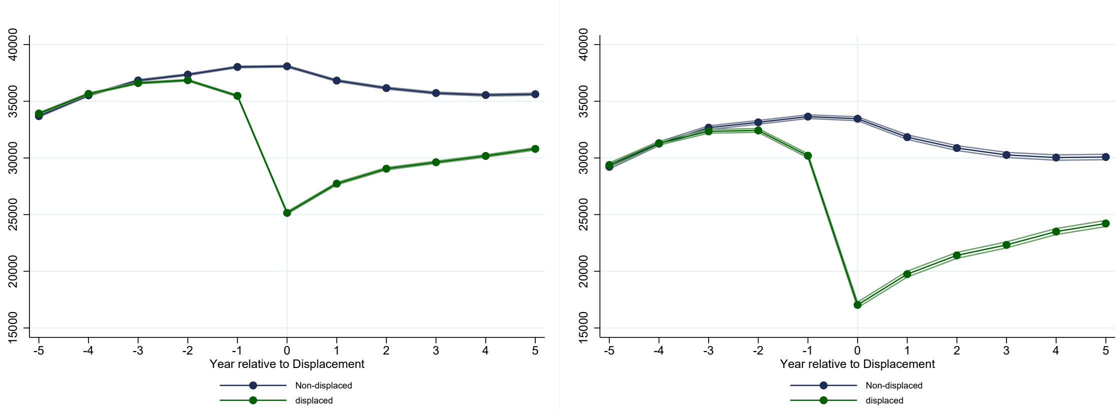
	(1) Non-Displaced Migrants	(2) Displaced Migrants	(3) Non-Displaced Natives	(4) Displaced Natives
Panel A: Individual Characteristics				
Years of Education	11.2	11.2	12.3	12.3
	[1.68]	[1.61]	[1.76]	[1.77]
Age	37.9	37.9	39.4	39.4
	[6.83]	[6.68]	[6.82]	[6.71]
Tenure	6.37	6.38	6.19	6.20
	[2.60]	[2.56]	[2.46]	[2.43]
Real Daily Wage (EUR)	91.3	89.2	104.1	102.3
	[30.1]	[30.8]	[36.1]	[36.7]
Total Yearly Earnings	33644.5	30194.9	38028.3	35477.8
	[11159.3]	[11844.1]	[13486.1]	[14189.6]
Days Worked in Year	362.7	335.5	362.8	344.2
	[15.1]	[53.9]	[14.1]	[45.6]
Panel B: Regional Characteristics				
Lives in City	0.77	0.80	0.55	0.57
	[0.42]	[0.40]	[0.50]	[0.50]
Lives in East Germany	0.031	0.041	0.22	0.25
	[0.17]	[0.20]	[0.42]	[0.43]
Local UR Change (between $t = 0$ and $t = 1$)	0.014	0.027	0.019	0.035
	[0.14]	[0.14]	[0.13]	[0.14]
Panel C: Establishment Characteristics				
Establishment Size	277.3	291.1	328.9	347.2
	[532.0]	[490.4]	[723.2]	[636.8]
Share Migrant Workers	0.22	0.25	0.064	0.074
	[0.19]	[0.19]	[0.085]	[0.095]
Share High-Skilled Workers	0.079	0.079	0.12	0.12
	[0.12]	[0.12]	[0.16]	[0.16]
Share Marginally Employed Workers	0.078	0.059	0.054	0.041
	[0.15]	[0.13]	[0.11]	[0.095]
Displaced from Complete Closure	0.00011	0.32	0.000077	0.32
	[0.011]	[0.47]	[0.0088]	[0.47]
Number of Observations	17605	17605	129701	129701

Notes: Characteristics of displaced and non-displaced workers in year prior to displacement year. Workers satisfy the following baseline restrictions: aged 24 to 50, working fulltime in pre-displacement year, at least 3 years of tenure, and establishment has at least 50 employees. Non-displaced sample of workers are matched to displaced workers using propensity score matching within year and industry cells. Non-displaced sample of workers is a random sample of workers (one per displaced worker) that satisfy the same baseline restrictions. Standard deviations in brackets. Source: IEB and BHP.©IAB

Panel A of Table 1 shows that the matched workers exhibit very similar predisplacement means in individual characteristics such as years of education and tenure. In contrast, displaced workers' wages, earnings, and days worked are lower than those of matched controls. The main reason for this is our definition of displacement: As workers are displaced between June 30 in $t = -1$ and $t = 0$, the average wages of the displaced worker sample are already lower in $t = -1$ by construction. Another explanation are anticipation effects (Ashenfelter (1978)). Note that for this reason, we use log wages in $t = -3$ and $t = -4$ for our propensity score matching algorithm. As Figures 1 and 2 show, both levels and trends in log earnings are, however, remarkably similar for displaced workers and nondisplaced workers in all periods leading up to $t = -1$.

Figure 1: Migrant and Native Workers' Earnings Losses Before and After Displacement Without Controls

(a) Yearly Earnings, Natives **(b) Yearly Earnings, Migrants**



Notes: This figure plots raw earnings losses for displaced compared to non-displaced workers and natives (Panel A) compared to migrants (Panel B). The blue line shows earnings trajectories for non-displaced workers, the green line shows earnings trajectories for workers displaced between $t = 0$ and $t = -1$. Displaced workers are matched to non-displaced workers using propensity score matching. Workers in our sample are displaced in 2001-2011, and they are observed from 1996-2017. In $t = -1$, we observe 35,210 migrants and 259,402 natives. Source: IEB.©IAB

Panel B of Table 1 focuses on regional characteristics. It shows that the majority of displaced and nondisplaced workers in our sample live in cities in West Germany. The change in local (municipality) unemployment rates between $t = 0$ and $t = 1$ is substantially larger for displaced workers, suggesting that some of the layoffs disrupt local labor markets.

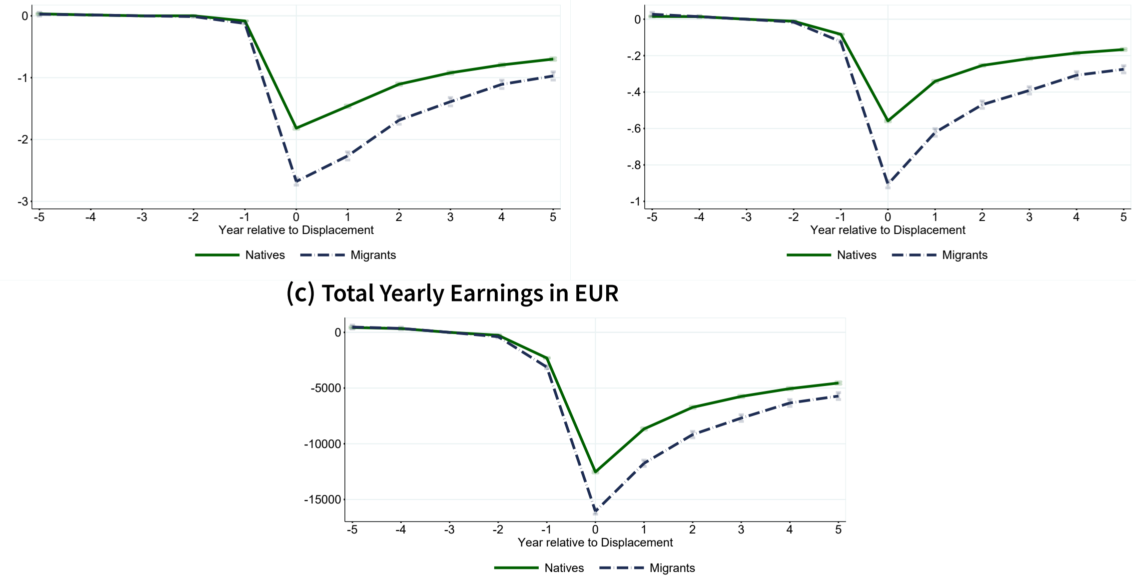
Panel C of Table 1 shows that matched workers work for establishments that are similar in terms of worker composition. One difference is that displaced workers tend to work in slightly larger establishments. Approximately one-third of workers are displaced from a complete establishment closure (100 percent layoff rate). We moreover see that a tiny fraction of nondisplaced workers are laid off in complete closures. This is because we do not impose any restrictions with respect to employment on this control group after pseudotreatment following Schmieder/von Wachter/Heining (2020). Some of the control workers are thus also laid-off in future years.

When comparing displaced migrants to natives, a few differences stand out: Migrants have substantially lower wages and consequently lower yearly earnings (30,000 EUR vs. 35,000 EUR). They report fewer years in formal education (11.2 vs. 12.3 years of education). The vast majority of migrants live in cities (80 percent), compared to only 57 percent of natives. Migrants also work in different types of establishments: These are, on average, smaller, have a substantially higher average share of migrant workers (25 percent vs. 7.4 percent) and a

Figure 2: Event Study Regression Coefficients of Earnings Losses - Migrants vs. Natives

(a) Yearly Log(Earnings+1) **(b) Yearly Log(Earnings)**

(c) Total Yearly Earnings in EUR



Notes: This figure shows losses in yearly log(earnings+1) (Panel A), yearly log earnings (Panel B), and yearly earnings in EUR (Panel C) for displaced and non-displaced workers. The solid green line reports results for our sample of native workers, the dashed blue line reports results for our sample of migrant workers. Vertical bars indicate the estimated 95 percent confidence interval based on standard errors clustered at the individual level. Our regression controls for year fixed effects, year since displacement fixed effects, age polynomials, and worker fixed effects. We omit $t = -3$ as reference category. Displaced workers are matched to non-displaced workers using propensity score matching. Workers in our sample are displaced in 2001-2011, and they are observed from 1996-2017. Tables 12 and 13 report corresponding coefficients. Source: IEB.©IAB

lower share of high-skilled workers (7.9 percent vs. 12 percent).

Tables 10 and 11 in the Appendix report the predisplacement distributions of migrants and natives (and their respective matched control group) across industries and occupations. In groups of migration status and due to our exact matching within industry cells, the distribution of displaced and nondisplaced workers across industries is the same. However, there are differences between migrants and natives; e.g., migrants are more likely to work in food manufacturing, in the hospitality sector, and in the production goods sector. Natives, in turn, are more likely to work in education, the nonprofit sector, and public administration. With respect to occupations, migrants are more likely to work in occupations with simple, manual tasks. Natives more often work in high-skilled occupations such as engineering, qualified services, and qualified administrative tasks.

This shows that directly comparing migrant to native workers is a challenge. For our regression analysis, we will therefore reweight migrants to natives with respect to individual characteristics, industries, and occupations, using the reweighting scheme first proposed by DiNardo/Fortin/Lemieux (1996) and first applied in the context of job displacement by Illing/

Schmieder/Trenkle (2021).

3 The Costs of Job Loss for Migrants and Natives

Section 3 presents our main results. As a benchmark without controls, we first present descriptive statistics (Section 3.1). We proceed with the results of both the event study regression model and the reweighting scheme (Section 3.2).

3.1 Labor Market Outcomes Without Controls

We first present descriptive statistics on how average yearly earnings develop before and after job loss. Panel A of Figure 1 shows how earnings (without controls) evolve differently for displaced (green line) and nondisplaced (blue line) natives in the five years before and after job loss. While trends and levels in pretreatment earnings are remarkably similar between displaced workers and matched controls, displaced workers' earnings start decreasing from $t = -1$ onwards. Between $t = -2$ and $t = 0$, displaced workers' earnings decrease from approximately EUR 37,000 to EUR 25,000. While they recover slightly in the years following job loss, they do not catch up with average earnings in the control group even five years after displacement. Panel B of Figure 1 shows earnings losses for migrant workers. Displaced migrants' average earnings are already lower than natives' pre displacement, and they lose more, both in absolute and relative terms: Their earnings drop from roughly EUR 33,000 in $t = -2$ to EUR 17,000 in $t = 0$.[11] Again, these earnings losses are persistent for up to five years.

Figure 1 moreover shows that for the control groups of nondisplaced workers, log earnings slightly fall from $t = 1$ onwards. Recall that in the year before (pseudo-) displacement, both displaced and nondisplaced workers have to be employed with three years of tenure. This ensures that both groups display relatively stable employment careers before job loss. Starting with period $t = 0$, we, however, allow nondisplaced workers to leave social security records for reasons such as unemployment, self-employment, or parental leave; their average earnings thus naturally decrease. This does not present a threat to the validity of our analysis, as we think of our control group as a random sample of worker biographies, which we do not want to artificially restrict to being employed. Given the decreasing trends in the control group, even if there were bias, we would under- rather than overestimate our effects.

[11] Note that migrants who have contributed to social security in Germany for at least one year are entitled to receive unemployment benefits according to the same rules as German workers. Due to our baseline restrictions, all displaced workers in our sample have at least three years of experience in the German labor market upon displacement.

3.2 Event Study Regression

When analyzing the effects of job loss on migrants' and natives' labor market outcomes, we follow the seminal study by Jacobson/LaLonde/Sullivan (1993) and estimate an event study regression model with worker and time fixed effects. Specifically, we estimate the following regression specification separately for migrants and natives:

$$Y_{itc} = \sum_{j=-5, j\neq -3}^{5} \alpha_j * I(t = c+1+j) * Disp_i + \sum_{j=-5, j\neq -3}^{5} \gamma_j * I(t = c+1+j) + \theta_t + \gamma_i + X_{it}\beta + \epsilon_{itc} \tag{0.1}$$

where the dependent variable Y_{itc} denotes average labor market outcomes (e.g., log yearly earnings, log daily wages, employment, number of days worked) of individual i, belonging to cohort c in year t.[12] $Disp_i$ is a dummy indicating whether a worker is displaced, which is interacted with dummies $I(t = c + 1 + j)$ for years -5 to 5 since job loss. We omit period $t = -3$ as the reference category, as it should not be affected by Ashenfelter (1978) anticipation effects. The coefficients of interest are α_j, which present the change in labor market outcomes of displaced workers relative to the trends of the nondisplaced control group. Following Schmieder/von Wachter/Heining (2020), we include dummies for the year since displacement in the regression equation. In addition, θ_t adds year fixed effects, γ_i captures individual fixed effects, and X_{it} is a vector of age polynomials. We cluster standard errors at the worker level.

Panel A of Figure 2 presents the event study coefficients for yearly earnings losses, both for migrants (dashed blue line) and natives (solid green line). The results underscore the descriptive results from Figure 1. Yearly log earnings decline significantly both for migrant (56 log points) and native (91 log points) displaced workers between $t-1$ and t. Migrants' losses are substantially higher. Neither displaced migrants nor displaced natives have fully recovered 5 years after job loss. From t onwards, migrants' average recovery rate is faster, but their earnings losses are still higher than those of natives five years after job loss.[13]

Note that for Panel B of Figure 2, we report log (earnings+1) and thus include unemployment spells in our measure of earnings losses. While including workers with zero earnings substan-

[12] For all workers laid off in year $t = 0$, the baseline year is $t = -1$, which is also their cohort, c.

[13] Table 19 in the Appendix shows earnings losses separately for migrants from different origin groups as defined by Battisti/Romiti/Peri (2018). The table shows that differences in earnings losses from natives are less pronounced for specific origin groups, such as European migrants and migrants from Western countries, the former USSR, and Central and South America. In contrast, losses for migrants from Turkey, Asia and the Middle East and Africa are particularly high. See Table 22 for an overview of the origin group definition.

tially increases the size of our coefficients, Panel B of Figure 2 shows that the overall pattern holds: Both migrant and native displaced workers face large earnings losses, with a substantial gap between migrant and native displaced workers. We observe the same pattern in Panel C, which shows total yearly earnings (in EUR). Overall, our findings of large and persistent earnings losses after job loss are in line – in terms of magnitude and pattern – with existing studies from the U.S. and Germany (e.g., Jacobson/LaLonde/Sullivan (1993), Couch/Placzek (2010), von Wachter/Song/Manchester (2011), Schmieder/von Wachter/Heining (2020)).

Thus far, we have compared migrant and native workers without accounting for the fact that they display differences in individual characteristics and sort into different industries and occupations. To account for these differences, we follow Illing/Schmieder/Trenkle (2021) and use a reweighting scheme first proposed by DiNardo/Fortin/Lemieux (1996). Thus, we reweight migrants to native workers in terms of observable characteristics before job loss. Migrants who are more similar to natives on characteristics such as years of education and tenure receive a higher weight. The intuition is that after reweighting migrants to natives, we can attribute the differences in their outcomes after job loss to how they respond to displacement or to the difficulties they face, rather than to their characteristics.

Econometrically, we approach this as follows: First, we estimate a probit regression model, where the dependent variable is a dummy that takes value 1 for all native workers. We regress this dummy on a set of individual and establishment characteristics. These are log wage ($t = -3, t = -4$), age ($t = -1$), years of education ($t = -1$), tenure ($t = -1$), and being a city resident ($t = -1$). In addition, we control for establishment size ($t = -1$), 1-digit industry ($t = -1$) and occupations ($t = -1$) following the definition of Blossfeld (1985). For each displaced migrant worker, we then use the estimated propensity score $\hat{ps}$ to assign an individual $weight = \frac{\hat{ps}}{1-\hat{ps}}$. Following Illing/Schmieder/Trenkle (2021), we compute these weights only for displaced migrants and then ensure that the weights are constant within matched worker pairs. In a robustness check in section 5, we show that our results do not change if we reweight natives to migrants, instead.

Table 9 presents summary statistics of displaced workers in our sample in $t = -1$. Column (1) shows the characteristics of a random 2-percent sample of migrants in Germany, which we compare to our baseline sample of migrants (column 2) and migrants after reweighting (column 3). Migrants in our sample have substantially higher tenure, wages, and earnings than the random sample of migrants. A similar pattern holds for a random sample of native workers (column 4) compared to native workers in our sample (column 5). This reflects our baseline restrictions, which ensure that we focus on a sample of long-tenure workers with strong attachment to the labor market. Comparing our reweighted sample of migrants (column 3) to baseline native workers (column 5) shows that they are very similar in terms of characteristics. After reweighting, hardly any differences between migrants and natives remain in terms of characteristics such as years of education, age, earnings, and establishment types.

Figure 3 presents the results from our event study regression model, where the solid green line shows the trajectory for natives, the dashed blue line shows the trajectory for migrants, and the dashed light blue line shows the trajectory for reweighted migrants. Panel A presents our results for log(earnings). The light blue line shows that controlling for individual and establishment characteristics as well as occupations halves the original migrant-native gap in earnings. Nevertheless, differences in observable characteristics cannot fully explain the differences in earnings losses.

We next decompose earnings losses into wage and employment losses. Panel B of Figure 3 shows that migrants face substantially higher wage losses than natives (40 vs. 20 log points in $t = 0$), but observable characteristics can almost fully explain these losses. In contrast, as Panels C and D show, observable characteristics cannot explain the migrant-native gap in employment losses.

Panel C shows that migrants and natives are both less likely to be employed in the years following their job loss. Here, the outcome variable is a dummy for being employed at least once in a given year (this includes full-time, part-time, and marginal employment). Migrants' employment decreases substantially and more than natives' (20 vs. 13 percentage points), and observable characteristics cannot explain the differences. Even five years after displacement, migrants have not fully caught up with natives.[14]

Panel D presents a very similar pattern with respect to days worked per year. Again, the reduction is larger for migrants (approximately 150 days) than natives (approximately 100 days). As the light blue line shows, observable characteristics cannot explain these differences. Migrants never fully catch up with natives, even though the gap substantially shrinks from $t = 4$ onwards; after five years, neither group has fully recovered from displacement in terms of days worked. Panels E and F show that migrants are more likely to take up part-time rather than full-time employment after layoff. This is another explanation for migrants' higher earnings losses and suggests that they are offered worse employment contracts.

Overall, Figure 3 offers two key takeaways. First, if migrants find a new job after displacement, their wage losses are slightly higher, but observable characteristics can explain this gap. Second, migrants experience greater difficulty finding a new job than natives in the first place. Neither individual characteristics nor differential sorting across industries and occupations can explain this employment gap.

[14] Our findings are in line with recent work on the Dutch labor market by Meekes/Hassink (2020). While the focus of their paper is gender differences in job flexibility outcomes after job loss, they also show in their online appendix that relative to individuals born in the Netherlands, the foreign born (non-natives) are less likely to become re-employed (10 percentage points) after job loss. Conditional on employment, they find no differential effect on hourly wages.

4 Explaining Differences in Earnings Losses

We have established that while both migrants and natives face large and persistent earnings losses after displacement, migrants' losses are substantially higher. In particular, migrants have greater difficulties finding a new job, and neither individual characteristics nor differential sorting across industries and occupations can fully explain this pattern. In the following, we shed more light on the potential channels underlying our results.

To this end, we first explore what types of establishments migrants and natives select after job loss. If displaced migrants sorted into establishments with lower average wages, then this would explain part of their higher wage losses. We moreover assess whether differences in mobility patterns can partly explain differences in labor market outcomes. Workers who are willing to move geographically will potentially face lower wage losses and will find a new job more quickly. Last, we explore the extent to which local labor market concentration, proxied by the local unemployment rate, city residency, and the share of the same-nationality population at the time of displacement, impacts the migrant-native gap in earnings losses after displacement. We conceive of this as follows: In labor markets with highly elastic labor supply, establishments have more choice regarding the types of workers they hire. If they can choose between equally qualified native and migrant workers, they may prefer to hire a native worker. Similarly, if an employer can choose between two migrants with similar skills, they may prefer migrant workers without layoff experience.

4.1 Establishment Characteristics

Given seniority wages (e.g., Lazear (1979) and Lazear (1981)) and firm-specific human capital accumulation (e.g., Becker (1962)), wage losses for displaced workers who are forced to change establishment come as no surprise. In our study, we focus on a sample of high-tenured workers at time of displacement; their wages thus partly reflect their experience at the displacement establishment. However, wages also mirror the overall productivity of an establishment. We therefore investigate the types of establishments workers reallocate to after displacement. We assume these establishments to be, on average, a negative selection compared to pre-displacement establishments for two reasons: First, displacement is a negative signal. If labor supply is elastic enough, high quality establishments may thus be reluctant to hire displaced workers. Second, we think of displacement as an exogenous shock to workers' careers, which came as surprise. If workers face high pressure to find a new job, they will be more willing to accept bad offers.

If displacement has similar effects on migrant and native workers, then we expect them to, on average, sort into similar establishments. Yet as we have shown, migrant and native workers differ in observable characteristics, and workers with particular characteristics may sort into specific types of establishments. In the following analysis, we therefore estimate regression equation 0.1 with establishment-specific outcome variables, including a specification where we reweight migrant to native workers on individual characteristics, industries, and occupations.

The dashed dark blue lines in Panels A-C of Figure 4 show that both displaced migrants and natives sort into worse establishments after displacement. These establishments pay lower average wages (Panel A), have lower wage premia (Panel B), and have higher shares of marginally employed workers (Panel C). However, once we control for observable characteristics, these differences largely disappear (dashed light blue lines in Panels A, B, and C), suggesting that they can explain the differential sorting of migrants and natives.

Panel D of Figure 4 shows that after job loss, both migrants and natives sort into establishments with a lower share of migrant workers compared to control workers.[15] Initially, this share is particularly low for migrants but they catch up with natives as time passes. For the re-weighted sample, the difference in establishments' migrant share disappears starting from the second year after displacement.

4.2 Geographic Mobility

While the type of establishment is important in explaining differential wage losses after displacement, the channel underlying different unemployment durations is still unclear. In this section, we discuss one characteristic that could explain differences in the success of finding a new job: geographic mobility. Internal geographic mobility is an important tool to adjust regional labor market imbalances and, hence, raise local labor market efficiency (Blanchard/Katz, 1992). Displaced workers who move geographically may be rewarded with higher job search success. Nudges for displaced workers to reallocate are particularly high if they work in highly concentrated labor markets with fewer outside options (Haller/Heuermann, 2019). While previous literature has shown that migrants tend to be more geographically mobile than natives (e.g., Borjas (2001), Cadena/Kovak (2016)), this pattern may reverse in regions with tight housing markets (Clark/Drever (2000)).

For this section, we make use of the geographic information recorded in the IAB data. We know the municipality, county, and federal state in which a worker lives and works.[16] It is

[15] Note that for the share of migrant workers in an establishment, we compute the "leave-one-out mean", as otherwise the share mechanically increases if displaced migrants start working at a new establishment.

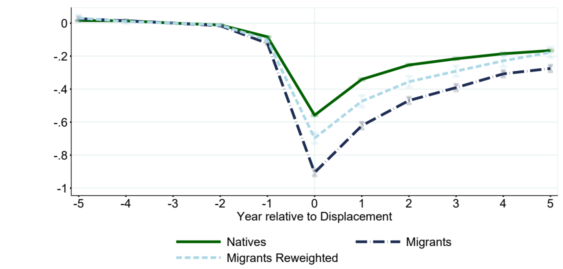
[16] Germany exhibits widespread federalism. Therefore, there exist different administrative units (according to size): (i) federal states and city states, (ii) administrative districts, (iii) counties and cities, and (iv) municipalities. In 2010, there were a total of 11,993 municipalities and 401 counties in Germany. According to data provided by the *German Federal Statistical Office*, on average, a municipality had 4,954 inhabitants, and a county had

important to keep in mind that we only observe this information for *employed* natives and migrants. To draw conclusions on all employees, we have to assume that employed workers' mobility patterns reflect mobility patterns in the overall population of migrants and natives.

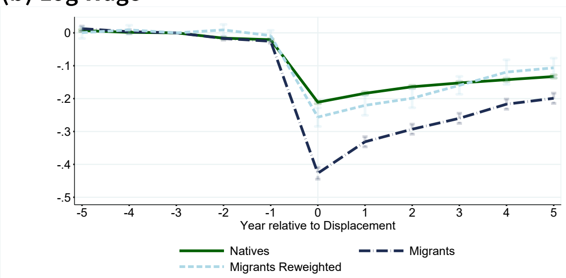
186,596 inhabitants in 2010.

Figure 3: Event Study Regression Coefficients of Labor Market Outcomes - Migrants vs. Natives

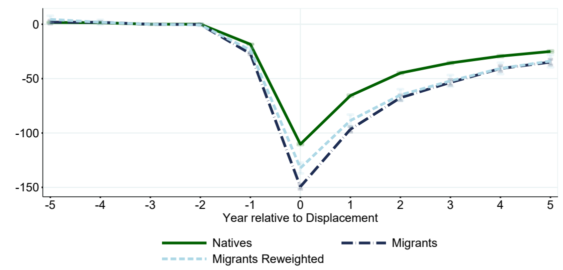
(a) Yearly Log(Earnings)



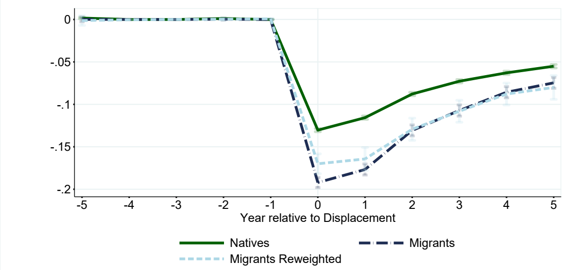
(b) Log Wage



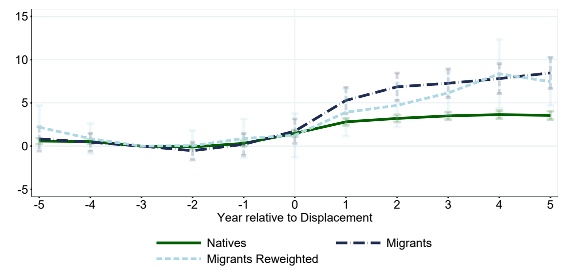
(c) Days Worked per Year



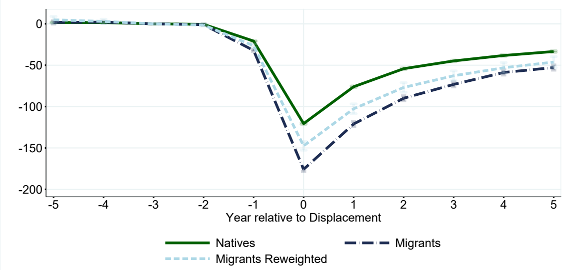
(d) Employment



(e) Days Worked in Part-time Employment per Year

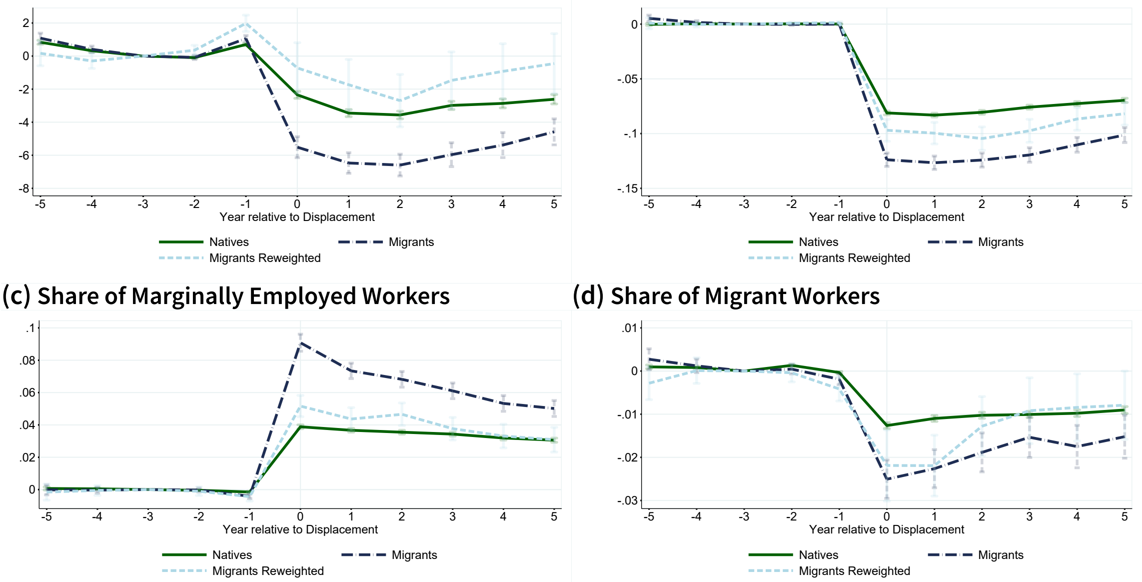


(f) Days Worked in Full-time Employmen per Year



Notes: This figure shows losses in log (earnings) (Panel A), log wages (Panel B), yearly days worked (Panel C), employment (Panel D), part-time employment (Panel E), and full-time employment (Panel F) for displaced and non-displaced workers. The solid green line reports results for our sample of native workers, the dashed blue line reports results for our sample of migrant workers, and the light blue line reports results for our sample of reweighted migrant workers. Reweighting characteristics are log wage ($t = -3$, $t = -4$), age ($t = -1$), years of education ($t = -1$), tenure ($t = -1$), being a city resident ($t = -1$), establishment size ($t = -1$), 1-digit industry ($t = -1$), and for 1-digit occupations ($t = -1$). Vertical bars indicate the estimated 95 percent confidence interval based on standard errors clustered at the individual level. Our regression controls for year fixed effects, year since displacement fixed effects, age polynomials, and worker fixed effects. We omit $t = -3$ as reference category. Displaced workers are matched to non-displaced workers using propensity score matching. Workers in our sample are displaced in 2001-2011, and they are observed from 1996-2017. Tables 12 and 13 report corresponding coefficients. Source: IEB.©IAB

Figure 4: Event Study Regression Coefficients of Establishment Characteristics - Migrants vs. Natives



(a) Average Establishment Full-time Wage

(b) AKM Establishment Effect

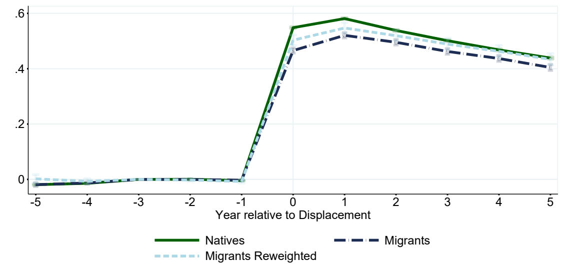
(c) Share of Marginally Employed Workers

(d) Share of Migrant Workers

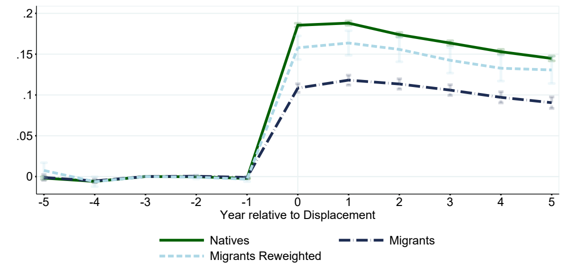
Notes: This figure shows average establishment full-time wages (Panel A), AKM-style establishment fixed effects (Panel B), the share of marginally employed workers in an establishment (Panel C), and the share of migrant workers in an establishment (Panel D, leave-one-out mean) for displaced and non-displaced workers. The solid green line reports results for our sample of native workers, the dashed blue line reports results for our sample of migrant workers, and the light blue line reports results for our sample of reweighted migrant workers. Reweighting characteristics are log wage ($t = -3, t = -4$), age ($t = -1$), years of education ($t = -1$), tenure ($t = -1$), being a city resident ($t = -1$), establishment size ($t = -1$), 1-digit industry ($t = -1$), and for 1-digit occupations ($t = -1$). Vertical bars indicate the estimated 95 percent confidence interval based on standard errors clustered at the individual level. Our regression controls for year fixed effects, year since displacement fixed effects, age polynomials, and worker fixed effects. We omit $t = -3$ as reference category. Displaced workers are matched to non-displaced workers using propensity score matching. Workers in our sample are displaced in 2001-2011, and they are observed from 1996-2017. Table 17 and 18 report corresponding coefficients. Source: IEB, BHP.©IAB

Figure 5: Event Study Regression Coefficients of Geographic Mobility - Migrants vs. Natives

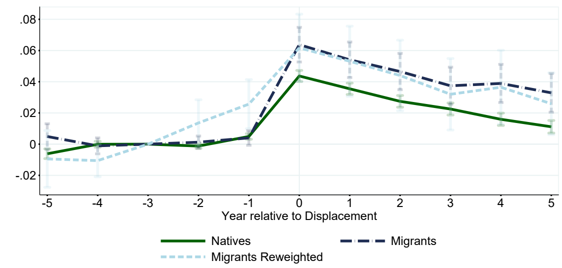
(a) Changed Workplace Municipality since t=-1



(b) Changed Workplace State since t=-1



(c) Commutes



Notes: This figure shows the propensity to change workplace to a different municipality from $t = -1$ (Panel A), the propensity to change workplace to a different federal state (Panel B), and the propensity to commute (Panel C). The propensity to commute is defined as working and living in different municipalities. The solid green line reports results for our sample of native workers, the dashed blue line reports results for our sample of migrant workers, and the light blue line reports results for our sample of reweighted migrant workers. Reweighting characteristics are log wage ($t = -3$, $t = -4$), age ($t = -1$), years of education ($t = -1$), tenure ($t = -1$), being a city resident ($t = -1$), establishment size ($t = -1$), 1-digit industry ($t = -1$), and for 1-digit occupations ($t = -1$). . Vertical bars indicate the estimated 95 percent confidence interval based on standard errors clustered at the individual level. Our regression controls for year fixed effects, year since displacement fixed effects, age polynomials, and worker fixed effects. We omit $t = -3$ as reference category. Displaced workers are matched to non-displaced workers using propensity score matching. Workers in our sample are displaced in 2001-2011, and they are observed from 1996-2017. Tables 15 and 16 report corresponding coefficients. Source: IEB.©IAB

Panel A of Figure 5 reports event study coefficients for workplace changes as the outcome variable. Specifically, we create a dummy variable indicating whether the workplace municipality changed from the workplace municipality in $t = -1$. In line with our expectation, displaced workers' likelihood of moving workplaces substantially increases following job loss. In $t = 0$, displaced natives were approximately 58 percent more likely to change workplaces than nondisplaced controls. For migrants, this number is slightly lower (approximately 50 percent). Once we control for observable characteristics, hardly any differences between migrants and natives remain.[17]

Panel B of Figure 5 shows that mobility across federal states follows a similar pattern. Approximately 19 percent of displaced natives changed their workplace to a different federal state from $t = -1$ to $t = 0$. In contrast, only 12 percent of migrants moved to a different federal state after displacement. After reweighting migrants to natives, this difference reduces to 3 percentage points but remains significant. Under the assumption that employment is exogenous to mobility, lower geographic mobility may thus partly explain why migrants experience greater difficulty reintegrating into the labor market after displacement.

Finally, Panel C of Figure 5 shows how commuting patterns evolve after displacement, where commuting is defined as working and living in different municipalities. This shows that following displacement, the likelihood of commuting increases substantially. Slightly more migrants (6 percent) than natives (4 percent) start commuting following displacement.[18]

Overall, our results on geographic mobility suggest that migrants face higher mobility constraints (e.g., due to tight housing markets or because migrants are particularly dependent on local networks) in terms of moving to a different workplace after displacement. While they attempt to compensate for this by commuting slightly more, this may not be enough to catch up in terms of job search success.

4.3 Competition at Time of Displacement

In the previous sections, we discussed whether sorting into different establishments after displacement and differences in geographic mobility can explain the migrant-native earnings gap after job loss. Our results showed that migrants tend to sort into low-paying establishments with a higher share of migrants and that they tend to be slightly more likely to commute. However, we still do not know why migrants experience greater difficulty finding a new job after displacement.

[17] This result is robust to adapting the mobility definition to include only workplace moves over a distance of more than 50 km.
[18] This result is robust to defining commuting at the county rather than municipality level.

In this section, we explore one last channel: How concentrated is the local environment at the time of displacement? We believe that concentration matters in two ways. First, if displaced workers live and work in labor markets with a high concentration of similar workers, then finding a new job will be particularly challenging for them (e.g., Haller/Heuermann (2019), Caldwell/Danieli (2021)), and this may hold in particular for migrants (Bratsberg/Barth/Raaum (2006)). On the one hand, prospective employers may find it difficult to judge migrants' skill portfolio, especially if they did not receive their qualifications in Germany (Brücker et al. (2021)). They may thus perceive asymmetric information to be a more severe issue when hiring migrants and prefer to hire native workers instead. On the other hand, establishments may display taste-based or statistical discrimination against migrants. If labor supply is very elastic and employers can choose between a migrant and native candidate, they may thus opt for the native worker. Second, migrants may compete for jobs among each other. While previous studies have shown that migrants benefit from better social networks (e.g., Edin/Fredriksson/Åslund (2003), Munshi (2003)), migrants may also suffer from within-network competition (e.g., Albert/Glitz/Llull (2020), Beaman (2012), Calvo-Armengol/Jackson (2004)). Migrants living in counties with a particularly high share of same-nationality population may compete for a limited number of jobs[19].

For our empirical approach, we follow Schmieder/von Wachter/Heining (2020) and estimate a DID regression model, where we proceed in two steps. In the first step, within each matched worker pair, we construct an individual-level measure of earnings losses (and other outcomes), which we call the DID outcome. For this purpose, we calculate the mean difference in earnings before and after job loss within each displaced and nondisplaced worker match:

$$\Delta y_{ic}^{DID} = \Delta y_{ic}^{DP} - \Delta y_{ic}^{NDP} \qquad (0.2)$$

where Δy_{ic}^{DP} reports the difference in average earnings for displaced worker i in cohort c before ($t = -5$ to $t = -2$) and after ($t = 0$ to $t = 3$) job loss. Δy_{ic}^{NDP} reports the measure for the corresponding nondisplaced worker. Δy_{ic}^{DID} then indicates the extent to which these differences in means vary within matched worker pairs. We can interpret this difference as the individual treatment effect from job loss.

In the second step, we estimate three OLS regression models for displaced workers only, where we use Δy_{ic}^{DID} as the outcome variable and consecutively include three regressors as proxy measures for local labor market concentration:

$$\Delta y_{ic}^{DID} = \alpha Mig + \beta_1 UR_{ic} + \beta_2 UR_{ic} * Mig + \phi X_{ic} + \epsilon_{ic} \qquad (0.3)$$

[19] It is plausible to assume that migrants with the same nationality are similar in terms of characteristics, e.g., because of similar education systems in their countries of origin, and therefore substitutes.

$$\Delta y_{ic}^{DID} = \alpha Mig + \gamma_1 City_{ic} + \gamma_2 City_{ic} * Mig + \phi X_{ic} + \epsilon_{ic} \quad (0.4)$$

$$\Delta y_{ic}^{DID} = \alpha Mig + \delta_1 EthnicShare_{ic} + \delta_2 EthnicShare_{ic} * Mig + \phi X_{ic} + \epsilon_{ic} \quad (0.5)$$

Our first proxy measure for concentration is UR_{ic}, which measures the percentage change in the unemployment rate in the workplace municipality between $t = -1$ and $t = 0$ for displaced worker i in cohort c. Our second concentration proxy, $City_{ic}$, is a dummy indicating whether a worker lives in a city at the time of displacement.[20]

Last, $EthnicShare_{ic}$ reports the share of the working age population of a worker's nationality by the total working age population in his workplace county at $t = -1$. We use data on working age population by nationality and county from the *German Federal Statistical Office (Destatis)*.[21] In addition to these variables of interest, we include a vector X_{ic} with individual, industry, and occupation controls measured in the year before displacement. We cluster standard errors at the baseline county level.

[20] To define cities, we use a classification proposed by the *German Federal Institute for Research on Building, Urban Affairs and Spatial Development* (BBSR), which is based on characteristics such as inhabitants per square meter and total number of inhabitants at the municipality level.

[21] For our analysis, we use the dataset *Population and Employment, Foreign Population, Results of the Central Register of Foreigners, Destatis, 2019*. This dataset reports the population in Germany on December 31 by county, nationality, and age for each year in the period 1998-2017. It is based on records from the German foreigners' registration office. For the majority of foreigners' registration offices, the jurisdictions coincide with German counties. However, in Saarland, Hesse, and Brandenburg, a county-specific assignment of data is not always possible. Therefore, it is not possible to determine the percentage of the working-age population of a certain nationality for all German counties over the whole period. This is only a minor issue for our analysis, as the vast majority of counties (especially the five largest metropolitan areas (Berlin, Cologne, Frankfurt, Hamburg, and Munich) are included in the sample.

Table 2: Explaining Differences in Earnings Losses by Competition

	(1) Log (Earnings)	(2) Log (Earnings)	(3) Log (Earnings)	(4) Log (Earnings)	(5) Log (Earnings)	(6) Log (Earnings)
Migrant	-0.19**	-0.19**	-0.13**	-0.20	-0.12**	-0.25*
	(0.016)	(0.017)	(0.022)	(0.13)	(0.023)	(0.12)
Local UR Change		-0.11**			-0.12**	-0.12**
		(0.041)			(0.041)	(0.042)
Migrant*UR Change		-0.090			-0.14	-0.15
		(0.12)			(0.12)	(0.12)
City Resident			-0.056**		-0.058**	-0.064**
			(0.012)		(0.012)	(0.011)
Migrant*City Resident			-0.058*		-0.063*	-0.040
			(0.027)		(0.027)	(0.028)
Share Same Nationality				-0.053		-0.17
				(0.14)		(0.12)
Migrant*Share Same Nationality				-3.03**		-2.96**
				(0.82)		(0.78)
Observations	127653	126524	126924	123542	125834	122635
R^2	0.049	0.050	0.050	0.050	0.050	0.052
Mean Dep. Var (Native)	-0.36	-0.36	-0.36	-0.36	-0.36	-0.36

Notes: The table shows the effect of being a migrant on earnings losses, where we include spells with 0 earnings. All outcome variables are based on the individual difference-in-differences estimate derived from equation 0.2. In column 1, we control for individual characteristics (age, age squared, years of education, tenure, experience, fulltime work, log wage in t=-3, and log firm size), 1-digit industries and occupations according to Blossfeld (1985) in the year before displacement. We then successively add controls for local unemployment rate changes (from t=-1 to t=0) reported on the municipality level (column 2), city residency (column 3), and the share of co-ethnic working age population in a county (column 4), all measured in the year before displacement. Columns (5) and (6) show the coefficients when all controls are included simultaneously. We cluster standard errors at displacement establishment level. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Workers in our sample are displaced in 2001-2011, and they are observed from 1996-2017. Source: IEB, BBSR, Destatis. ©IAB

Table 2 reports the results from regression equation 0.3, where we consecutively include controls. The outcome variable is $log(earnings)$. In column (1), we control for a set of individual characteristics[22], 1-digit industries (in $t = -1$), and occupations according to Blossfeld (1985) (in $t = -1$). The average loss of earnings is 36 log points for native workers (see the mean of the dependent variable), and for migrants, this loss increases by an additional 19 log points[23] (Column (1)). This confirms that even after controlling for observable characteristics, migrants face larger earnings losses.

We then add our first proxy for local labor market concentration and local unemployment rate changes in column (2). The result implies that a 1 percent increase in the municipality unemployment rate from $t = -1$ to $t = 0$ increases earnings losses – regardless of migration status – by 11 percent. This supports our hypothesis that higher local unemployment rates reduce workers' outside options and thus increase displaced workers' earnings losses. The coefficient on the interaction of local unemployment rate changes and the migrant dummy is negative but estimated very imprecisely. In column (3), we include city residency as another proxy for concentration. The coefficients confirm the negative relationship between living in a city at the time of displacement and earnings losses, as documented by Haller/Heuermann (2019). Earnings losses of displaced workers that live in cities at time of displacement are 5.6 percent larger. This effect is approximately twice the size for migrant workers.

Column (4) reveals that the concentration of similar workers, proxied by the share of the working-age population of a worker's nationality by the total working-age population in his workplace county before job loss, substantially increases migrants' earnings losses. Note that if we simultaneously control for all concentration proxies (column 6), the interaction of the migrant dummy with city residency becomes insignificant. This suggests that a large part of the city effect for migrants can be explained by a higher share of the same-nationality working-age population in cities.

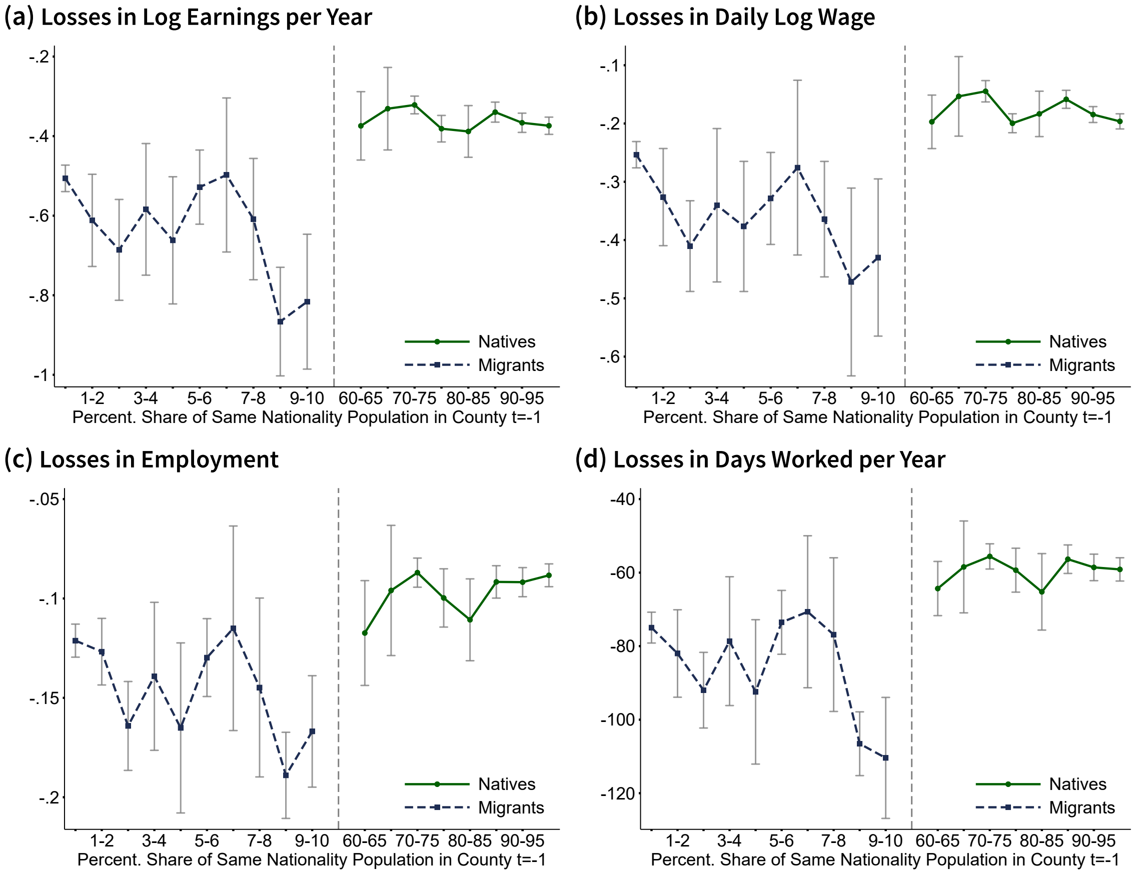
We do not want to interpret the magnitude of the coefficient on the interaction between migrants and shares of the same nationality since the effect may vary substantially depending on a migrant's position in the share distribution. To show this, we regress the individual DID term for log(earnings) on 18 categories for the share of same-nationality working age population in $t = -1$. We plot the respective coefficients in Figure 6, where the x-axis reports the 18 categories. While earnings losses for natives (Panel A, solid green line) are constant and do not vary substantially by the percentage share of same-nationality working age population, there is a clear pattern for migrants (dashed blue line): Earnings losses are particularly high for migrants working in counties with a share of same-nationality working age population of 8-10 percent. This pattern is driven by larger log wage losses (Panel B) and larger employment

[22] These are age, age squared, years of education, tenure, experience, full-time employment, log firm size (all measured in $t = -1$), and log wage in $t = -3$.

[23] This corresponds to an increase of 20.92 percent ($100 * (e^{0.19} - 1) = 20.92\%$).

losses, both on the extensive and intensive margins (Panels C and D).

Figure 6: Costs of Job Loss and Share of Same-Nationality Working Age Population in t=-1



Notes: This figure shows how costs of job loss differ by the share of the same-nationality working-age population in a worker's workplace county in t=-1. This share ranges from 0 to 10 percent for migrants and from 60 to 100 percent for natives. For the distribution of the share, see Figure 7. Panel A reports log(earnings), Panel B reports log(wage), Panel C reports employment probability, and Panel D reports number of days worked per year. We regress workers' individual difference-in-differences outcomes on the categories of same-nationality share reported on the x-axis, as well as individual, industry, and occupation controls. The solid green line reports the results for our sample of native workers, and the dashed blue line reports the results for our sample of migrant workers. Vertical bars indicate the estimated 95 percent confidence interval based on standard errors clustered at the displacement establishment level. Our regression controls for individual characteristics (age, age squared, years of education, tenure, experience, full-time work, log wage in t=-3, and log firm size), 1-digit industries, and occupations according to Blossfeld (1985) in the year before displacement. Source: IEB and Destatis.©IAB

Finally, we estimate versions of regression equation 0.3 for different outcome variables, such as DID terms for employment, log wage, commuting, and establishment characteristics. Panel A of Table 3 reports the coefficient on the migrant dummy for a regression with only individual, industry, and occupation controls. The coefficient on migrants roughly confirms our previous results.

We next add our concentration proxy controls in Panel B. The respective coefficients confirm the pattern that we already observed in Table 2: 1) A larger increase in the local unemployment rate change from $t = -1$ to $t = 0$ leads to greater losses in terms of days worked per year. 2) Workers living in cities at the time of displacement face larger employment and wage losses; for migrants, this "city penalty" on wage losses is particularly high. 3) Migrants living in counties with a higher share of the same-nationality population face particularly large wages and employment losses. Overall, our results suggest that competition from workers of the same nationality – not from native workers – is an important driver of the higher costs of job loss for migrants.

Table 3: Explaining Costs of Job Loss by Competition

	(1) Employed	(2) Days Worked	(3) Log Wage	(4) Commutes	(5) AKM Effect	(6) Share Migrants	(7) Share Marginally Employed
Panel A: Controlling for Individual Characteristics, Industry, and Occupation							
Migrant	-0.040**	-21.1**	-0.11**	-0.0070	-0.030**	0.0014	0.028**
	(0.0044)	(2.10)	(0.011)	(0.0096)	(0.0066)	(0.0035)	(0.0031)
Observations	133338	133338	121866	121676	94866	119631	119291
R^2	0.020	0.034	0.047	0.018	0.093	0.007	0.021
Mean Dep. Var (Native)	-0.094	-58.7	-0.17	0.027	-0.072	-0.0098	0.034
Panel B: Adding Controls for Local Unemployment Rate Change, City Resident and Share of Coethnic Neighbors							
Migrant	0.012	-26.5	-0.15*	-0.016	0.0096	0.17**	-0.027
	(0.031)	(16.2)	(0.070)	(0.069)	(0.046)	(0.016)	(0.016)
Local UR Change	-0.014	-15.8*	-0.020	0.017	-0.039	0.0071	0.0069
	(0.011)	(6.21)	(0.023)	(0.017)	(0.044)	(0.0065)	(0.0070)
Migrant*UR Change	-0.0100	-6.46	-0.087	-0.064	0.053	-0.011	0.0089
	(0.027)	(14.8)	(0.076)	(0.053)	(0.044)	(0.032)	(0.025)
City Resident	-0.018**	-9.72**	-0.022**	0.059**	0.0024	0.00026	0.0037**
	(0.0035)	(1.61)	(0.0062)	(0.0099)	(0.0063)	(0.0012)	(0.0014)
Migrant*City Resident	0.0047	3.63	-0.073**	-0.024	-0.033**	-0.00053	0.018**
	(0.0066)	(3.10)	(0.019)	(0.019)	(0.0079)	(0.0062)	(0.0061)
Share Same Nationality	0.045	-12.1	-0.13	-0.0063	0.013	0.18**	-0.039*
	(0.033)	(17.1)	(0.073)	(0.073)	(0.050)	(0.017)	(0.016)
Migrant*Share Same Nationality	-0.76**	-329.3**	-2.06**	0.66	-0.70	0.13	0.38*
	(0.18)	(86.2)	(0.57)	(0.47)	(0.44)	(0.20)	(0.15)
Observations	128092	128092	117075	116885	91178	115078	114745
R^2	0.021	0.035	0.049	0.021	0.095	0.015	0.022
Mean Dep. Var (Native)	-0.094	-58.7	-0.17	0.027	-0.072	-0.0098	0.034

Notes: The table shows the effect of being a migrant on labor market outcomes. All outcome variables are based on the individual difference-in-differences estimate derived from equation 0.2. Panel (A) shows results controlling for individual characteristics, and sorting across industries and occupations in the year before displacement. Panel (B) adds controls for local unemployment rate changes (from t=-1 to t=0) reported on the municipality level, city residency, and the share of coethnic working age population in a county, all measured in the year before displacement. AKM Effect is a proxy for wage differentials across firms, based on Abowd/Kramarz/Margolis (1999). We cluster standard errors at displacement establishment level. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Workers in our sample are displaced in 2001-2011, and they are observed from 1996-2017. Source: IEB, BBSR, Destatis. ©IAB

5 Robustness

5.1 Robustness of Main Results

In the following, we perform three robustness checks to show that our main results from Section 3.2 do not change substantially if we i) exclude the financial crisis years from our sample, ii) exclude East Germany from our sample, and iii) change our reweighting algorithm to reweight natives to migrants.

For the first robustness check, we estimate regression equation 0.1 only for baseline years up to 2007. Thus, we ensure that none of the workers in our analysis sample lose their jobs during the financial crisis. This may matter because, as discussed, migrants particularly suffer during recessions (e.g., Borjas/Cassidy (2020), Freeman et al. (1973), Fairlie/Couch/Xu (2020), Montenovo et al. (2020))). The financial crisis years may thus bias our results in the direction of particularly large earnings losses for migrants. As Table 4 shows, this is not the case: Our results are remarkably robust to excluding the financial crisis years. Migrants displaced in 2001-2007 face substantially larger earnings losses (columns 1 and 2), wage losses (columns 3 and 4), employment losses (columns 5 and 6), and losses in yearly days worked (columns 7 and 8) than native workers.[24] We thus conclude that the financial crisis does not drive our results.

For our second robustness check, we exclude workers displaced in East Germany from our sample. We do this because our observation period ranges from 1996-2017. Thus, it starts only six years after German reunification and covers a time when East Germany underwent major economic transitions. This could lead to different displacement effects for workers in East Germany from those in West Germany. For migrants in East Germany, reintegration into the labor market may be particularly difficult. In Table 5, however, we see that our results are robust to estimating our regression based on a sample for workers displaced in West Germany only. Again, migrants displaced in West Germany face higher earnings losses (columns 1 and 2), wage losses (columns 3 and 4), employment losses (columns 5 and 6), and losses in yearly days worked (columns and 8) than native workers.

Finally, we show that our reweighting scheme is robust to the direction of reweighting. For our main regression results, we reweighted migrants to natives following DiNardo/Fortin/Lemieux (1996). However, if only a few migrants are comparable to native workers, these workers may receive very high weights and drive our results. We therefore check whether

[24] Since our post-job-loss period spans five years, restricting the observation period to 2007, the year before the financial crisis, could not suffice – the crisis could also have reduced job search success in $t = 1$ up to $t = 5$. We therefore run an additional robustness check, where we only include matched worker pairs with baseline years up to 2003 in our sample (see Table 21). The resulting patterns are very similar to our main results: Migrants face larger earnings and employment losses.

Table 4: **Robustness Check: Restricting to Baseline Years up to 2007 (Pre Financial Crisis)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (Earnings)		Log Wage		Employment		Days Worked	
	Natives	Migrants	Natives	Migrants	Natives	Migrants	Natives	Migrants
Year (Disp) t-5	0.015**	0.036**	0.0053**	0.0014	0.0024**	-0.0012	2.13**	6.02**
	(0.0018)	(0.010)	(0.0016)	(0.010)	(0.00052)	(0.0033)	(0.31)	(1.91)
Year (Disp) t-4	0.014**	0.015*	0.00039	0.011	-0.000023	-0.00045**	1.46**	2.95*
	(0.0011)	(0.0072)	(0.0014)	(0.0081)	(0.000024)	(0.00016)	(0.17)	(1.22)
Year (Disp) t-2	-0.011**	-0.014**	-0.016**	0.0089	0.0014**	0.00046	0.11	-0.65
	(0.00091)	(0.0039)	(0.0013)	(0.0097)	(0.00028)	(0.00087)	(0.16)	(0.60)
Year (Disp) t-1	-0.085**	-0.11**	-0.020**	-0.0063	-0.0000051	0.00092**	-18.8**	-24.1**
	(0.0011)	(0.0062)	(0.0015)	(0.0094)	(0.000036)	(0.00033)	(0.17)	(1.01)
Year (Disp) t	-0.58**	-0.70**	-0.22**	-0.24**	-0.14**	-0.18**	-114.1**	-135.2**
	(0.0032)	(0.019)	(0.0026)	(0.016)	(0.0011)	(0.0068)	(0.45)	(2.86)
Year (Disp) t+1	-0.36**	-0.50**	-0.19**	-0.23**	-0.12**	-0.17**	-68.9**	-92.3**
	(0.0032)	(0.021)	(0.0024)	(0.018)	(0.0011)	(0.0078)	(0.47)	(3.16)
Year (Disp) t+2	-0.27**	-0.37**	-0.17**	-0.21**	-0.094**	-0.14**	-47.4**	-67.6**
	(0.0032)	(0.020)	(0.0025)	(0.017)	(0.0011)	(0.0077)	(0.48)	(3.09)
Year (Disp) t+3	-0.23**	-0.30**	-0.16**	-0.17**	-0.078**	-0.11**	-37.5**	-53.8**
	(0.0032)	(0.019)	(0.0026)	(0.016)	(0.0012)	(0.0076)	(0.49)	(3.12)
Year (Disp) t+4	-0.19**	-0.24**	-0.15**	-0.12**	-0.067**	-0.092**	-30.8**	-42.4**
	(0.0032)	(0.021)	(0.0027)	(0.022)	(0.0012)	(0.0075)	(0.49)	(3.05)
Year (Disp) t+5	-0.17**	-0.17**	-0.14**	-0.10**	-0.059**	-0.089**	-26.1**	-36.1**
	(0.0032)	(0.019)	(0.0027)	(0.017)	(0.0012)	(0.0083)	(0.48)	(3.31)
Observations	2215070	265244	2144405	254099	2311627	282494	2311627	282494
R^2	0.104	0.115	0.050	0.049	0.072	0.104	0.153	0.190
Mean of dep. var	10.4	10.2	4.62	4.42	0.96	0.94	332.5	321.3

Notes: The table returns coefficients α_j from regression equation 0.1. The sample is restricted to pre financial crisis baseline years, e.g., all years up to 2007. Year $t = -3$ is omitted as base cateogry. The outcome variables are log (earnings+1) (columns 1 and 2), log wage (columns 3 and 4), employment (columns 5 and 6), and days worked (columns 7 and 8). In all columns, we control for year since displacement, year, and age polynomials. Standard errors are clustered on the individual level. Migrants are reweighted to natives using individual characteristics, industries, and occupations. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Source: IEB. ©IAB

our results differ if we instead reweight natives to migrants. We use the same reweighting algorithm as described in Section 3.2. The only difference is that instead of a dummy for native workers as an outcome variable in our probit regression, we now regress a dummy for *migrant* workers on a set of predisplacement individual characteristics, 1-digit industries, and occupations as defined by Blossfeld (1985). Table 6 reports the regression results, confirming that the migrant-native gap in costs of job loss is robust to changing the reweighting scheme. Some of the coefficients slightly increase in size, and the gap between migrants and natives increases for all labor market outcomes.

Table 5: Robustness Check: Restricting Sample to Workplace in West Germany at Time of Displacement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (Earnings)		Log Wage		Employment		Days Worked	
	Natives	Migrants	Natives	Migrants	Natives	Migrants	Natives	Migrants
Year (Disp) t-5	0.025**	0.0081	0.014**	-0.056	0.0037**	-0.0043	3.40**	11.3
	(0.0030)	(0.037)	(0.0022)	(0.034)	(0.00081)	(0.019)	(0.49)	(8.19)
Year (Disp) t-4	0.018**	0.059	0.0039*	0.017	-0.00012**	-0.00030	2.11**	12.0*
	(0.0018)	(0.034)	(0.0018)	(0.025)	(0.000043)	(0.00079)	(0.27)	(5.18)
Year (Disp) t-2	-0.015**	-0.018	-0.020**	-0.0017	0.00068	0.0033	-0.35	1.55
	(0.0014)	(0.017)	(0.0017)	(0.022)	(0.00040)	(0.0022)	(0.24)	(1.76)
Year (Disp) t-1	-0.091**	-0.10**	-0.026**	-0.031	0.000026	0.00026	-20.0**	-22.3**
	(0.0016)	(0.019)	(0.0019)	(0.021)	(0.000064)	(0.0015)	(0.27)	(2.96)
Year (Disp) t	-0.61**	-0.79**	-0.20**	-0.20**	-0.14**	-0.20**	-120.4**	-148.8**
	(0.0049)	(0.092)	(0.0037)	(0.052)	(0.0016)	(0.023)	(0.66)	(12.3)
Year (Disp) t+1	-0.35**	-0.56**	-0.17**	-0.28**	-0.12**	-0.17**	-70.2**	-91.9**
	(0.0049)	(0.095)	(0.0034)	(0.058)	(0.0017)	(0.031)	(0.71)	(13.5)
Year (Disp) t+2	-0.26**	-0.41**	-0.15**	-0.27**	-0.093**	-0.15**	-48.0**	-66.9**
	(0.0048)	(0.069)	(0.0035)	(0.052)	(0.0017)	(0.023)	(0.72)	(10.5)
Year (Disp) t+3	-0.22**	-0.42**	-0.14**	-0.20**	-0.078**	-0.13**	-38.3**	-67.4**
	(0.0049)	(0.083)	(0.0036)	(0.049)	(0.0018)	(0.023)	(0.73)	(11.4)
Year (Disp) t+4	-0.19**	-0.28**	-0.13**	-0.15**	-0.069**	-0.15**	-32.0**	-58.4**
	(0.0048)	(0.062)	(0.0037)	(0.050)	(0.0018)	(0.028)	(0.73)	(11.6)
Year (Disp) t+5	-0.17**	-0.21**	-0.12**	-0.15**	-0.061**	-0.13**	-27.8**	-47.6**
	(0.0047)	(0.061)	(0.0038)	(0.046)	(0.0018)	(0.025)	(0.73)	(11.0)
Observations	1021363	23973	983096	22811	1068103	25903	1068103	25903
R^2	0.110	0.135	0.054	0.061	0.074	0.118	0.164	0.209
Mean of dep. var	10.2	10.1	4.43	4.33	0.96	0.93	328.7	313.8

Notes: The table returns coefficients α_j from regression equation 0.1. The sample is restricted to workers employed in West Germany at time of displacement. Year $t = -3$ is omitted as base cateogry. The outcome variables are log (earnings+1) (columns 1 and 2), log wage (columns 3 and 4), employment (columns 5 and 6), and days worked (columns 7 and 8). In all columns, we control for year since displacement, year, and age polynomials. Standard errors are clustered on the individual level. Migrants are reweighted to natives using individual characteristics, industries, and occupations. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Source: IEB. ©IAB

5.2 Layoffs vs. Complete Closures

Throughout this paper, our aim is to make the migrants and natives in our sample as comparable as possible. We undertake a number of steps to achieve this: We reweight migrants to natives based on individual characteristics, industries, and occupations, and we control for regional labor market characteristics. However, thus far, our sample includes both workers displaced from complete establishment closures and from layoffs where only part of the workforce is laid off. In this section, we first estimate our event study regression model only for workers laid off in complete closures. We then proceed to control for the establishment from which workers are displaced.

In the spirit of Gibbons/Katz (1991), we assume that workers displaced in mass layoffs are

Table 6: Robustness Check: Reweighting Natives to Migrants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (Earnings)		Log Wage		Employment		Days Worked	
	Natives	Migrants	Natives	Migrants	Natives	Migrants	Natives	Migrants
Year (Disp) t-5	0.0066*	0.027**	0.017**	0.013**	-0.00033	0.00012	-1.27*	1.92*
	(0.0033)	(0.0054)	(0.0025)	(0.0039)	(0.00088)	(0.0014)	(0.52)	(0.86)
Year (Disp) t-4	0.015**	0.014**	0.0084**	0.0036	0.00031**	0.000017	1.13**	1.79**
	(0.0021)	(0.0029)	(0.0022)	(0.0030)	(0.000045)	(0.000076)	(0.28)	(0.45)
Year (Disp) t-2	-0.018**	-0.016**	-0.022**	-0.017**	0.0016**	0.00032	-0.011	-0.24
	(0.0017)	(0.0023)	(0.0018)	(0.0026)	(0.00041)	(0.00057)	(0.24)	(0.35)
Year (Disp) t-1	-0.10**	-0.12**	-0.028**	-0.025**	-0.00072**	-0.000047	-21.8**	-27.0**
	(0.0020)	(0.0028)	(0.0020)	(0.0029)	(0.000072)	(0.00014)	(0.27)	(0.47)
Year (Disp) t	-0.66**	-0.91**	-0.26**	-0.43**	-0.14**	-0.19**	-120.4**	-149.4**
	(0.0050)	(0.0099)	(0.0040)	(0.0090)	(0.0015)	(0.0030)	(0.63)	(1.16)
Year (Disp) t+1	-0.43**	-0.62**	-0.23**	-0.33**	-0.12**	-0.18**	-74.2**	-96.6**
	(0.0048)	(0.010)	(0.0036)	(0.0078)	(0.0016)	(0.0033)	(0.66)	(1.30)
Year (Disp) t+2	-0.33**	-0.47**	-0.21**	-0.29**	-0.096**	-0.13**	-52.5**	-67.6**
	(0.0048)	(0.010)	(0.0036)	(0.0077)	(0.0016)	(0.0032)	(0.68)	(1.32)
Year (Disp) t+3	-0.29**	-0.39**	-0.19**	-0.26**	-0.082**	-0.11**	-42.5**	-53.5**
	(0.0048)	(0.010)	(0.0037)	(0.0078)	(0.0016)	(0.0033)	(0.68)	(1.34)
Year (Disp) t+4	-0.25**	-0.31**	-0.18**	-0.22**	-0.070**	-0.086**	-35.3**	-40.7**
	(0.0048)	(0.0099)	(0.0037)	(0.0078)	(0.0016)	(0.0033)	(0.67)	(1.34)
Year (Disp) t+5	-0.23**	-0.27**	-0.17**	-0.20**	-0.063**	-0.075**	-30.2**	-34.8**
	(0.0049)	(0.0100)	(0.0039)	(0.0079)	(0.0016)	(0.0032)	(0.66)	(1.33)
Observations	2589001	355810	2507729	341462	2696370	376467	2696370	376467
R^2	0.120	0.147	0.069	0.078	0.069	0.103	0.154	0.203
Mean of dep. var	10.3	10.2	4.60	4.40	0.96	0.95	334.0	323.5

Notes: The table returns coefficients α_j from regression equation 0.1. Year $t = -3$ is omitted as base cateogry. The outcome variables are log (earnings+1) (columns 1 and 2), log wage (columns 3 and 4), employment (columns 5 and 6), and days worked (columns 7 and 8). In all columns, we control for year since displacement, year, and age polynomials. Standard errors are clustered on the individual level. Natives are reweighted to migrants using individual characteristics, industries, and occupations. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Source: IEB. ©IAB

different from workers laid off during complete establishment closures: If establishments decide whom to lay off, they are more likely to first fire workers of low ability, without family obligations, or bad matches. Being laid off could thus be a negative signal to future employers.[25] In contrast, workers laid off in a complete establishment closure will not systematically differ in characteristics. We thus assume that migrants and natives laid off in complete closures are particularly comparable.

Table 7 shows that for most labor market outcomes, our DID results for complete closures are very similar to the results from the full sample. The coefficients on earnings, employment, and wage losses are comparable to Panel A in Table 3. The coefficients on the local concentration proxies in Panel B confirm the pattern for the full sample: Displaced workers living in municipalities with a higher change in unemployment rates from $t = -1$ to $t = 0$

[25] Gibbons/Katz (1991) show that workers displaced from mass layoffs have larger wage losses and higher unemployment durations than workers laid off in complete closures.

lose more; the same holds for city residents. Migrants living in counties with a high share of the same-nationality working-age population have particularly large losses.

In a second robustness check, we add fixed effects for the establishment from which workers are displaced to our regression model. We do this because workers may sort into specific establishments prior to displacement. By including establishment fixed effects, we account for this potential sorting and make our worker sample even more comparable. Again, our DID results, as reported in Table 8, are remarkably stable.

Table 7: Explaining Costs of Job Loss by Local Labor Market Concentration and Controlling for Displacement Establishment

	(1) Log (Earnings)	(2) Employed	(3) Days Worked	(4) Log Wage	(5) Commutes	(6) AKM Effect	(7) Share Migrants	(8) Share Marg. Employed
Panel A: Controlling for Individual Characteristics, Industry, and Occupation								
Migrant	-0.20**	-0.040**	-22.1**	-0.12**	-0.00098	-0.032**	0.016**	0.024**
	(0.016)	(0.0049)	(2.20)	(0.012)	(0.0084)	(0.0050)	(0.0029)	(0.0031)
Observations	127653	133338	133338	121866	121676	94866	119631	119291
R^2	0.063	0.031	0.048	0.057	0.036	0.189	0.043	0.034
Mean of dep. var	-0.39	-0.099	-61.6	-0.19	0.028	-0.077	-0.010	0.038
Panel B: Adding Controls for Local Unemployment Rate Change, City Resident and Share of Coethnic Neighbors								
Migrant	0.33**	0.090*	46.0**	0.13	0.18**	0.044	0.048*	-0.028
	(0.11)	(0.036)	(16.2)	(0.078)	(0.059)	(0.033)	(0.020)	(0.018)
Local UR Change	-0.14**	-0.017	-18.2**	-0.053*	0.037*	-0.014	0.0064	0.0076
	(0.044)	(0.011)	(6.68)	(0.022)	(0.015)	(0.015)	(0.0058)	(0.0066)
Migrant*UR Change	-0.15	-0.0062	-5.27	-0.086	-0.055	0.035	-0.024	0.014
	(0.11)	(0.025)	(13.6)	(0.069)	(0.047)	(0.039)	(0.026)	(0.023)
City Resident	-0.058**	-0.015**	-8.81**	-0.017**	0.053**	-0.0020	0.0023*	0.0035**
	(0.0077)	(0.0024)	(1.06)	(0.0053)	(0.010)	(0.0023)	(0.00093)	(0.0013)
Migrant*City Resident	-0.049	0.0033	2.44	-0.077**	-0.034	-0.029**	0.00041	0.018**
	(0.028)	(0.0068)	(3.26)	(0.020)	(0.019)	(0.0072)	(0.0059)	(0.0059)
Share Same Nationality	0.49**	0.14**	70.6**	0.19*	0.18**	0.052	0.040	-0.039*
	(0.12)	(0.039)	(17.9)	(0.084)	(0.065)	(0.036)	(0.022)	(0.020)
Migrant*Share Same Nationality	-3.68**	-0.83**	-420.3**	-2.45**	-0.12	-0.95**	0.32	0.38*
	(0.81)	(0.17)	(93.8)	(0.59)	(0.38)	(0.32)	(0.21)	(0.15)
Observations	122635	128092	128092	117075	116885	91177	115078	114745
R^2	0.065	0.033	0.049	0.059	0.039	0.193	0.043	0.035
Mean of dep. var	-0.39	-0.099	-61.6	-0.19	0.028	-0.077	-0.010	0.038

Notes: The table shows the effect of being a migrant on labor market outcomes. All outcome variables are based on the individual difference-in-differences estimate derived from equation 0.2. Panel (A) shows the results when controlling for individual characteristics, and sorting across industries, and occupations in the year before displacement. Panel (B) adds controls for local unemployment rate changes reported at the municipality level, city residency, and the share of coethnic working age population in a county, all measured in the year before displacement. The AKM effect is a proxy for wage differentials across firms, based on Abowd/Kramarz/Margolis (1999). In addition, all regressions control for displacement establishment fixed effects. We cluster standard errors at the baseline county level. ** and * refer to statistical significance at the 1 and 5 percent level, respectively. Workers in our sample are displaced in the period 2001-2011, and they are observed from 1996 to 2017. Source: IEB, BBSR, Destatis.©IAB

Table 8: Explaining Costs of Job Loss by Local Labor Market Concentration - Only Complete Closures

	(1) Log (Earnings)	(2) Employed	(3) Days Worked	(4) Log Wage	(5) Commutes	(6) AKM Effect	(7) Share Migrants	(8) Share Marg. Employed
Panel A: Controlling for Individual Characteristics, Industry, and Occupation								
Migrant	-0.18**	-0.044**	-19.3**	-0.11**	-0.0053	-0.027	-0.0038	0.029**
	(0.024)	(0.0067)	(3.10)	(0.015)	(0.013)	(0.015)	(0.0066)	(0.0053)
Observations	40851	42824	42824	39568	39252	26903	39135	38760
R^2	0.051	0.025	0.037	0.046	0.018	0.175	0.010	0.029
Mean of dep. var	-0.36	-0.092	-56.1	-0.20	0.038	-0.11	-0.011	0.038
Panel B: Adding Controls for Local Unemployment Rate Change, City Resident and Share of Coethnic Neighbors								
Migrant	-0.35*	-0.011	-44.4*	-0.18	-0.031	-0.0095	0.19**	0.023
	(0.15)	(0.041)	(18.1)	(0.12)	(0.14)	(0.12)	(0.039)	(0.024)
Local UR Change	-0.19**	-0.043*	-27.0**	0.0015	0.048	-0.11	0.025	0.011
	(0.066)	(0.021)	(9.86)	(0.048)	(0.049)	(0.091)	(0.022)	(0.014)
Migrant*UR Change	-0.13	-0.033	-10.6	-0.076	0.030	-0.0049	-0.0017	-0.026
	(0.25)	(0.048)	(26.5)	(0.14)	(0.093)	(0.10)	(0.067)	(0.043)
City Resident	-0.059**	-0.022**	-9.72**	-0.030**	0.053**	0.0026	-0.0034	0.0028
	(0.012)	(0.0035)	(1.58)	(0.0084)	(0.016)	(0.0094)	(0.0025)	(0.0023)
Migrant*City Resident	-0.059	0.0029	2.67	-0.096**	-0.012	-0.045*	-0.0042	0.018
	(0.041)	(0.011)	(4.54)	(0.028)	(0.031)	(0.018)	(0.0100)	(0.010)
Share Same Nationality	-0.31*	0.012	-37.1	-0.19	-0.019	-0.040	0.21**	0.016
	(0.15)	(0.042)	(19.1)	(0.12)	(0.15)	(0.13)	(0.041)	(0.026)
Migrant*Share Same Nationality	-4.02**	-1.18**	-529.8**	-2.15*	0.51	-1.63	0.10	0.57*
	(1.49)	(0.35)	(146.5)	(1.07)	(0.47)	(1.30)	(0.32)	(0.25)
Observations	39365	41257	41257	38120	37807	25812	37710	37344
R^2	0.054	0.027	0.039	0.048	0.020	0.185	0.021	0.031
Mean of dep. var	-0.36	-0.092	-56.1	-0.20	0.038	-0.11	-0.011	0.038

Notes: The table shows the effect of being a migrant on labor market outcomes. All outcome variables are based on the individual difference-in-differences estimate derived from equation 0.2. The sample includes only workers laid off from complete establishment closures. Panel (A) shows results controlling for individual characteristics, and sorting across industries and occupations in the year before displacement. Panel (B) adds controls for local unemployment rate changes (from t=-1 to t=0) reported on the municipality level, city residency, and the share of coethnic working age population in a county, all measured in the year before displacement. AKM Effect is a proxy for wage differentials across firms, based on Abowd/Kramarz/Margolis (1999). We cluster standard errors at displacement establishment level. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Workers in our sample are displaced in 2001-2011, and they are observed from 1996-2017. Source: IEB, BBSR, Destatis.©IAB

6 Conclusion

In this paper, we investigate differences in the costs of job loss for migrants compared to native workers. Previous literature has documented large and persistent earnings losses for displaced workers in general (e.g., Jacobson/LaLonde/Sullivan (1993), Couch/Placzek (2010), von Wachter/Song/Manchester (2011), Schmieder/von Wachter/Heining (2020)). While recent research has emphasized the importance of investigating the costs of job loss for different worker groups (see, e.g., Blien/Dauth/Roth (2020), Illing/Schmieder/Trenkle (2021), Meekes/Hassink (2020)), no study to date has focused explicitly on migrant workers. Following existing literature from the U.S. and Germany, in particular Illing/Schmieder/Trenkle (2021), Schmieder/von Wachter/Heining (2020), and Jacobson/LaLonde/Sullivan (1993), we fill this gap. Our empirical approach combines event study regressions with propensity score matching and DiNardo/Fortin/Lemieux (1996) reweighting to make migrants as comparable as possible to native workers. Our results provide valuable insights into the different challenges migrant and native workers face in the labor market after being laid off.

For our empirical analysis, we use rich administrative employer-employee data from Germany. Our main contribution is that we quantify differences in the costs of job loss for migrants compared to natives. We show that migrants face larger costs of job loss than natives, with substantial gaps in earnings losses (40 percentage points) and re-employment probability (5 percentage points) in the year after displacement. While migrants start catching up as time passes, differences still exist even five years after displacement. Observable individual and establishment characteristics can explain the difference in wage losses, but they cannot explain why migrants experience longer unemployment durations after displacement.

Second, we show that one explanation for migrants' higher wage losses is that they work for different types of establishments after job loss. After displacement, migrants, on average, work for establishments with lower average wages, lower AKM-style fixed effects, a higher share of marginally employed coworkers, and a higher share of foreign coworkers. These gaps between migrants and natives largely disappear once we control for individual characteristics and differential sorting across industries and occupations in the year before displacement. With respect to geographic mobility, we find that migrants are slightly more likely to commute (2 percentage points) but are less likely to move workplaces to a new federal state (3 percentage points). This suggests that mobility constraints can explain part of the migrant-native gap in earnings losses after displacement.

Third, our results suggest that local labor market concentration, as proxied by city residency, is an important contributor to displaced workers' costs of job loss. If displaced workers live in municipalities with a higher increase in local unemployment rates or in cities at the time of displacement, their earnings, wages, and employment losses are particularly high. This holds both for migrants and natives. Another important factor driving the migrant-native gap in earnings losses is competition by same-nationality workers: The higher the share of the working-age population of the same nationality in their workplace county predisplacement, the larger migrants' earnings losses are. This is consistent with the literature on within-network competition for migrants (e.g., Beaman (2012), Albert/Glitz/Llull (2020)), who may be particularly substitutable as a group.

Policymakers interested in improving migrants' labor market outcomes should pay attention to our finding that migrants face substantial difficulties in job search after displacement. When searching for a job, migrants may therefore need a different type of training than natives (e.g., language courses or training targeted at learning how the job application process in their destination country works). For authorities, it may be worthwhile to invest in different types of trainings for unemployed individuals, depending on their migration status.

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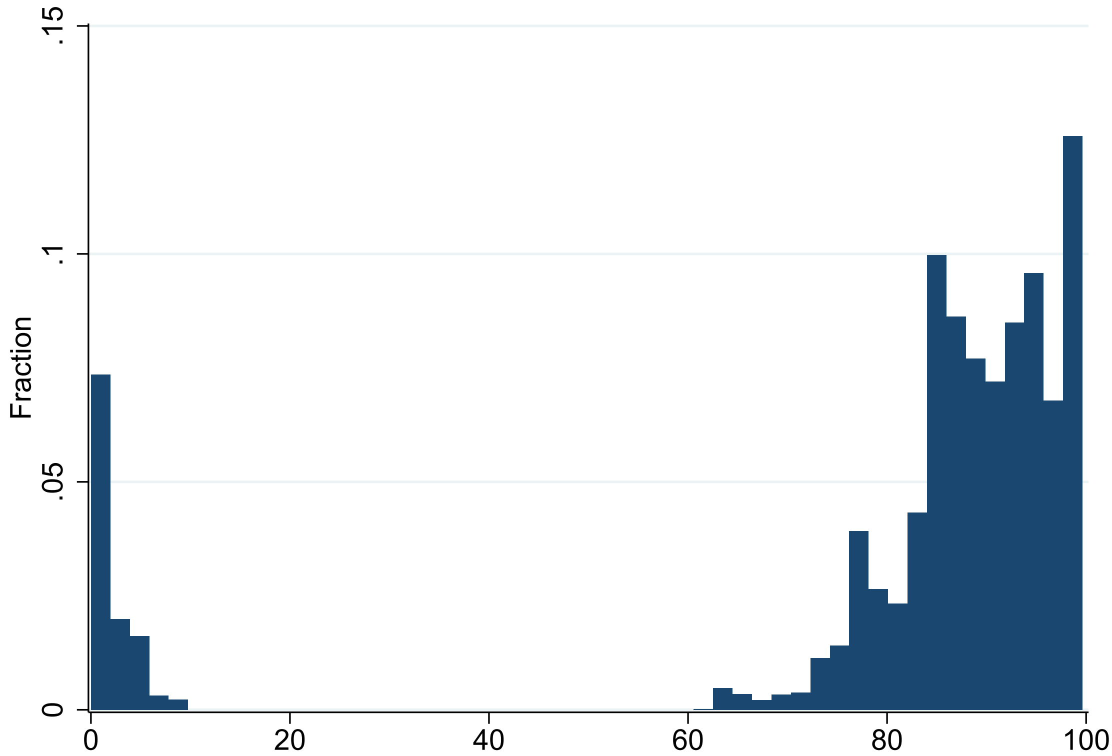
Appendix

Figure 7: Distribution of the Share of Same-Nationality Working Age Population
(a) Distribution Share Same-Nationality Working Age Population in County in t=-1



Notes: This figure shows the distribution of the share of same-nationality working age population in a county in $t = -1$ for our sample of displaced workers. For migrants, the share ranges from 0-10 percent; for natives, it ranges from 60-100 percent. Workers in our sample are displaced in the period 2001-2011, and they are observed from 1996 to 2017. In $t = -1$, we observe 17,605 displaced migrants and 129,701 displaced natives. Source: Destatis. ©IAB

Table 9: Comparing Displaced Workers in $t = -1$ to a Sample of Random Workers

	(1) All Workers Migrants	(2) Baseline Sample Migrants	(3) Reweighted Migrants	(4) All Workers Natives	(5) Baseline Sample Natives
Panel A: Individual Characteristics					
Years of Education	11.2	11.2	12.1	12.0	12.3
	[2.05]	[1.61]	[2.20]	[1.94]	[1.77]
Age	37.8	37.9	39.8	40.4	39.4
	[12.5]	[6.68]	[6.71]	[13.3]	[6.71]
Tenure	2.37	6.38	6.05	2.93	6.20
	[2.07]	[2.56]	[2.34]	[2.17]	[2.43]
Real Daily Wage	57.5	89.2	105.2	68.7	102.3
	[48.8]	[30.8]	[37.5]	[53.0]	[36.7]
Total Yearly Earnings	13620.3	30194.9	35928.0	20661.7	35477.8
	[16493.5]	[11844.1]	[14285.7]	[18855.8]	[14189.6]
Days per year working	214.8	335.5	338.7	281.9	344.2
	[158.6]	[53.9]	[51.1]	[135.1]	[45.6]
Panel B: Regional Characteristics					
Lives in City	0.64	0.80	0.58	0.44	0.57
	[0.48]	[0.40]	[0.49]	[0.50]	[0.50]
Lives in East Germany	0.063	0.041	0.060	0.19	0.25
	[0.24]	[0.20]	[0.24]	[0.39]	[0.43]
Panel C: Establishment Characteristics					
Size of establishment	1000.3	291.1	334.0	782.1	347.2
	[3922.8]	[490.4]	[640.6]	[3473.1]	[636.8]
Share Migrant Workers	0.30	0.24	0.18	0.053	0.075
	[0.27]	[0.19]	[0.18]	[0.086]	[0.095]
Share High-Skilled Workers	0.099	0.079	0.13	0.13	0.12
	[0.16]	[0.12]	[0.18]	[0.17]	[0.16]
Share Marginally Employed Workers	0.21	0.059	0.049	0.17	0.041
	[0.28]	[0.13]	[0.11]	[0.26]	[0.095]
Displaced from Complete Closure	.	0.32	0.32	.	0.32
		[0.47]	[0.47]		[0.47]
Number of Observations	574167	17605	17605	5882551	129701

Notes: This table summarizes characteristics of different samples of (displaced) migrants and natives. Columns (1) and (4) show characteristics of a random 2-percent sample of workers subject to social security in Germany 2000-2010. Columns (2) and (5) represent all displaced workers in the couple dataset fulfilling our baseline restrictions. We measure characteristics in t=-1. Column (3) reports migrants in our sample reweighted to natives. Standard deviations in brackets. Source: IEB. ©IAB

Table 10: Worker Characteristics of Displaced Workers and Matched Non-Displaced Workers One Year Prior to Displacement ($t = -1$), Distribution across Industries in t=-1

	(1) Non-Displaced Migrants	(2) Displaced Migrants	(3) Non-Displaced Natives	(4) Displaced Natives
Agriculture	0.00023	0.00023	0.00084	0.00084
	[0.015]	[0.015]	[0.029]	[0.029]
Mining, Energy	0.034	0.034	0.023	0.023
	[0.18]	[0.18]	[0.15]	[0.15]
Food Manufacturing	0.064	0.064	0.037	0.037
	[0.24]	[0.24]	[0.19]	[0.19]
Consumption Goods	0.10	0.10	0.070	0.070
	[0.30]	[0.30]	[0.25]	[0.25]
Production Goods	0.12	0.12	0.084	0.084
	[0.33]	[0.33]	[0.28]	[0.28]
Investment Goods	0.16	0.16	0.15	0.15
	[0.37]	[0.37]	[0.36]	[0.36]
Construction	0.039	0.039	0.086	0.086
	[0.19]	[0.19]	[0.28]	[0.28]
Retail	0.11	0.11	0.13	0.13
	[0.32]	[0.32]	[0.34]	[0.34]
Traffic, Telecommunication	0.075	0.075	0.069	0.069
	[0.26]	[0.26]	[0.25]	[0.25]
Credit, Insurance	0.0043	0.0043	0.015	0.015
	[0.066]	[0.066]	[0.12]	[0.12]
Restaurants	0.021	0.021	0.0052	0.0052
	[0.14]	[0.14]	[0.072]	[0.072]
Education	0.0022	0.0022	0.020	0.020
	[0.046]	[0.046]	[0.14]	[0.14]
Health	0.0051	0.0051	0.012	0.012
	[0.071]	[0.071]	[0.11]	[0.11]
Commercial Services	0.23	0.23	0.24	0.24
	[0.42]	[0.42]	[0.43]	[0.43]
Other Services	0.022	0.022	0.028	0.028
	[0.15]	[0.15]	[0.16]	[0.16]
Non-Profit	0.0092	0.0092	0.013	0.013
	[0.095]	[0.095]	[0.11]	[0.11]
Public Administration	0.0022	0.0022	0.018	0.018
	[0.047]	[0.047]	[0.13]	[0.13]
Number of Observations	17605	17605	129701	129701

Notes: Distribution across industries of displaced and non-displaced workers in year prior to displacement year. Workers satisfy the following baseline restrictions: Aged 24 to 50, working fulltime in pre-displacement year, at least 3 years of tenure, and establishment has at least 50 employees. Non-displaced sample of workers are matched to displaced workers using propensity score matching within year and industry cells. Non-displaced sample of workers is a random sample of workers (one per displaced worker) that satisfy the same baseline restrictions. Standard deviations in brackets. Source: IEB. ©IAB

Table 11: Worker Characteristics of Displaced Workers and Matched Non-Displaced Workers One Year Prior to Displacement ($t = -1$), Distribution across Occupations in t=-1

	(1) Non-Displaced Migrants	(2) Displaced Migrants	(3) Non-Displaced Natives	(4) Displaced Natives
Agriculture, gardening, work with animals	0.0066	0.0043	0.0072	0.0041
	[0.081]	[0.065]	[0.085]	[0.064]
Simple, manual tasks	0.42	0.46	0.22	0.24
	[0.49]	[0.50]	[0.41]	[0.42]
Qualified, manual tasks	0.18	0.17	0.24	0.26
	[0.38]	[0.38]	[0.43]	[0.44]
Technician	0.025	0.029	0.073	0.075
	[0.16]	[0.17]	[0.26]	[0.26]
Engineer	0.017	0.015	0.043	0.038
	[0.13]	[0.12]	[0.20]	[0.19]
Simple services	0.23	0.20	0.14	0.12
	[0.42]	[0.40]	[0.35]	[0.33]
Qualified services	0.013	0.012	0.019	0.017
	[0.11]	[0.11]	[0.14]	[0.13]
Semi-professions	0.0050	0.0047	0.016	0.015
	[0.071]	[0.069]	[0.13]	[0.12]
Professions	0.0039	0.0041	0.0084	0.011
	[0.062]	[0.064]	[0.091]	[0.10]
Simple commercial and admin. tasks	0.023	0.021	0.039	0.035
	[0.15]	[0.14]	[0.19]	[0.18]
Qualified commercial and admin. tasks	0.065	0.061	0.16	0.16
	[0.25]	[0.24]	[0.37]	[0.36]
Manager	0.010	0.012	0.029	0.029
	[0.10]	[0.11]	[0.17]	[0.17]
Not classified	0.0026	0.0025	0.0032	0.0030
	[0.050]	[0.050]	[0.057]	[0.055]
Number of Observations	17605	17605	129701	129701

Notes: Distribution across occupations of displaced and non-displaced workers in year prior to displacement year. Workers satisfy the following baseline restrictions: Aged 24 to 50, working fulltime in pre-displacement year, at least 3 years of tenure, and establishment has at least 50 employees. Non-displaced sample of workers are matched to displaced workers using propensity score matching within year and industry cells. Non-displaced sample of workers is a random sample of workers (one per displaced worker) that satisfy the same baseline restrictions. Standard deviations in brackets. Source: IEB. ©IAB.

Table 12: Event Study Regression Table with Reweighting: Labor Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log (Earnings+1)		Log Earnings		Log Wage		Employment		Days Worked	
	Natives	Migrants	Natives	Migrants	Natives	Migrants	Natives	Migrants	Natives	Migrants
Year (Disp) t-5	0.032**	0.016	0.015**	0.031**	0.0070**	0.00065	0.0017**	-0.0013	1.61**	4.52**
	(0.0051)	(0.031)	(0.0017)	(0.0092)	(0.0015)	(0.0089)	(0.00048)	(0.0028)	(0.28)	(1.66)
Year (Disp) t-4	0.014**	0.0065	0.014**	0.0098	0.0015	0.0091	-0.000013	-0.00032*	1.43**	1.82
	(0.0011)	(0.0067)	(0.0010)	(0.0066)	(0.0013)	(0.0070)	(0.000028)	(0.00015)	(0.15)	(1.11)
Year (Disp) t-2	0.00076	-0.0086	-0.011**	-0.012**	-0.016**	0.0089	0.0011**	0.00032	0.072	-0.55
	(0.0027)	(0.0086)	(0.00081)	(0.0035)	(0.0012)	(0.0085)	(0.00024)	(0.00075)	(0.14)	(0.52)
Year (Disp) t-1	-0.083**	-0.096**	-0.083**	-0.10**	-0.021**	-0.0084	-0.000025	0.00075*	-18.4**	-23.6**
	(0.0011)	(0.0064)	(0.00097)	(0.0053)	(0.0013)	(0.0081)	(0.000036)	(0.00029)	(0.15)	(0.87)
Year (Disp) t	-1.82**	-2.32**	-0.56**	-0.70**	-0.21**	-0.26**	-0.13**	-0.17**	-110.3**	-132.2**
	(0.0096)	(0.062)	(0.0029)	(0.016)	(0.0023)	(0.014)	(0.00094)	(0.0058)	(0.40)	(2.46)
Year (Disp) t+1	-1.46**	-2.05**	-0.34**	-0.47**	-0.18**	-0.22**	-0.12**	-0.16**	-65.6**	-88.5**
	(0.010)	(0.072)	(0.0028)	(0.018)	(0.0022)	(0.015)	(0.0010)	(0.0068)	(0.42)	(2.72)
Year (Disp) t+2	-1.11**	-1.60**	-0.25**	-0.36**	-0.16**	-0.20**	-0.088**	-0.13**	-44.8**	-65.0**
	(0.010)	(0.069)	(0.0028)	(0.017)	(0.0022)	(0.014)	(0.0010)	(0.0066)	(0.42)	(2.65)
Year (Disp) t+3	-0.92**	-1.34**	-0.22**	-0.29**	-0.15**	-0.16**	-0.073**	-0.11**	-35.6**	-52.1**
	(0.011)	(0.069)	(0.0028)	(0.016)	(0.0023)	(0.014)	(0.0010)	(0.0065)	(0.43)	(2.67)
Year (Disp) t+4	-0.79**	-1.09**	-0.19**	-0.23**	-0.14**	-0.12**	-0.063**	-0.088**	-29.3**	-40.6**
	(0.011)	(0.069)	(0.0028)	(0.018)	(0.0024)	(0.019)	(0.0010)	(0.0064)	(0.43)	(2.62)
Year (Disp) t+5	-0.70**	-0.97**	-0.17**	-0.18**	-0.13**	-0.11**	-0.055**	-0.080**	-25.0**	-33.9**
	(0.011)	(0.075)	(0.0028)	(0.016)	(0.0024)	(0.015)	(0.0010)	(0.0070)	(0.42)	(2.82)
Observations	2805581	361806	2696597	341398	2613829	327302	2805581	361806	2805581	361806
R^2	0.103	0.143	0.103	0.113	0.054	0.049	0.068	0.099	0.146	0.184
Mean of dep. var	9.94	9.60	10.3	10.2	4.60	4.40	0.96	0.95	334.0	323.5

Notes: The table returns coefficients α_j from regression equation 0.1. Year $t = -3$ is omitted as base cateogry. The outcome variables are log (earnings+1) (columns 1 and 2), log earnings (columns 3 and 4), log wage (columns 5 and 6), employment (columns 7 and 8), and days worked (columns 9 and 10). In all columns, we control for year since displacement, year, and age polynomials. Standard errors are clustered on the individual level. Migrants are reweighted to natives using individual characteristics, industries, and occupations. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Source: IEB. ©IAB.

Table 13: Event Study Regression Table without Reweighting: Labor Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log (Earnings+1)		Log Earnings		Log Wage		Employment		Days Worked	
	Natives	Migrants	Natives	Migrants	Natives	Migrants	Natives	Migrants	Natives	Migrants
Year (Disp) t-5	0.032**	0.027	0.015**	0.027**	0.0070**	0.013**	0.0017**	0.00012	1.61**	1.92*
	(0.0051)	(0.015)	(0.0017)	(0.0054)	(0.0015)	(0.0039)	(0.00048)	(0.0014)	(0.28)	(0.86)
Year (Disp) t-4	0.014**	0.014**	0.014**	0.014**	0.0015	0.0036	-0.000013	0.000017	1.43**	1.79**
	(0.0011)	(0.0030)	(0.0010)	(0.0029)	(0.0013)	(0.0030)	(0.000028)	(0.000076)	(0.15)	(0.45)
Year (Disp) t-2	0.00076	-0.012	-0.011**	-0.016**	-0.016**	-0.017**	0.0011**	0.00032	0.072	-0.24
	(0.0027)	(0.0063)	(0.00081)	(0.0023)	(0.0012)	(0.0026)	(0.00024)	(0.00057)	(0.14)	(0.35)
Year (Disp) t-1	-0.083**	-0.12**	-0.083**	-0.12**	-0.021**	-0.025**	-0.000025	-0.000047	-18.4**	-27.0**
	(0.0011)	(0.0032)	(0.00097)	(0.0028)	(0.0013)	(0.0029)	(0.000036)	(0.00014)	(0.15)	(0.47)
Year (Disp) t	-1.82**	-2.68**	-0.56**	-0.91**	-0.21**	-0.43**	-0.13**	-0.19**	-110.3**	-149.4**
	(0.0096)	(0.030)	(0.0029)	(0.0099)	(0.0023)	(0.0090)	(0.00094)	(0.0030)	(0.40)	(1.16)
Year (Disp) t+1	-1.46**	-2.27**	-0.34**	-0.62**	-0.18**	-0.33**	-0.12**	-0.18**	-65.6**	-96.6**
	(0.010)	(0.033)	(0.0028)	(0.010)	(0.0022)	(0.0078)	(0.0010)	(0.0033)	(0.42)	(1.30)
Year (Disp) t+2	-1.11**	-1.69**	-0.25**	-0.47**	-0.16**	-0.29**	-0.088**	-0.13**	-44.8**	-67.6**
	(0.010)	(0.033)	(0.0028)	(0.010)	(0.0022)	(0.0077)	(0.0010)	(0.0032)	(0.42)	(1.32)
Year (Disp) t+3	-0.92**	-1.39**	-0.22**	-0.39**	-0.15**	-0.26**	-0.073**	-0.11**	-35.6**	-53.5**
	(0.011)	(0.034)	(0.0028)	(0.010)	(0.0023)	(0.0078)	(0.0010)	(0.0033)	(0.43)	(1.34)
Year (Disp) t+4	-0.79**	-1.11**	-0.19**	-0.31**	-0.14**	-0.22**	-0.063**	-0.086**	-29.3**	-40.7**
	(0.011)	(0.034)	(0.0028)	(0.0099)	(0.0024)	(0.0078)	(0.0010)	(0.0033)	(0.43)	(1.34)
Year (Disp) t+5	-0.70**	-0.97**	-0.17**	-0.27**	-0.13**	-0.20**	-0.055**	-0.075**	-25.0**	-34.8**
	(0.011)	(0.033)	(0.0028)	(0.0100)	(0.0024)	(0.0079)	(0.0010)	(0.0032)	(0.42)	(1.33)
Observations	2805581	376467	2696597	355810	2613829	341462	2805581	376467	2805581	376467
R^2	0.103	0.162	0.103	0.147	0.054	0.078	0.068	0.103	0.146	0.203
Mean of dep. var	9.94	9.60	10.3	10.2	4.60	4.40	0.96	0.95	334.0	323.5

Notes: The table returns coefficients α_j from regression equation 0.1. Year $t = -3$ is omitted as base cateogry. The outcome variables are log (earnings+1) (columns 1 and 2), log earnings (columns 3 and 4), log wage (columns 5 and 6), employment (columns 7 and 8), and days worked (columns 9 and 10). In all columns, we control for year since displacement, year, and age polynomials. Standard errors are clustered on the individual level. All regression results reported are without reweighting migrants to natives. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Source: IEB. ©IAB

Table 14: Event Study Regression Table: Days Worked

	(1)	(2)	(3)	(4)	(5)	(6)
	Days Worked Full-time			Days Worked Part-time		
	Natives	Migrants	Migrants	Natives	Migrants	Migrants
	Non-reweighted		Reweighted	Non-reweighted		Reweighted
Year (Disp) t-5	1.61**	1.71	4.88*	0.59**	0.83	2.19
	(0.33)	(1.02)	(2.03)	(0.17)	(0.70)	(1.25)
Year (Disp) t-4	1.55**	2.10**	2.95*	0.53**	0.45	0.86
	(0.19)	(0.58)	(1.32)	(0.13)	(0.52)	(0.88)
Year (Disp) t-2	-0.57**	-0.99*	-1.44*	-0.097	-0.53	0.053
	(0.17)	(0.47)	(0.67)	(0.12)	(0.50)	(0.88)
Year (Disp) t-1	-20.8**	-32.1**	-26.4**	0.32*	0.21	0.89
	(0.21)	(0.63)	(1.04)	(0.15)	(0.63)	(1.12)
Year (Disp) t	-120.6**	-175.8**	-147.4**	1.48**	1.74*	1.25
	(0.44)	(1.27)	(2.63)	(0.18)	(0.70)	(1.26)
Year (Disp) t+1	-76.0**	-121.0**	-102.6**	2.81**	5.28**	3.92**
	(0.47)	(1.46)	(2.97)	(0.20)	(0.76)	(1.38)
Year (Disp) t+2	-54.2**	-90.0**	-76.9**	3.20**	6.86**	4.71**
	(0.48)	(1.53)	(2.91)	(0.21)	(0.80)	(1.25)
Year (Disp) t+3	-44.8**	-73.2**	-62.8**	3.50**	7.27**	6.15**
	(0.49)	(1.57)	(2.97)	(0.22)	(0.83)	(1.24)
Year (Disp) t+4	-38.2**	-58.8**	-53.1**	3.64**	7.81**	8.37**
	(0.50)	(1.59)	(3.17)	(0.23)	(0.87)	(1.99)
Year (Disp) t+5	-33.5**	-52.8**	-46.2**	3.55**	8.47**	7.46**
	(0.50)	(1.60)	(3.33)	(0.24)	(0.90)	(1.39)
Observations	2805581	376467	361806	2805581	376467	361806
R^2	0.159	0.234	0.201	0.007	0.029	0.026
Mean of dep. var	326.3	310.2	310.2	5.05	9.93	9.93

Notes: The table returns coefficients α_j from regression equation 0.1. Year $t = -3$ is omitted as the baseline cateogry. The outcome variables are days worked part-time (columns 1, 2, and 3), and days worked part-time (columns 4,5, and 6). In all columns, we control for year since displacement, year, and age polynomials. Standard errors are clustered at the individual level. Regression results in columns (3) and (6) are from regression models where we reweight migrants to natives. ** and * refer to statistical significance at the 1 and 5 percent level, respectively. Source: IEB. ©IAB

Table 15: Event Study Regression Table with Reweighting: Geographic Mobility

	(1)	(2)	(3)	(4)
	Moved		Commutes	
	Natives	Migrants	Natives	Migrants
Year (Disp) t-5	-0.019**	0.0020	-0.0062**	-0.0095
	(0.0013)	(0.0077)	(0.0016)	(0.0091)
Year (Disp) t-4	-0.014**	-0.0069	-0.000077	-0.011*
	(0.00088)	(0.0048)	(0.00095)	(0.0052)
Year (Disp) t-2	0.00038	-0.0022	-0.0012	0.014
	(0.00051)	(0.0022)	(0.00076)	(0.0074)
Year (Disp) t-1	-0.0042**	-0.0076*	0.0049**	0.026**
	(0.00061)	(0.0030)	(0.00090)	(0.0079)
Year (Disp) t	0.55**	0.50**	0.044**	0.062**
	(0.0016)	(0.0095)	(0.0018)	(0.011)
Year (Disp) t+1	0.58**	0.55**	0.035**	0.053**
	(0.0017)	(0.0098)	(0.0018)	(0.011)
Year (Disp) t+2	0.54**	0.52**	0.027**	0.044**
	(0.0018)	(0.0098)	(0.0019)	(0.011)
Year (Disp) t+3	0.50**	0.49**	0.023**	0.032**
	(0.0018)	(0.010)	(0.0019)	(0.011)
Year (Disp) t+4	0.47**	0.46**	0.016**	0.036**
	(0.0019)	(0.011)	(0.0020)	(0.012)
Year (Disp) t+5	0.44**	0.43**	0.011**	0.026**
	(0.0019)	(0.011)	(0.0020)	(0.0099)
Observations	2696597	341398	2397458	306193
R^2	0.417	0.384	0.006	0.008
Mean of dep. var	0.23	0.20	0.69	0.59

Notes: The table returns coefficients α_j from regression equation 0.1. Year $t = -3$ is omitted as base cateogry. The outcome variables are moving to a different municipality compared to $t = -1$ (columns 1 and 2) and commuting (columns 3 and 4). Commuting is defined as working and living in different municipalities. In all columns, we control for year since displacement, year, and age polynomials. Standard errors are clustered on the individual level. Migrants are reweighted to natives using individual characteristics, industries, and occupations. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Source: IEB. ©IAB

Table 16: Event Study Regression Table without Reweighting: Geographic Mobility

	(1)	(2)	(3)	(4)
	Moved		Commutes	
	Natives	Migrants	Natives	Migrants
Year (Disp) t-5	-0.019**	-0.019**	-0.0062**	0.0049
	(0.0013)	(0.0035)	(0.0016)	(0.0041)
Year (Disp) t-4	-0.014**	-0.013**	-0.000077	-0.0011
	(0.00088)	(0.0022)	(0.00095)	(0.0026)
Year (Disp) t-2	0.00038	-0.00040	-0.0012	0.0013
	(0.00051)	(0.0013)	(0.00076)	(0.0020)
Year (Disp) t-1	-0.0042**	-0.0027	0.0049**	0.0040
	(0.00061)	(0.0016)	(0.00090)	(0.0024)
Year (Disp) t	0.55**	0.47**	0.044**	0.064**
	(0.0016)	(0.0044)	(0.0018)	(0.0056)
Year (Disp) t+1	0.58**	0.52**	0.035**	0.054**
	(0.0017)	(0.0047)	(0.0018)	(0.0057)
Year (Disp) t+2	0.54**	0.50**	0.027**	0.047**
	(0.0018)	(0.0049)	(0.0019)	(0.0058)
Year (Disp) t+3	0.50**	0.46**	0.023**	0.037**
	(0.0018)	(0.0051)	(0.0019)	(0.0060)
Year (Disp) t+4	0.47**	0.44**	0.016**	0.039**
	(0.0019)	(0.0053)	(0.0020)	(0.0061)
Year (Disp) t+5	0.44**	0.40**	0.011**	0.033**
	(0.0019)	(0.0054)	(0.0020)	(0.0062)
Observations	2696597	355810	2397458	320149
R^2	0.417	0.372	0.006	0.010
Mean of dep. var	0.23	0.20	0.69	0.59

Notes: The table returns coefficients α_j from regression equation 0.1. Year $t = -3$ is omitted as base cateogry. The outcome variables are moving to a different municipality compared to $t = -1$ (columns 1 and 2) and commuting (columns 3 and 4). Commuting is defined as working and living in different municipalities. In all columns, we control for year since displacement, year, and age polynomials. Standard errors are clustered on the individual level. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Source: IEB. ©IAB

Table 17: Event Study Regression Table with Reweighting: Establishment Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ave. Estab Wages		AKM Effect		Share Marg. Employed		Share Migrant Workers	
	Natives	Migrants	Natives	Migrants	Natives	Migrants	Natives	Migrants
Year (Disp) t-5	0.84**	0.17	-0.00026	0.00083	0.00068	-0.0015	0.00097**	-0.0028
	(0.061)	(0.38)	(0.00049)	(0.0026)	(0.00047)	(0.0025)	(0.00022)	(0.0019)
Year (Disp) t-4	0.32**	-0.30	0.00038	-0.00032	0.00048	-0.00052	0.00082**	0.00011
	(0.041)	(0.23)	(0.00025)	(0.0012)	(0.00028)	(0.0015)	(0.00015)	(0.0015)
Year (Disp) t-2	-0.094**	0.36*	0.00027*	0.00082	-0.00043*	-0.0010	0.0013**	-0.00040
	(0.028)	(0.15)	(0.00012)	(0.00049)	(0.00019)	(0.0013)	(0.00011)	(0.0011)
Year (Disp) t-1	0.70**	1.98**	0.000095	0.0013*	-0.0015**	-0.0044**	-0.00034**	-0.0042**
	(0.039)	(0.25)	(0.00011)	(0.00053)	(0.00022)	(0.0014)	(0.00013)	(0.0014)
Year (Disp) t	-2.35**	-0.72	-0.081**	-0.097**	0.039**	0.052**	-0.013**	-0.022**
	(0.11)	(0.76)	(0.00087)	(0.0050)	(0.00060)	(0.0033)	(0.00034)	(0.0041)
Year (Disp) t+1	-3.45**	-1.73*	-0.083**	-0.100**	0.037**	0.044**	-0.011**	-0.022**
	(0.11)	(0.77)	(0.00088)	(0.0049)	(0.00058)	(0.0035)	(0.00035)	(0.0035)
Year (Disp) t+2	-3.56**	-2.70**	-0.081**	-0.10**	0.036**	0.047**	-0.010**	-0.013**
	(0.12)	(0.79)	(0.00091)	(0.0053)	(0.00060)	(0.0035)	(0.00036)	(0.0034)
Year (Disp) t+3	-2.99**	-1.47	-0.076**	-0.097**	0.034**	0.038**	-0.010**	-0.0092*
	(0.13)	(0.86)	(0.00093)	(0.0053)	(0.00062)	(0.0035)	(0.00037)	(0.0038)
Year (Disp) t+4	-2.86**	-0.93	-0.073**	-0.087**	0.032**	0.033**	-0.0098**	-0.0084*
	(0.14)	(0.84)	(0.00096)	(0.0051)	(0.00063)	(0.0037)	(0.00038)	(0.0039)
Year (Disp) t+5	-2.61**	-0.46	-0.070**	-0.082**	0.031**	0.031**	-0.0090**	-0.0079*
	(0.14)	(0.91)	(0.00097)	(0.0051)	(0.00065)	(0.0038)	(0.00040)	(0.0040)
Observations	2579140	320001	2360559	297088	2368993	301326	2579373	321237
R^2	0.109	0.098	0.074	0.084	0.041	0.053	0.016	0.018
Mean of dep. var	96.7	90.9	-0.22	-0.21	0.062	0.091	0.067	0.22

Notes: The table returns coefficients α_j from regression equation 0.1. Year $t = -3$ is omitted as the baseline cateogry. The outcome variables are average establishment wages (columns 1 and 2), AKM-style establishment fixed effects (columns 3 and 4), the share of marginally employed workers in an establishment (columns 5 and 6), and the share of migrant workers in an establishment (columns 7 and 8). In all columns, we control for year since displacement, year, and age polynomials. Standard errors are clustered at the individual level. Migrants are reweighted to natives using individual characteristics, industries, and occupations. ** and * refer to statistical significance at the 1 and 5 percent level, respectively. Source: IEB. ©IAB

Table 18: Event Study Regression Table without Reweighting: Establishment Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ave. Estab Wages		Estab FE		Share Marg. Employed		Share Migrant Workers	
	Natives	Migrants	Natives	Migrants	Natives	Migrants	Natives	Migrants
Year (Disp) t-5	0.84**	1.08**	-0.00026	0.0053**	0.00068	-0.00018	0.00097**	0.0027*
	(0.061)	(0.15)	(0.00049)	(0.0015)	(0.00047)	(0.0015)	(0.00022)	(0.0012)
Year (Disp) t-4	0.32**	0.41**	0.00038	0.0015	0.00048	-0.00029	0.00082**	0.0012
	(0.041)	(0.098)	(0.00025)	(0.00083)	(0.00028)	(0.00094)	(0.00015)	(0.00079)
Year (Disp) t-2	-0.094**	-0.080	0.00027*	-0.00024	-0.00043*	-0.00024	0.0013**	0.00045
	(0.028)	(0.066)	(0.00012)	(0.00044)	(0.00019)	(0.00062)	(0.00011)	(0.00056)
Year (Disp) t-1	0.70**	1.06**	0.000095	-0.000019	-0.0015**	-0.0041**	-0.00034**	-0.0019**
	(0.039)	(0.092)	(0.00011)	(0.00041)	(0.00022)	(0.00074)	(0.00013)	(0.00064)
Year (Disp) t	-2.35**	-5.51**	-0.081**	-0.12**	0.039**	0.091**	-0.013**	-0.025**
	(0.11)	(0.32)	(0.00087)	(0.0031)	(0.00060)	(0.0026)	(0.00034)	(0.0022)
Year (Disp) t+1	-3.45**	-6.47**	-0.083**	-0.13**	0.037**	0.073**	-0.011**	-0.023**
	(0.11)	(0.31)	(0.00088)	(0.0031)	(0.00058)	(0.0024)	(0.00035)	(0.0022)
Year (Disp) t+2	-3.56**	-6.59**	-0.081**	-0.12**	0.036**	0.068**	-0.010**	-0.019**
	(0.12)	(0.33)	(0.00091)	(0.0032)	(0.00060)	(0.0024)	(0.00036)	(0.0023)
Year (Disp) t+3	-2.99**	-5.96**	-0.076**	-0.12**	0.034**	0.061**	-0.010**	-0.015**
	(0.13)	(0.36)	(0.00093)	(0.0033)	(0.00062)	(0.0024)	(0.00037)	(0.0023)
Year (Disp) t+4	-2.86**	-5.38**	-0.073**	-0.11**	0.032**	0.053**	-0.0098**	-0.018**
	(0.14)	(0.38)	(0.00096)	(0.0034)	(0.00063)	(0.0024)	(0.00038)	(0.0025)
Year (Disp) t+5	-2.61**	-4.58**	-0.070**	-0.10**	0.031**	0.050**	-0.0090**	-0.015**
	(0.14)	(0.39)	(0.00097)	(0.0034)	(0.00065)	(0.0025)	(0.00040)	(0.0025)
Observations	2579140	333965	2360559	310842	2368993	315137	2579373	335221
R^2	0.109	0.103	0.074	0.100	0.041	0.068	0.016	0.022
Mean of dep. var	96.7	90.9	-0.22	-0.21	0.062	0.091	0.067	0.22

Notes: The table returns coefficients α_j from regression equation 0.1. Year $t = -3$ is omitted as base cateogry. The outcome variables are average establishment wages (columns 1 and 2), AKM-style establishment fixed effects (columns 3 and 4), the share of marginally employed workers in an establishment (columns 5 and 6), and the share of migrant workers in an establishment (columns 7 and 8). In all columns, we control for year since displacement, year, and age polynomials. Standard errors are clustered on the individual level. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Source: IEB. ©IAB

Table 19: Earnings Losses by Origin Group

	(1) Natives	(2) Migrants	(3) Western	(4) Eastern Europe	(5) South-Eastern Europe	(6) Turkey	(7) Former USSR	(8) Asia and Middle East	(9) Africa	(10) Central and South America
Year (Disp) t-5	0.015**	0.031**	0.023	0.10	0.019	0.035*	-0.042	0.00035	0.084	-0.034
	(0.0017)	(0.0092)	(0.013)	(0.058)	(0.027)	(0.017)	(0.079)	(0.040)	(0.046)	(0.071)
Year (Disp) t-4	0.014**	0.0098	0.0054	0.0021	0.00031	0.011	0.11*	0.0092	-0.012	0.046
	(0.0010)	(0.0066)	(0.0093)	(0.049)	(0.012)	(0.0088)	(0.045)	(0.017)	(0.059)	(0.046)
Year (Disp) t-2	-0.011**	-0.012**	-0.00040	-0.0052	-0.026**	-0.026**	-0.018	-0.017	0.0059	0.18
	(0.00081)	(0.0035)	(0.0054)	(0.016)	(0.0088)	(0.0066)	(0.015)	(0.014)	(0.018)	(0.13)
Year (Disp) t-1	-0.083**	-0.10**	-0.10**	-0.097**	-0.089**	-0.13**	-0.078**	-0.10**	-0.084**	-0.032
	(0.00097)	(0.0053)	(0.0097)	(0.026)	(0.013)	(0.0095)	(0.019)	(0.017)	(0.021)	(0.058)
Year (Disp) t	-0.56**	-0.70**	-0.58**	-0.62**	-0.61**	-0.95**	-0.61**	-1.03**	-0.72**	-0.43**
	(0.0029)	(0.016)	(0.026)	(0.088)	(0.041)	(0.026)	(0.061)	(0.065)	(0.070)	(0.11)
Year (Disp) t+1	-0.34**	-0.47**	-0.34**	-0.46**	-0.38**	-0.70**	-0.26**	-0.81**	-0.70**	-0.35**
	(0.0028)	(0.018)	(0.028)	(0.11)	(0.043)	(0.028)	(0.064)	(0.070)	(0.11)	(0.12)
Year (Disp) t+2	-0.25**	-0.36**	-0.28**	-0.40**	-0.31**	-0.51**	-0.20**	-0.49**	-0.54**	-0.40**
	(0.0028)	(0.017)	(0.029)	(0.10)	(0.043)	(0.026)	(0.062)	(0.064)	(0.086)	(0.15)
Year (Disp) t+3	-0.22**	-0.29**	-0.18**	-0.16	-0.31**	-0.47**	-0.089	-0.41**	-0.56**	-0.28
	(0.0028)	(0.016)	(0.025)	(0.11)	(0.047)	(0.026)	(0.053)	(0.064)	(0.099)	(0.15)
Year (Disp) t+4	-0.19**	-0.23**	-0.16**	-0.32**	-0.20**	-0.35**	-0.063	-0.46**	-0.28**	-0.13
	(0.0028)	(0.018)	(0.022)	(0.11)	(0.042)	(0.026)	(0.055)	(0.15)	(0.059)	(0.086)
Year (Disp) t+5	-0.17**	-0.18**	-0.11**	-0.19	-0.13*	-0.31**	-0.031	-0.27**	-0.19**	-0.14
	(0.0028)	(0.016)	(0.024)	(0.10)	(0.061)	(0.027)	(0.069)	(0.070)	(0.074)	(0.11)
Observations	2696597	341398	96606	10996	35560	127477	11207	21819	17937	1956
R^2	0.103	0.113	0.096	0.137	0.106	0.158	0.114	0.192	0.141	0.104
Mean of dep. var	10.3	10.2	10.3	10.1	10.2	10.1	10.0	9.94	9.96	10.2

Notes: The table returns coefficients α_j from regression equation 0.1. Year $t = -3$ is omitted as base cateogry. The outcome variable in all columns is log(earnings+1). In all columns, we control for year since displacement, year, and age polynomials. Standard errors are clustered on the individual level. Migrants in columns (2) to (10) are reweighted to natives using individual characteristics, industries, and occupations. Migrants' origin groups definition comes from Battisti et. al. (2018). Table 22 provides an overview of the countries within the origin groups. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Source: IEB. ©IAB

Table 20: Differences in Labor Market Outcomes for Women

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (Earnings)		Log Wage		Employment		Days Worked	
	Natives	Migrants	Natives	Migrants	Natives	Migrants	Natives	Migrants
Year (Disp) t-5	0.026**	0.020	0.013**	-0.012	0.0038**	0.018	4.39**	9.62*
	(0.0028)	(0.020)	(0.0023)	(0.014)	(0.00079)	(0.0095)	(0.45)	(4.12)
Year (Disp) t-4	0.016**	0.018	0.0043*	-0.0062	0.000022	0.00029	2.13**	4.17*
	(0.0017)	(0.011)	(0.0017)	(0.010)	(0.000039)	(0.00027)	(0.24)	(1.79)
Year (Disp) t-2	-0.012**	-0.0080	-0.015**	-0.0031	-0.00034	-0.0032	-0.38	-2.69*
	(0.0014)	(0.0080)	(0.0015)	(0.0083)	(0.00032)	(0.0025)	(0.20)	(1.24)
Year (Disp) t-1	-0.096**	-0.11**	-0.029**	-0.017	-0.000042	-0.00046	-20.4**	-25.5**
	(0.0017)	(0.011)	(0.0018)	(0.010)	(0.000050)	(0.00058)	(0.24)	(1.56)
Year (Disp) t	-0.56**	-0.70**	-0.24**	-0.27**	-0.13**	-0.18**	-101.4**	-132.6**
	(0.0044)	(0.034)	(0.0034)	(0.023)	(0.0013)	(0.0091)	(0.59)	(4.92)
Year (Disp) t+1	-0.38**	-0.49**	-0.23**	-0.26**	-0.11**	-0.17**	-60.2**	-83.9**
	(0.0046)	(0.039)	(0.0035)	(0.026)	(0.0015)	(0.011)	(0.63)	(5.16)
Year (Disp) t+2	-0.31**	-0.37**	-0.22**	-0.22**	-0.079**	-0.12**	-38.9**	-59.2**
	(0.0047)	(0.044)	(0.0036)	(0.030)	(0.0015)	(0.012)	(0.64)	(5.34)
Year (Disp) t+3	-0.27**	-0.32**	-0.20**	-0.21**	-0.059**	-0.097**	-28.0**	-45.0**
	(0.0047)	(0.038)	(0.0038)	(0.029)	(0.0015)	(0.011)	(0.65)	(4.95)
Year (Disp) t+4	-0.23**	-0.26**	-0.19**	-0.21**	-0.049**	-0.076**	-21.7**	-33.5**
	(0.0047)	(0.037)	(0.0039)	(0.029)	(0.0015)	(0.011)	(0.65)	(4.84)
Year (Disp) t+5	-0.21**	-0.22**	-0.18**	-0.18**	-0.039**	-0.057**	-17.5**	-23.8**
	(0.0048)	(0.037)	(0.0040)	(0.032)	(0.0015)	(0.011)	(0.64)	(4.98)
Observations	1347579	110135	1309314	105704	1408547	120035	1408547	120035
R^2	0.084	0.108	0.057	0.069	0.066	0.102	0.125	0.174
Mean of dep. var	10.1	9.87	4.35	4.10	0.96	0.92	331.6	310.5

Notes: The table returns coefficients α_j from regression equation 0.1, estimated on a sample of female workers. Year $t = -3$ is omitted as base category. The outcome variables are log (earnings+1) (columns 1 and 2), log wage (columns 3 and 4), employment (columns 5 and 6), and days worked (columns 7 and 8). In all columns, we control for year since displacement, year, and age polynomials. Standard errors are clustered on the individual level. Migrants are reweighted to natives using individual characteristics, industries, and occupations. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Source: IEB. ©IAB

Table 21: Robustness Check: Restricting to Baseline Years up to 2003 (Pre Financial Crisis)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (Earnings)		Log Wage		Employment		Days Worked	
	Natives	Migrants	Natives	Migrants	Natives	Migrants	Natives	Migrants
Year (Disp) t-5	0.018**	0.042**	0.0042*	-0.0027	0.0029**	0.0031	2.66**	8.44**
	(0.0023)	(0.014)	(0.0019)	(0.012)	(0.00066)	(0.0040)	(0.39)	(2.47)
Year (Disp) t-4	0.014**	0.022*	-0.00071	0.0099	-0.000048	-0.00042*	1.55**	4.43**
	(0.0015)	(0.0100)	(0.0016)	(0.010)	(0.000030)	(0.00019)	(0.22)	(1.67)
Year (Disp) t-2	-0.0084**	-0.017**	-0.014**	0.0077	0.0022**	0.00067	0.51*	-0.91
	(0.0012)	(0.0051)	(0.0017)	(0.012)	(0.00041)	(0.0013)	(0.21)	(0.84)
Year (Disp) t-1	-0.081**	-0.11**	-0.024**	-0.016	-0.0000073	0.0013*	-17.6**	-23.0**
	(0.0013)	(0.0083)	(0.0018)	(0.012)	(0.000040)	(0.00052)	(0.21)	(1.29)
Year (Disp) t	-0.59**	-0.69**	-0.20**	-0.20**	-0.15**	-0.18**	-119.9**	-138.2**
	(0.0041)	(0.025)	(0.0031)	(0.019)	(0.0013)	(0.0093)	(0.56)	(3.89)
Year (Disp) t+1	-0.37**	-0.51**	-0.18**	-0.22**	-0.13**	-0.17**	-72.6**	-96.1**
	(0.0041)	(0.029)	(0.0030)	(0.022)	(0.0014)	(0.011)	(0.60)	(4.32)
Year (Disp) t+2	-0.27**	-0.38**	-0.16**	-0.20**	-0.10**	-0.15**	-50.0**	-73.1**
	(0.0041)	(0.027)	(0.0031)	(0.020)	(0.0015)	(0.011)	(0.62)	(4.26)
Year (Disp) t+3	-0.23**	-0.30**	-0.15**	-0.15**	-0.083**	-0.12**	-39.5**	-56.6**
	(0.0041)	(0.026)	(0.0033)	(0.020)	(0.0015)	(0.010)	(0.62)	(4.26)
Year (Disp) t+4	-0.19**	-0.25**	-0.14**	-0.11**	-0.071**	-0.095**	-32.0**	-45.3**
	(0.0041)	(0.028)	(0.0033)	(0.031)	(0.0015)	(0.010)	(0.62)	(4.09)
Year (Disp) t+5	-0.17**	-0.16**	-0.13**	-0.11**	-0.063**	-0.097**	-27.0**	-38.2**
	(0.0040)	(0.025)	(0.0034)	(0.022)	(0.0015)	(0.011)	(0.62)	(4.51)
Observations	1469255	150594	1418583	143951	1540502	161467	1540502	161467
R^2	0.103	0.112	0.049	0.046	0.077	0.109	0.162	0.198
Mean of dep. var	10.3	10.2	4.62	4.45	0.95	0.93	329.7	317.8

Notes: The table returns coefficients α_j from regression equation 0.1. The sample is restricted to pre financial crisis baseline years, e.g., all years up to 2003. Year $t = -3$ is omitted as base cateogry. The outcome variables are log (earnings+1) (columns 1 and 2), log wage (columns 3 and 4), employment (columns 5 and 6), and days worked (columns 7 and 8). In all columns, we control for year since displacement, year, and age polynomials. Standard errors are clustered on the individual level. Migrants are reweighted to natives using individual characteristics, industries, and occupations. ** and * refer to statistical significance at the 0.01 and 0.05 percent level, respectively. Source: IEB. ©IAB

Table 22: Overview Origin Groups as in Battisti et al. (2018)

	(1) Group name	(2) Countries	
1	Germany	Germany	
2	Western incl. Western European Countries	Australia Austria Canada Denmark Finland France Greece Italy Ireland Netherlands	New Zealand Norway Portugal Samoa Spain Sweden Switzerland United Kingdom USA
3	Eastern Europe	Czech Republic Hungary Poland	Slovakia Slovenia
4	South-Eastern Europe	Albania Bosnia and Herzegovina Bulgaria Kosovo Croatia	Former Jugoslavia Northmazedonia Mazedonia Romania Serbia
5	Turkey	Turkey	
6	Former USSR	Armenia Azerbaijan Belarus Estonia Georgia Kazakhstan Kyrgyzstan Latvia	Lithuania Moldova Russian Federation Tajikistan Turkmenistan Ukraine Uzbekistan
7	Asia and Middle East		
8	Africa		
9	Central and South America		
10	Other		

Notes: This table shows how we assign migrants to origin groups following Battisti/Romiti/Peri (2018). We use these origin groups in our heterogeneity analysis in table 19.©IAB

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