Geographic Labor Mobility and Statutory Minimum Wages

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Abstract

I exploit the German statutory minimum wage introduction in 2015 to estimate its effects on geographic labor mobility using a 2% sample of administrative data. I find an increase in out-migration due to the minimum wage of low-skilled workers with migrant background from counties where a high-share of workers is subject to the minimum wage to urban labor market regions. The increase in out-migration is mainly attributable to optimal workplace reallocation of respective workers to better quality establishments. In contrast, native low-skilled workers do also relocate to better quality establishments, however, while not moving. The difference in reallocation behavior shows that migrants react stronger to changing local labor market conditions. Therefore, the results emphasize that statutory minimum wages lead to changes in the socio-demographic structure of local labor markets and a possible concentration of low-skilled workers with migrant background in urban labor market regions. *[144 words]*

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1. Introduction

Internal migration plays an integral role in the study of geographic labor mobility, and its analysis is important for understanding changes in the spatial socio-demographic distribution of the labor force. In Germany, two internal migration patterns dominated, significantly altering the spatial socio-demographic distribution. The first was the east-west migration following reunification in 1990 (see, e.g., Rosenbaum-Feldbrügge, Stawarz, and Sander (2022)) , and the second was migration across the urban-rural sphere (see, e.g., Stawarz and Sander (2019)). Both internal migration patterns have resulted in alterations to the socio-demographic structure, particularly in former East German rural regions, with older individuals remaining and younger individuals leaving (Rosenbaum-Feldbrügge et al., 2022). Stawarz and Sander (2019) also note that the process of urbanization and subsequent suburbanization into economically more prosperous regions accelerated the aforementioned socio-demographic change in rural East German regions as well as in rural West German regions. The economic literature describes internal migration in Germany as predominantly driven by economic factors, such as relatively higher (expected and short-term) regional unemployment, which leads individuals to migrate out of a region (push factor), and relatively higher expected regional income which leads individuals to either move into a region or to stay in a region (pull or restraining factor) (see, e.g., Bauer, Rulff, and Tamminga (2019); Fuchs-Schündeln and Schündeln (2009); Mitze and Reinkowski (2011)). In light of the fact that regional unemployment and wages represent the primary economic driving forces behind internal migration, the question that arises is to what extent the observed patterns of internal migration may be subject to change in the event of the implementation of a policy that is theoretically capable of affecting both of these channels.

Minimum wages are a popular policy tool aimed at reducing poverty and economic inequality by increasing wages at the lower end of the wage distribution. Moreover, as postulated by neo-classical labor market theory, minimum wages may exert a negative effect on employment, potentially leading to an increase in unemployment in regions where minimum wages are introduced or increased.[1] Monras (2019) develop a spatial model for analyzing the impact of minimum wage increases on the internal migration of low-wage workers. He identifies two main theoretical mechanisms for internal migration: increasing expected regional wages as a pull factor and increasing expected unemployment as a push factor for low-wage workers. For the U.S., he identifies an increase in the out-migration of low-skilled workers[2] in states where minimum wages are introduced or increased. This is primarily driven by increases in regional unemployment due to minimum wage increases, i.e. the

[1] In monopsonistic and oligopsonistic labor markets, imposing minimum wages theoretically can lead to positive employment effects (see, e.g., Bhaskar, Manning, and To (2002)).

[2] Monras (2019) employs low-skilled workers as a proxy group to represent workers who are subject to the minimum wage.

push factor dominates the pull factor. However, the U.S. is a patchwork of different minimum wage laws at the federal, state, and county level, which makes it difficult to make direct comparisons to Germany. In 2015, Germany introduced a statutory minimum wage of 8.50 euros. The objective of statutory minimum wage is to increase the wages of all workers earning below the minimum wage to a predefined level. However, the proportion of workers subject to the minimum wage can vary across regions. In Germany, for instance, the average proportion of workers subject to the minimum wage introduction was between 10 and 15 percent. In rural counties[3] of former East Germany, the introduction of the minimum wage affected up to 30% of the employed population, whereas in urban areas or in former West Germany, the impact was relatively limited.[4] In the remainder of this paper, the term "high-bite regions" will be used to refer to areas with a high proportion of workers subject to the minimum wage, while "low-bite regions" will be used to refer to areas with a low proportion of workers subject to the minimum wage.[5] Given the strong regional variation at the county level in the share of workers subject to the minimum wage, this paper adapts the theory proposed by Monras (2019) to a statutory minimum wage introduction.

Therefore, I theoretically motivate that the decision of low-wage workers to relocate is dependent on both spatial differences in the expected regional wages and the regional probability of becoming unemployed due to the introduction of the statutory minimum wage. By holding the probability of becoming unemployed constant, high-bite regions become relatively more attractive because the increase in expected regional wages in high-bite regions due to the statutory minimum wage introduction is higher relative to the increase in low-bite regions. Therefore, low-wage workers would start to in-migrate to high-bite regions. However, if the relative increase in the probability of becoming unemployed in high-bite regions is sufficiently higher than the relative increase in expected wages, low-wage workers will begin to out-migrate from high-bite to low-bite regions. The existing literature on the German minimum wage, though, finds only modest negative effects on employment in high-bite regions, which could have increased the regional probability of becoming unemployed. It is interesting to note that Dustmann, Lindner, Schönberg, Umkehrer, and vom Berge (2021) identify an increase in the closure of small establishments in German high-bite municipalities,[6] which is then followed by an increase in labor mobility to qualitatively "better" establishments.[7]. Therefore, a potential impact on out-migration may be attributed to the reallocation to "better" establishments. Furthermore, an increase in the perceived (short-

[3] County refers to the NUTS-3 regional classification. Germany is organized in 400 counties.

[4] For reference see panel (A.1) in figure 1 of section 2.1.

[5] The term "bite" refers to how deeply the introduction of the minimum wage has bitten into the regional wage distribution.

[6] As of December 31, 2021, Germany is organized into 10,994 municipalities. These municipalities constitute a subset of the regional classification NUTS-3, i.e. counties.

[7] The authors describe "better" establishments as large and stable, i.e with a low turnover rate. I will use the same terminology as Dustmann et al. (2021) for the remainder of this paper.

term) probability of becoming unemployed due to the closure of small establishments in high-bite regions could reinforce a potential effect on out-migration. In the event that the perceived increase is sufficiently high, workers subject to the minimum wage may subsequently relocate their workplace from high-bite regions to low-bite regions.

I aggregate the weakly anonymized version of the Employment Panel of Integrated Employment Histories (SIAB) (Graf et al., 2023) at the county-year level. This enables me to quantify the number of in- and out-migrants by county on an annual basis. Due to the nature of the respective variables as count variables, I utilize a conditional fixed effects Poisson model in which I employ a difference-in-differences specification with continuous treatment to estimate the potential effect.[8]

In doing so, I contribute to the existing literature in several ways. Firstly, I adapt the theoretical framework proposed by Monras (2019) for a statutory minimum wage introduction. By estimating the treatment effects of the minimum wage introduction on in- and out-migration of workers subject to the minimum wage separately, it is possible to distinguish between the push and pull effects of the statutory minimum wage introduction, namely increases in the regional perceived probability of becoming unemployed and increases in expected regional wages, respectively.

Secondly, I provide novel and detailed empirical evidence on the effects of the introduction of the German statutory minimum wage in 2015 on geographic labor mobility. I find no effect on in-migration to high-bite counties. However, I do find an increase in the average out-migration from high-income counties of low-skilled workers with a migrant background, rising by 24% in 2015 and more than tripling in size by 2019. I can attribute a substantial proportion of the effect to the optimal reallocation of low-skilled workers with migrant background to higher-quality establishments in urban labor market regions. The remaining proportion can be attributed to an increase in the perceived probability of becoming unemployed in high-bite regions, which, according to theory, induces out-migration. In contrast, I identify no effect on internal migration for natives but an increase in reallocation to "better" establishments across county borders without moving. In light of this, I provide further evidence to support the findings of Dustmann et al. (2021) on an increase in optimal reallocation of workers to "better" establishments as a result of the introduction of a minimum wage. However, in contrast to Dustmann et al. (2021) who explained the mechanism of the reallocation effect by an increase in commuting distance, I offer several explanations. On the one hand, I observe a similar mechanism in workplace reallocation for natives in low-skilled employment who are likely to relocate to nearby establishments where commuting is feasible. On the other hand, a substantial proportion of the out-migration effect of low-skilled workers with a migrant background is driven by migration to more distant regions to improve

[8]The difference-in-differences specification with continuous treatment is a commonly used identification strategy in the minimum wage literature (see, e.g., Card (1992))

the quality of their establishment of employment. Therefore, they relocate their place of residence and, simultaneously, their place of work to other labor market regions. Furthermore, the potential for network effects among individuals with similar migrant backgrounds may have contributed to an increasing tendency of out-migration over time. The differentiation in mechanisms is important because it points towards a socio-demographic shift in local labor markets and a concentration of respective group of workers in urban labor market regions induced by the statutory minimum wage.

Thirdly, I find support for Cadena (2013) findings also for the German labor market. He shows for the U.S. that short-term migrants are more sensitive to changing local labor market conditions than natives by moving longer distances after changes in the minimum wage. For Germany, I find that low-skilled workers with migrant background enhance the quality of their employing establishment due to the minimum wage introduction. Furthermore, these workers tend to migrate to regions where a greater concentration of "better" establishments is located. This finding is corroborated by the out-migration effect, which is driven by migration across labor market regions to urban/suburban counties where commuting from the origin is unlikely to be feasible. In contrast, my findings indicate that natives tend to remain in their home county and enhance establishment quality by relocating to a different county of employment. One potential explanation for this is that natives typically possess stronger personal ties to their home region compared to individuals with a migrant background, who are often more flexible in their residential choices. Therefore, individuals with a migrant background demonstrate a stronger reaction to changing local labor market conditions, evidenced by a greater mobility in terms of their place of residence and workplace, in comparison to natives who remain in the same location.

The remainder is structured as follows. Section 2 theoretically motivates potential effects of a statutory minimum wage introduction on internal migration. Section 3 to section 5 present the main dataset, describe the main identification strategy and analyze and discuss respective results. Section 6 concludes.

2. Internal migration and a statutory minimum wage introduction

I start this section, by motivating possible economic channels of the minimum wage introduction on internal migration by theory and former evidence in section 2.1 to section 2.3. I conclude this chapter by providing a summary of key objectives relevant for the analysis in section 2.4.

2.1. Spatial reallocation of low-wage workers

In order to illustrate the theoretical effects of the introduction of the statutory minimum wage in Germany in 2015 on internal migration, I adapt the theory presented by Monras (2019) which demonstrates the theoretical effect of the introduction of non-statutory minimum wage on the geographic mobility of low-wage workers. Therefore, an individual's decision to relocate to another region is driven by the expected utility they perceive. If the expected utility in another region exceeds the current expected utility, the individual would rationally decide to move. Monras (2019) models a worker's indirect utility function for each region s as a function between receiving unemployment benefits or going to work as follows.[9]

$$V_s = u_s B^\rho + (1 - u_s)(1 - \tau)^\rho w_s^\rho \tag{1}$$

where u_s is the regional probability of becoming unemployed, B are statutory unemployment benefits, τ the tax rate, ρ a measure of risk aversion and w_s is the expected regional wage. Given $B < (1 - \tau)w_s$, the decision to move is fully captured by spatial differences in u_s and w_s.[10] Therefore, the lower the probability of becoming unemployed in a region or the higher the expected regional wage, the higher the indirect utility of living in that region. In contrast to Monras (2019), I analyze a statutory minimum wage introduction, which simplifies the model such that after the introduction, regional wages of workers affected by the minimum wage ($w^{min} > w_s$) initially increase and equalize across regions, thus $w_s = w^{min}$. This allows me to analyze the indifference condition directly. For simplicity, I illustrate potential effects on the geographic mobility of low-wage workers in a two-regions world where the indifference condition is $V_1 = V_2$. A worker considers to move from region 1 to region 2 either if regional wages in region 2 increase stronger than in region 1 or if the probability of becoming unemployed in region 1 increases stronger than in region 2 such that region 2 becomes relatively more attractive than region 1. To incorporate the potential effect of an introduction of a statutory minimum wage, I assume region 1 to be a high-bite region and region 2 to be a low-bite region such that $w_1 < w_2 < w_{min}$. Holding the probability of becoming unemployed constant, high-bite regions become relatively more attractive because $\Delta w_1 > \Delta w_2$ due to the minimum wage introduction. Therefore, in-migration to high-bite regions increase. Nevertheless, the introduction of a minimum wage may also result in a stronger increase in the (perceived) probability of becoming unemployed in high-bite regions relative to low-bite regions. This may be due to stronger negative regional employment effects or a greater number of regional firm closures in high-bite regions resulting from the introduction

[9] Assuming constant price levels across regions and a reservation wage of 0.

[10] Unemployment benefits are assumed to be lower than net wages. This makes sense because workers would not work if unemployment benefits exceed their respective net wages.

of a minimum wage. Therefore, an individual living in region 1 would move to region 2 if Δu_1 is sufficiently higher than Δu_2 such that the gain in utility due to increasing regional wages is reversed by the increase in the regional (perceived) probability of becoming unemployed. Accordingly, the theoretical anticipated effect of the implementation of the statutory minimum wage on internal migration may result in either an increase in in-migration or an increase in out-migration in high-bite regions.

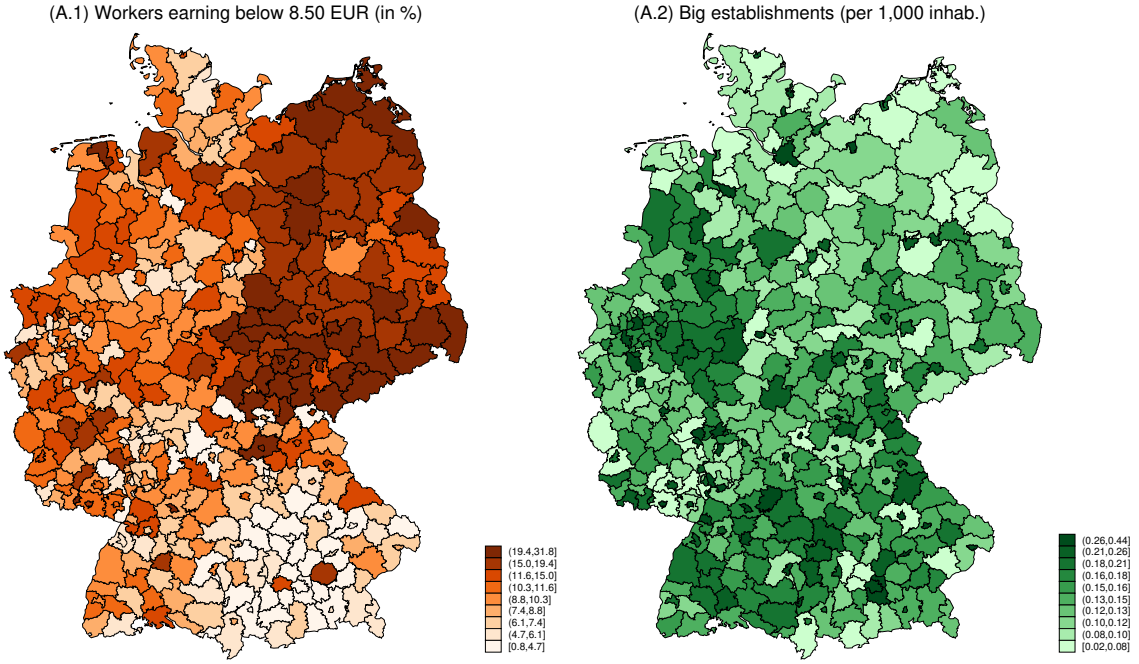
On the one hand, the empirical literature does find positive (regional) wage effects of the minimum wage introduction up until the 50%-percentile of the wage distribution (Bossler & Schank, 2023). On the the other hand, only modest negative employment effects of the German minimum wage introduction are found.[11] Therefore, the empirical literature points towards a potential in-migration effect into high-bite regions. However, a recent strand of the German minimum wage literature shows reallocation effects of workers across establishments (Dustmann et al., 2021; Haelbig, Mertens, & Müller, 2023). For example, while not reporting average negative employment effects, Dustmann et al. (2021) find reallocation effects of low-wage workers from small to "better" establishments due to the introduction of the minimum wage. The reported effect is attributed to the closure of small establishments located in high-bite municipalities. Given this findings, two channels which lead to out-migration from high-bite regions are likely.

Firstly, individuals who relocate across establishments do out-migrate from high-bite regions to other regions where "better" establishments are located. Therefore, the migration decision also depends on the location of "better" establishments which are characterized as large and stable, i.e. with more than 250 employees and a low turnover rate (Dustmann et al., 2021). Figure 1 presents the share of workers subject to the minimum wage (A.1), i.e. the minimum wage bite, and the regional concentration of establishments with more than 250 employees (per capita) (A.2) as a proxy for "better" establishments, both for the year 2014. Comparing (A.1) and (A.2) indicates a negative spatial correlation between the concentration of large establishments and high-bite regions. This suggests a workplace reallocation effect from high-bite counties into low-bite counties because large establishments seem to be more densely in latter counties. On the one hand, workplace reallocation can lead to an increase in the commuting distance as found by Dustmann et al. (2021) or can lead to out-migration.[12] Since the figure indicates that high-bite counties are mainly located in rural and/or former East Germany and large establishments are more densely located in urban areas or former West Germany, out-migration from high-bite counties may increase due to the closure of small establishments and the reallocation of workers to "better" establishments into regions

[11] For example, Bossler, Liang, and Schank (2024) do find a negative employment effect for the subgroup of individuals working in marginal employment due to the minimum wage introduction.

[12] Dustmann et al. (2021) do not estimate a potential internal migration effect of workers subject to the minimum wage introduction.

Figure 1: Minimum wage bite and concentration of big establishments in 2014



Note: Workers earning below 8.50 EUR for establishments with more than 10 employees: mean=10.84%, sd=6.01%; Big establishments (per 1,000 inhabitants): mean=0.159, sd=0.071. Big establishments are defined as establishments with more than 250 employees. *Source: Structure of earnings survey (SES) and Regionaldatenbank (2024a), own calculations*

where commuting is not feasible.

Secondly, the closure of small establishments as described by Dustmann et al. (2021) in high-bite regions could additionally lead to an increase in the perceived probability of becoming unemployed by low-wage workers, e.g. because their peers lose their jobs and start working elsewhere. If respective increase in the perceived probability of becoming unemployed is sufficiently high the indirect utility in low-bite regions becomes relatively higher. Therefore, workers would start to out-migrate from high-bite regions according to theory.

2.2. Spatial reallocation of individuals with migrant background

The literature on internal migration shows that in the U.S. immigrants choose their destination based on differences in regional labor market conditions, particularly in terms of expected earnings. Cadena (2013) reports empirical evidence that individuals with short-term migration backgrounds move longer distances and are more responsive to changes in local labor market conditions. He shows that short-term migrants who work in low-wage employment tend to be more sensitive to changes in wages and tend to be more flexible in their residential choice if the minimum wage increases in a region. Therefore, a potential effect on

internal migration, as described in section 2.1, may be more pronounced among individuals with a migrant background than among natives, as the former group tend to be more sensitive to changes in local labor market conditions due to the introduction of the minimum wage.

2.3. Spatial reallocation of unemployed

By relaxing the assumption $B < (1 - \tau)w_s$ and allowing a reservation wage of greater than zero, one can use the indirect utility function of equation (1) to describe possible migration patterns of unemployed individuals due to the introduction of a statutory minimum wage. In this simple framework, unemployed individuals start to relocate to regions where regional wages w_s exceed their reservation wage w_{reserv} in order to start working as long as the (perceived) probability of becoming unemployed is sufficiently low. In the case of a statutory minimum wage, two types of unemployed can be distinguished. First, there is a group of unemployed where $w^{reserv} > w^{min}$ still holds after expected regional wages increase due to the minimum wage introduction. This group of unemployed will not start working anyway. Second, there is a group of unemployed where $w^{reserv} > w_s$ changes to $w^{reserv} < w^{min}$ due to increases in expected regional wages due to the minimum wage introduction. Because no lower bound spatial wage differentials remain after the minimum wage is introduced, respective unemployed would follow a similar migration pattern as low-wage workers, determined by expected increases in regional wages and increases in the regional probability of becoming unemployment as described in section 2.1.

2.4. Key objectives

In summary, I will examine whether the introduction of a statutory minimum wage in Germany in 2015 increases internal migration of workers subject to the minimum wage introduction. The statutory minimum wage introduction could either lead to an increase in in-migration to high-bite regions due to stronger increases in expected regional wages. However, it could also lead to out-migration from high-bite regions. Out-migration may increase due to the reallocation of workers to "better" establishments or due to sufficiently high increases in the regional (perceived) probability of becoming unemployed. Therefore, the effect directions is not clear and is subject to the empirical analysis in section 5. Moreover, I will examine whether the effects are stronger for individuals with migrant background and I will exploit whether parts of the unemployed population do also start to migrate across county borders.

3. Data, sample selection and descriptive statistics

In order to analyze the effect of the introduction of the statutory minimum wage on internal migration flows, I use microdata on employment histories of individuals from the Employment Panel of Integrated Employment Histories (SIAB) provided by the Institute for Employment Research (IAB) (Graf et al., 2023).[13] The dataset comprises the years from 1975 to 2021 and is a 2% representative sample of administrative data covering employees subject to social security contributions and the unemployed population in Germany. It excludes civil servants and self-employed. However, it covers the majority of the German labor force.[14] The dataset merges spells of social security records with spells of unemployment records from the Federal Employment Agency. Most importantly, the SIAB contains information on the county of residence of an individual and, if employed, the county in which the individual works. In order to construct a micro panel dataset, I use December 31 as the cut-off date for each year. In case of parallel spells on the cut-off date, I consider the spell with the highest wage as the main occupation for the respective observation.[15] Also, I exclude workers in marginal employment from my main specification because it seems unlikely that such workers would change their county of residence if they are marginally employed in their main job, given the unfeasible costs of moving. However, because marginally employed workers are likely to be strongly affected by the introduction of the minimum wage, I will use them for sensitivity analysis. In addition, I exclude interns, working students, apprentices, family workers, sailors, irregular workers, and (part-time) retirees because their decision to move is rather influenced by the valuation of non-pecuniary motives than monetary motives.

Based on the micro panel dataset, I construct an aggregate panel dataset with the dimensions county s and year t which tracks in-migration flows ($Inf_{s,t}$) and out-migration flows ($Out_{s,t}$) by county per year. Respective variables are measured as follows.

$$Inf_{s,t} = \sum_{i}^{N} 1\left[s_{i,t} \neq s_{i,t-1}\right]_{i,s,t} \quad \text{or} \quad Out_{s,t} = \left[\sum_{i}^{N} 1\left[s_{i,t} \neq s_{i,t+1}\right]_{i,s,t}\right]_{t-1} \tag{2}$$

To capture in-migration flows, I first construct an indicator variable that is 1 if an individual changes county s between $t-1$ and t and 0 otherwise. Then I sum the indicator variable over all individuals living in county s and year t. Therefore, the sum of the indicator variable reflects the number of in-migrants to a county per year. Out-migration flows are constructed similarly, except that the indicator variable is 1 if an individual changes their county of residence between t and $t+1$ and 0 otherwise. Therefore, the sum measures the number of

[13] For more information on the dataset refer to the dataset manual (Schmucker, Seth, & vom Berge, 2023).

[14] It covers about 80% of the German labor force. For comparison see, e.g. Microcensus 2022.

[15] In general, I follow the data preparation procedure of Stüber, Dauth, and Eppelsheimer (2023) to construct a yearly panel from the raw spell data.

out-migrants for the year $t+1$ in year t. To map the right value to the correct year, the value calculated for year $t-1$ of the out-migration flow variable must be considered in year t. Measurement error may occur if employees report their new residence to their employers with some delay. However, the annual structure should limit this bias. In addition, it is not clear whether individuals report their first or second residence to their employer, which could lead an incorrect assignment of individuals to a county. However, this would only pose a problem, e.g. if individuals changed their primary residence to their secondary residence by reporting the change to their employer without actually relocating and vice versa. I expect that to happen very rarely.

According to section 2, I additionally measure in-migration flows and out-migration flows based on whether individuals have a migrant background or are native. The SIAB contains information on an individuals citizenship where I classify individuals with a German citizenship as native and individuals with a non-German citizenship as having a migrant background. I further distinguish between being unemployed or being employed in a low-skilled or a medium/high-skilled occupation.[16] The skill level of a worker's occupation is based on Blossfeld (1987) occupational classification. All occupations classified as unskilled according to Blossfeld (1987) enter the group of low-skilled employment and all other enter the group of medium-/high-skilled employment. The underlying assumption is that low-skilled employed workers are a good proxy for low-wage workers, i.e. workers subject to the minimum wage.

Table 1 illustrates the average number of annual in-migration and out-migration for relevant sub-samples over the five years before the minimum wage introduction, compared with the corresponding average over the five years after the minimum wage introduction. Net migration (in-migration minus out-migration) is zero for the total sample and close to zero for all sub-samples which ensures that the data generation process is robust to errors and not biased by panel attrition in the micro sample.[17] Average annual internal migration decreases for native individuals after the minimum wage introduction, while the decrease is close to zero for low-skilled workers. However, the internal migration of individuals with a migrant background increases by about 92% to 95% after the introduction of the minimum wage, with the internal migration of workers in low-skilled employment and unemployed

[16] An individual's unemployment status or occupational skill level refers to the period before the move, i.e., the status may change after the move. Therefore, the flows are based on the respective state in the county of origin.

[17] Since in-migration flows are a backward-looking measure while out-migration flows are a forward-looking measure (as described in section 3), slight differences occur due to individuals changing their primary citizenship between 2014 and 2015 from German to any other nationality and vice versa. For example an individual changes their nationality from French to German between 2014 and 2015 and moves between county a and b. Therefore, the move counts as in-migration flow to b for the native sub-sample and as out-migration flow from a for the migrant background sub-sample. Changing the nationality only pose a threat to identification if changing the nationality would count as additional in-migration or out-migration flow for counties b and a, respectively. However, this is not the case in the data generation process.

Table 1: Average in- and out-migration by sub-sample

	Mean		
	2010-2014	2015-2019	Δ%
In-migration	45.132	45.836	1.56%
In-migration (native-born)	41.176	38.245	−7.11%
In-migration (native-born, low-skilled)	8.693	8.527	−1.91%
In-migration (native-born, unemployed)	4.646	3.918	−15.69%
In-migration (mig. back.)	3.955	7.590	92.94%
In-migration (mig. back., low-skilled)	1.204	2.982	147.12%
In-migration (mig. back., unemployed)	0.815	1.868	128.87%
Out-migration	45.132	45.836	1.56%
Out-migration (native-born)	41.178	38.170	−7.33%
Out-migration (native-born, low-skilled)	8.711	8.532	−2.05%
Out-migration (native-born, unemployed)	4.607	3.845	−16.58%
Out-migration (mig. back.)	3.954	7.665	94.51%
Out-migration (mig. back., low-skilled)	1.185	2.978	151.21%
Out-migration (mig. back., unemployed)	0.853	1.942	127.78%

Notes: In-migration flows $Inf_{s,t}$ and out-migration flows $Out_{s,t}$ measure the number of individuals (given restrictions) who move into our out of counties per year according to equation (2). A full table for all generated variables is provided in table A2 and table A3. Descriptive statistics on the socio-demographic structure of the underlying micro data is provided in table A1. *Source: SIAB, own calculations*

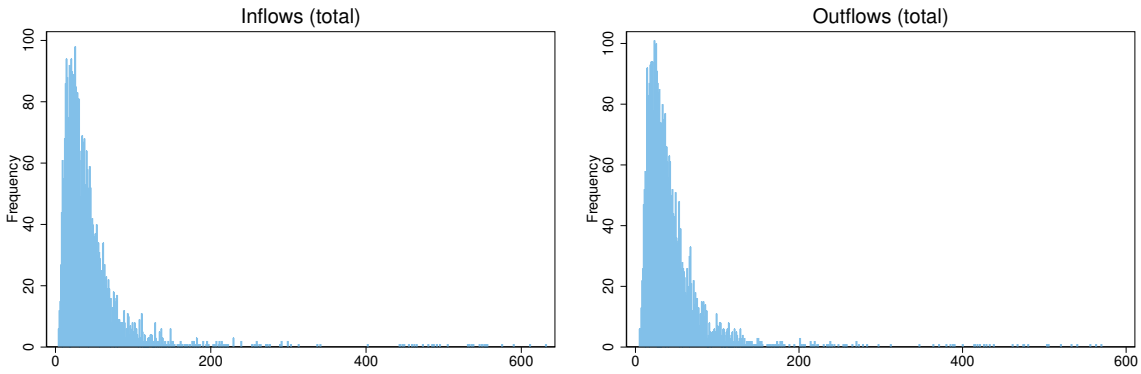
more than doubling. The increases in internal migration for the migrant background sample could be partly due to the increase in sample size due to the migration waves in 2015 and 2016,[18] and partly due to the introduction of the minimum wage in 2015. Therefore, I will empirically test the latter. For natives, it remains unclear given the general negative development of internal migration. The decrease in internal migration of natives could be driven by restraining effects of the minimum wage introduction.

4. Identification strategy

To estimate effects of the minimum wage introduction on internal migration, I make use of a difference-in-differences specification with a continuous treatment that varies at the regional level similar to, e.g. Card (1992) which is widely used in the minimum wage literature to study changes in economic outcomes due to the introduction of a minimum wage. The continuous treatment variable $Bite_s$ is measured between 0 and 1 as the percentage of employees earning less than 8.50 Euros in the last pre-treatment year 2014 per county, i.e. it reflects the treatment intensity by measuring how deep the minimum wage introduction has

[18] For the sample size refer to table A1 in appendix A.

Figure 2: Distribution of in- and out-migration flows (2010 - 2019)



Note: This figure shows the distribution of the variables $Inf_{s,t}$ and $Out_{s,t}$ for all workers subject to social security and unemployed individuals. For the distribution of respective variables for further sub-groups used in the analysis refer to appendix B. Source: SIAB, own calculations.

bitten into the regional wage distribution.[19] Therefore, I exploit the regional variation in the share of workers subject to the minimum wage by comparing changes in internal migration flows in high-bite counties to changes in internal migration flows in low-bite counties to identify the treatment effect on respective outcome variables. For identification, $Bite_s$ must be conditionally exogenous to changes in migration flows and therefore changes in wages in post-treatment periods, since expected wages in post-treatment periods affect the moving decisions of workers earning below the minimum wage threshold in 2014 and also unemployed individuals, as discussed in section 2. There may be anticipation effects on wages, i.e. treatment effects on wages are measurable for the year 2014 because the minimum wage has already been publicly debated and the law has passed in the respective year. This could pose a threat to conditional exogeneity since the minimum wage bite would already influence an individual's decision to move in pre-treatment periods. However, the findings of Bossler and Schank (2023) show an anticipation effect on wages only for the 20th percentile of the wage distribution, though, most likely due to collective bargaining. Given the limited evidence for anticipation effects on wages and since the decision to move is a consequence of the effect on wages, I find it convincing that the conditional exogeneity conditions for the minimum wage bite defined in 2014 hold.

The main dependent variables are measured as non-negative integers reflecting the number of individuals moving into ($Inf_{s,t}$) or out of ($Out_{s,t}$) a county s within a year t as described in section 3. As is common for count data, the distribution is centered around small values with a long tail but also includes zeros (see figure 2). The distribution is mainly due to counties having different population sizes, with the majority of counties having relatively small

[19] For the geographical distribution of the minimum wage bite see panel (A.1) in figure 1.

populations, while a few county have relatively large populations, both with corresponding numbers of in- and out-migration relative to the population size. Given the nature of the respective dependent variables, I start by employing an "event-study"-type difference-in-differences specification in a pooled Poisson model of the following form.

$$P(y_{s,t} = h_{s,t}|\mathbf{x}_{s,t}) = \frac{exp[-z(\mathbf{x}_{s,t})][z(\mathbf{x}_{s,t})]^{h_{s,t}}}{h_{s,t}!}, \;\; h_{s,t} = 0, 1, 2, \ldots \tag{3}$$

where $y_{s,t}$ denotes either $Inf_{s,t}$ or $Out_{s,t}$ and $z(\mathbf{x}_{s,t})$ is the conditional mean, which includes the difference-in-differences specification as follows.

$$E(y_{s,t}|\mathbf{x}_{s,t}) = exp\left(\alpha + \beta Bite_s + \sum_{t=2010, t\neq 2013}^{2019} \delta_t Year_t + \sum_{t=2010, t\neq 2013}^{2019} \gamma_t Bite_s \cdot Year_t\right) \tag{4}$$

Here, the coefficients of interest are γ_t which identify the average treatment effects of the minimum wage introduction on the number of in- and out-migration flows of counties as the percentage change given the treatment intensity per year. The advantage of using a Poisson model is that it produces consistent estimates regardless of the underlying distribution. Compared to estimating a log-linear model, the Poisson model takes into account changes in flows from or to zero. These changes are omitted in the log-linear model because a logarithm is not defined for zero.[20] The Poisson estimator also allows for over- and underdispersion and serial correlation as long as cluster-robust standard errors are estimated.

Due to the presence of panel data and because it is likely that county-level time-invariant factors influence both an individual's decision to move into or out of a county and differences between high- and low-bite areas, I use a conditional fixed effects Poisson model. This additionally controls for respective (short-term) time-invariant unobserved heterogeneity. Time-invariant factors that the model accounts for are, for instance, the infrastructure of a county, where poor infrastructure may cause individuals to move out of a county. Moreover, poor infrastructure is a potential determinant of relatively lower wages compared to regions with a good infrastructure, which would lead to biased estimates in the pooled model. Therefore, I employ a conditional fixed effects Poisson model with the conditional mean specified as

[20] As is common practice, zero values are typically replaced with a small number before log-transforming, however, which is not recommendable since it leads to inconsistent estimates (Silva & Tenreyro, 2006). Moreover, Silva and Tenreyro (2006) show that log-linear specifications lead to biased estimates under heteroskedasticity even when estimating a fixed effects model. To further underline the choice of the Poisson model, I compare estimates from a log-linear model with fixed effects to the Poisson estimates in section 5.1.

follows.

$$E(y_{s,t}|c_s, \mathbf{x}_{s,2010}, \ldots, \mathbf{x}_{s,2019}) = c_s exp\left(\sum_{t=2010, t\neq 2013}^{2019} \delta_t Year_t + \sum_{t=2010, t\neq 2014}^{2019} \gamma_t Bite_s \cdot Year_t\right) \tag{5}$$

In contrast to the pooled case, the conditional mean now additionally depends on other time-invariant unobserved factors c_s at the county level. All assumptions remain identical to the pooled Poisson estimator and average treatment effects are also estimated by γ_t given the treatment intensity. Therefore, it also allows for any kind of variance-mean relationship, meaning over- and underdispersion do not lead to biased standard errors, and it allows for serial correlation as long as the standard errors are clustered (Wooldridge, 2021).[21] However, it is important to note that by using a fixed effects Poisson model, the estimators may be less precise because only the within-county variation is used for identification compared to the pooled estimator.[22]

Crucial for difference-in-differences specifications is that the inference depends on the parallel trends assumption not being violated. To test whether the parallel trends assumption holds in a nonlinear setting, I perform a cluster-robust Wald test for the joint significance of $\hat{\gamma}_{2010}, \ldots, \hat{\gamma}_{2014}$ as suggested by Wooldridge (2022). I do this in addition to a graphical inspection for pre-trends. The test statistics show whether pre-treatment period estimators are statistically different from zero. Thus, insignificance of the test statistics indicates no violation of the parallel trends assumption. If the parallel trends assumption is violated, a linear pre-trend correction is added to the conditional mean specification as follows.

$$E(y_{s,t}|c_s, \mathbf{x}_{s,2010}, \ldots, \mathbf{x}_{s,2019}) = c_s exp\left(\sum_{t=2010, t\neq 2013}^{2019} \delta_t Year_t + \sum_{t=2015}^{2019} \gamma_t Bite_s \cdot Year_t + \pi Bite_s \cdot Trend_t\right) \tag{6}$$

Here, only post-treatment periods are interacted with the minimum wage bite while controlling for a bite-specific trend estimated by π. Since, pre-treatment periods are excluded in the second term, π captures the bite-specific pre-trend and corrects $\gamma_{2015}, \ldots, \gamma_{2019}$ for it. However, a linear pre-trend correction is not formally derived yet for a fixed effects Poisson

[21] A crucial assumption for Poisson models, however, is the assumption that the conditional mean is correctly specified. To examine that it is correctly specified, I perform a RESET-type test for each specification as suggested by Wooldridge (1999). To do so, I first estimate the Poisson model with the conditional mean specified as in equation (3) and compute the predicted values. I then re-estimate the model by additionally including a quadratic and a cubic term of the predicted values and perform a simple Wald test on both estimators. If they are jointly insignificant, this indicates that the model is correctly specified.

[22] Observations are dropped from the model if all observations of a county are 0, i.e., if a county has no within-variation. If counties are dropped, I report the number of dropped counties in the notes of respective table or figure.

model. Therefore, I check whether π actually reflects a bite-specific linear pre-trend in a non-linear setting. I suggest estimating a model only for pre-treatment periods, including only year-dummies and $Bite_s \cdot Trend_t$ as independent variables. If the estimate of $Bite_s \cdot Trend_t$ is very similar to that of π, it suggests that correcting for a linear bite-specific pre-trend is sufficient in the non-linear setting.

5. Internal migration and workplace reallocation

In this section, I analyze and discuss empirical results on the potential effects of the statutory minimum wage introduction in Germany on internal migration, workplace reallocation and commuting. Moreover, I conduct several robustness checks.

5.1. Treatment effects on internal migration

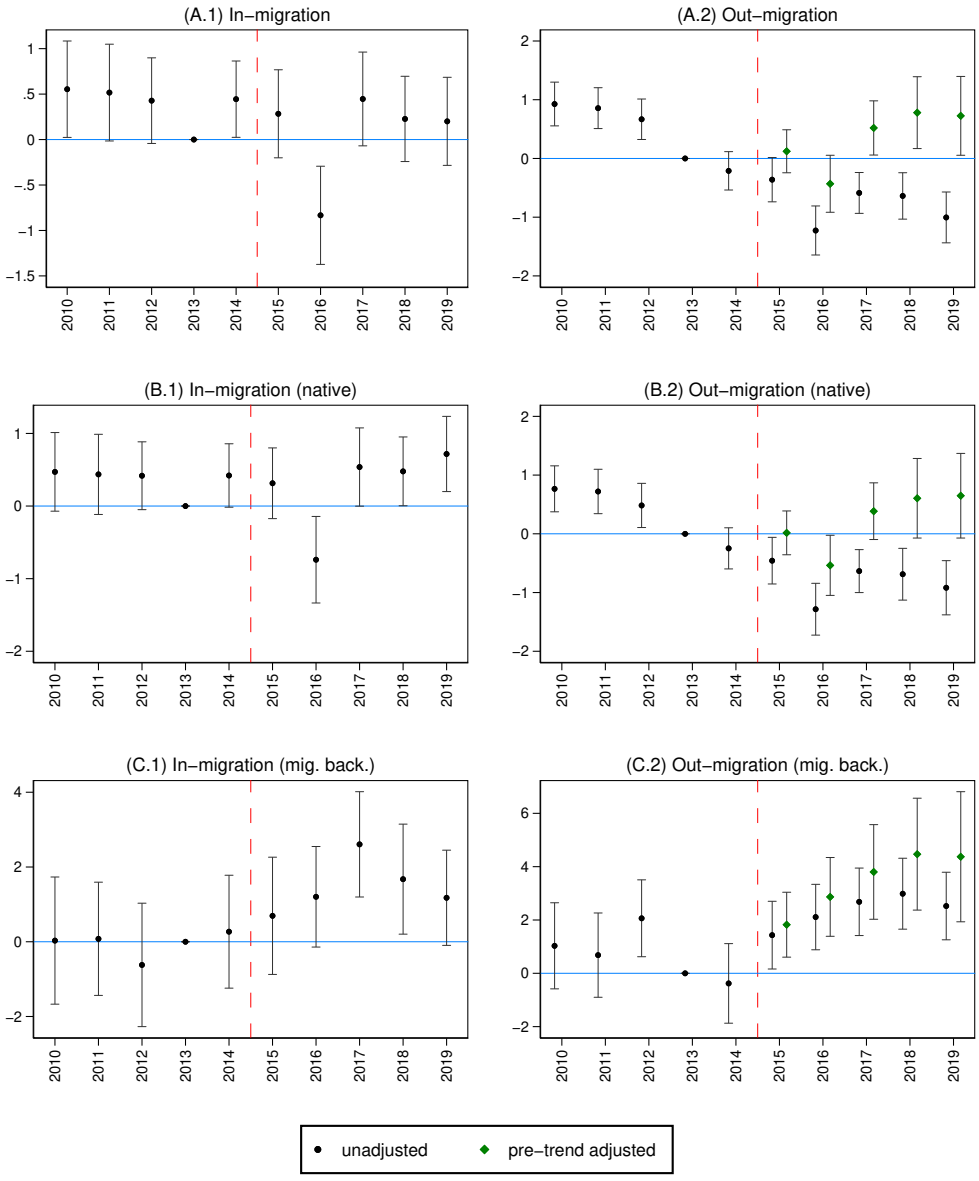
I begin by estimating the fixed effects Poisson model with the conditional mean specified as in equation (5) on the outcome variables measuring in- and out-migration flows per county. For the baseline results, I estimate the model once for the total population and separately for individuals with a migrant background and natives.

Figure 3 presents respective baseline results. The graphs in the left column illustrate the average treatment effects on in-migration for the years 2015 to 2019, separately by row for the total population, natives, and individuals with a migrant background. The graphs in the right column illustrate the treatment effects on out-migration for respective samples. The introduction of the minimum wage generally has no significant effect on in-migration to high-bite regions, as illustrated in graphs A.1, B.1 and C.1. In contrast, total out-migration from high-bite counties significantly increases by about 10% for the years 2017 to 2019 in comparison to pre-treatment periods due to the minimum wage.[23] An analysis of the sub-samples indicates that the impact on natives is approximately equivalent in magnitude but not statistically significant for the period 2017 to 2019. In contrast, the introduction of the minimum wage results in an initial increase of 18% in out-migration of individuals with a migrant background from high-bite counties, which materializes as a 43% increase in out-migration in 2019 in comparison to pre-treatment periods.[24] By comparing these estimates to the average increase in internal migration flows of 94% for individuals with a migrant background (see table 1), I can attribute approximately one-third of the increase in internal migration of the respective group to out-migration from high-bite counties due to the intro-

[23] Average treatment effects are calculated as $\hat{\gamma}_t$ times the average treatment intensity, i.e. the average value of $Bite_s$. The average value is c. 10% (see figure 1).

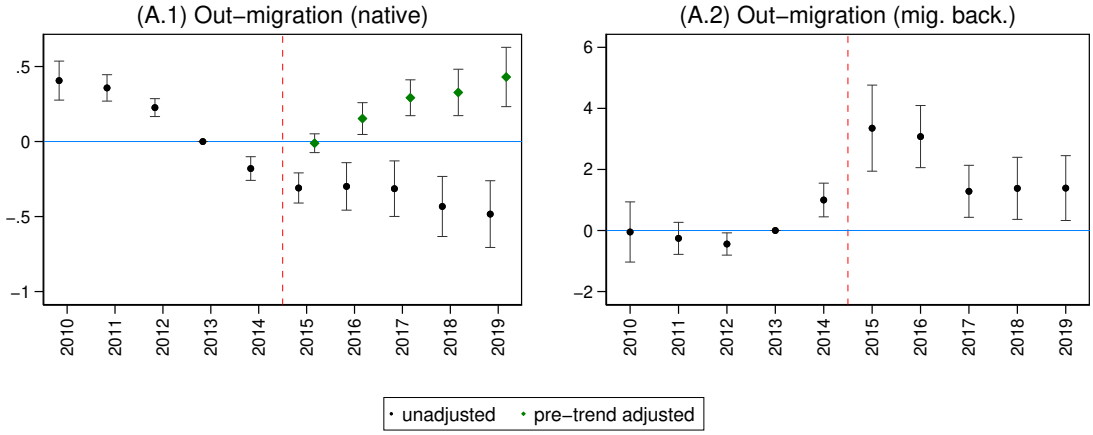
[24] It is worth noting that the average treatment effects corrected for linear bite-specific pre-trends are estimated with less precision due to less variation when including the pre-trend correction, as demonstrated in equation (6).

Figure 3: Treatment effects on internal migration flows



Notes: Cluster-robust standard errors are estimated and 95% confidence intervals are displayed. $N = 4,000$ over 400 counties. Coefficients shown are $\hat{\gamma}_t$ from estimating a fixed effects Poisson model with the conditional mean specified as in equation (5). The pre-trend Wald test suggests a significant pre-trend for following specifications: (A.2), $p = 0.000$; (B.2), $p = 0.000$; (C.2), $p = 0.024$. For the respective specifications, trend adjusted coefficients are estimated by specifying the conditional mean as in equation (6). For all pre-trend corrections, $\hat{\pi}$ and the alternative estimate for the coefficient on $Bite_s \cdot Trend_t$ are very similar – as described in section 4 to check whether equation (6) sufficiently corrects for a linear pre-trend. The magnitude of the average treatment effects should be interpreted by multiplying $\hat{\gamma}_t$ with the average treatment intensity of about 10%. *Source: SIAB, own calculations*

Figure 4: Baseline treatment effects on out-migration estimated with Destatis data



Notes: Cluster-robust standard errors are estimated and 95% confidence intervals are displayed. $N = 4,000$ over 400 counties. Coefficients shown are $\hat{\gamma}_t$ from estimating a fixed effects Poisson model with the conditional mean specified as in equation (5). The pre-trend Wald test suggests a significant pre-trend for following specification: Outflows (native), $p = 0.000$. For the respective specification, trend-adjusted coefficients are estimated by specifying the conditional mean as in equation (6). For all pre-trend corrections, $\hat{\pi}$ and the alternative estimate for the coefficient on $Bite_s \cdot Trend_t$ are very similar – as described in section 4 to check whether equation (6) sufficiently corrects for a linear pre-trend. The magnitude of the average treatment effects should be interpreted by multiplying $\hat{\gamma}_t$ with the average treatment intensity of about 10%. As a robustness check the results should be compared to the baseline estimates on outflows presented in figure 3. *Source: Regionaldatenbank (2024b), own calculations*

duction of the minimum wage.

The baseline results offer preliminary evidence that the perceived probability of becoming unemployed tends to outweigh the utility gain from a wage increase, which may contribute to out-migration from high-bite counties. Conversely, the introduction of the minimum wage may have prompted a reallocation of workers with migrant backgrounds to "better" establishments, leading to an increase in out-migration. The latter mechanism seems more likely since I do not find an in-migration effect to low-bite counties. This is in contrast to the findings of Dustmann et al. (2021) who attribute the majority of the reallocation of low-wage workers to an increase in commuting distance from high-bite municipalities. However, at this time, I have not distinguished between workers subject to the minimum wage and those who are not and how the reallocation works. Therefore, I will provide estimates for the subsample of workers subject to the minimum wage, conduct a quasi-placebo test, and shed light on the mechanisms in section 5.2.

To substantiate the robustness of my baseline results, I conduct a series of robustness checks. Firstly, I re-estimate my baseline results on out-migration flows of both groups using full population internal migration data from the German Federal Statistical Office (Destatis) (Regionaldatenbank, 2024b). The results are presented in figure 4. The treatment effects for both groups are approximately the same size as the estimates reported in figure 3 and

are significant, further confirming the robustness of measuring internal migration flows by aggregating the SIAB. It should be noted that Destatis utilizes civil register data to calculate internal migration flows, which limits the availability of information on qualification, wages, and occupational groups.[25] As a result, a comprehensive examination of the samples subject to the introduction of the minimum wage, as I conduct with the SIAB, is not feasible. Furthermore, the comparability of migration flows after 2016 with earlier periods is constrained due to methodological changes, which may pose an additional threat to identification, although the results on out-migration appear reliable.

Table 2: Robustness check: Estimates on out-migration including marginal employment

	Migrant background			Native	
	w/o marg. empl.	w/ marg. empl.	w/o mig. wave	w/o marg. empl.	w/ marg. empl.
$\hat{\gamma}_{2015}$	1.82***	1.04*	1.85***	0.02	0.14
$\hat{\gamma}_{2016}$	2.87***	2.49***	1.75**	−0.54**	−0.43*
$\hat{\gamma}_{2017}$	3.80***	3.13***	1.76*	0.39	0.50**
$\hat{\gamma}_{2018}$	4.47***	3.74***	2.94***	0.61*	0.80**
$\hat{\gamma}_{2019}$	4.37***	3.67***	2.84**	0.65*	0.84**

Notes: Pre-trend adjusted estimates for γ_t are provided for the baseline samples without marginal employment (w/o marg. empl.) and as a sensitivity analysis with marginal employment (w/ marg. empl.). For the migrant background sub-sample, one model excludes individuals subject to the migration wave in 2015 and 2016. γ_t are estimated with a conditional fixed effects Poisson model. $\hat{\gamma}_{2014}$ is the base category. Cluster robust standard errors are estimated. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Source: SIAB, own calculations.*

Secondly, I re-estimate the baseline results by including marginally employed workers, as they are likely to be one of the groups most affected by the introduction of the minimum wage.[26] Table 2 reports the respective estimates compared to the estimates excluding marginally employed workers. For individuals with a migrant background, the estimates for γ_t including marginally employed are slightly lower than those excluding marginally employed, which is consistent with the assumption that marginally employed workers are unlikely to move due to the introduction of the minimum wage. For natives, the estimates are fairly similar in size and significance, and both substantiate the robustness of the baseline estimates.

Furthermore, the migration wave in 2015 and 2016 may have resulted in biased estimates for the migrant background sub-sample. For instance, migrants residing in high-bite counties, predominantly located in eastern German regions, may have been more likely to relocate than those settled in low-bite counties. This is particularly relevant for migrants who arrived in eastern Germany after 2015, who may perceive a higher level of insecurity due to the in-

[25] Destatis aggregates data from civil registers organized at the municipality level.
[26] I only report pre-trend adjusted estimates in table 2.

creased presence of right-wing parties. Therefore, I exclude migrants who arrived after 2015 from Syria, Afghanistan, Iraq, Eritrea and Iran.[27] Column 3 in table 2 presents the respective estimates for the migrant background sub-sample. The estimates are comparable in size and direction to the baseline estimates, which further reinforce their robustness.

Table 3: Robustness check: Estimates on out-migration varying between count data models

	migrant background			native		
	(1) FE Poisson	(2) pool. Poisson	(3) log-linear	(4) FE Poisson	(5) pool. Poisson	(6) log-linear
$\hat{\gamma}_{2010}$	1.41^{*}	1.30^{*}	22.22^{*}	1.01^{***}	0.95^{***}	1.00^{***}
$\hat{\gamma}_{2011}$	1.06	0.98	10.59	0.97^{***}	0.91^{***}	0.95^{***}
$\hat{\gamma}_{2012}$	2.44^{***}	2.27^{***}	26.61^{***}	0.73^{***}	0.68^{***}	0.66^{**}
$\hat{\gamma}_{2013}$	0.38	0.35	32.08^{***}	0.25	0.23	0.29
$\hat{\gamma}_{2014}$						
$\hat{\gamma}_{2015}$	1.81^{***}	1.68^{***}	23.58^{***}	-0.21	-0.20	-0.20
$\hat{\gamma}_{2016}$	2.49^{***}	2.32^{***}	38.02^{***}	-1.04^{***}	-0.96^{***}	-1.1^{***}
$\hat{\gamma}_{2017}$	3.06^{***}	2.86^{***}	36.95^{***}	-0.39^{**}	-0.36^{**}	-0.41^{*}
$\hat{\gamma}_{2018}$	3.36^{***}	3.15^{***}	41.92^{***}	-0.44^{*}	-0.41^{*}	-0.40
$\hat{\gamma}_{2019}$	2.90^{***}	2.71^{***}	46.87^{***}	-0.67^{***}	-0.62^{***}	-0.83^{***}

Notes: Estimates for γ_t are provided for the baseline samples. $\hat{\gamma}_t$ are estimated in column (1) and (4) with a conditional fixed effects Poisson model with the conditional mean specified as in equation (5). In column (2) and (5) $\hat{\gamma}_t$ are estimated with a pooled Poisson model with the conditional mean specified as in equation (3). In column (3) and (6) $\hat{\gamma}_t$ is estimated with a log-linear model as in equation (7). $\hat{\gamma}_{2014}$ is the base category. Cluster robust standard errors are estimated. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Source: SIAB, own calculations*

Thirdly, I compare the baseline estimates with two alternative specifications for count data, namely I estimate the difference-in-differences specification with a pooled Poisson model (see equation (3)) and with a log-linear fixed effects model. The estimator for the latter takes the following form.

$$ln(y_{s,t}) = c_s + \sum_{t=2010, t\neq 2014}^{2019} \delta_t Year_t + \sum_{t=2010, t\neq 2014}^{2019} \gamma_t Bite_s \cdot Year_t + u_{s,t} \tag{7}$$

As the log-linear model drops zeros in the dependent variable, I have added a very small number to all zero values before taking the natural logarithm, which is standard practice when using the corresponding model with count data. Table 3 provides the respective es-

[27] According to the Federal Office for Migration and Refugees (BAMF) these were the top 5 countries from where individuals who applied for asylum immigrated in 2016. https://www.bamf.de/SharedDocs/Meldungen/DE/2017/20170111-asylgeschaeftsstatistik-dezember.html?nn=282388

timates.[28] The pooled Poisson model estimates are comparable in magnitude and significance. This provides further evidence of the robustness of the estimates derived from the fixed-effects Poisson model. The estimates for the log-linear model are comparable in magnitude and significance for the native sample, which does not include zeros. For the migrant background sample, the log-linear model estimates indicate a similar direction of effect but a magnitude approximately ten times higher than that indicated by the conditional fixed effects Poisson estimates. This is due to the presence of zeros in the dependent variable for the migrant background sample. In this instance, the estimator of the log-linear model is inconsistent and produces an upward bias once the dependent variable includes zeros. Furthermore, the results are dependent on the very small number that is added to the zeros in order to consider changes between 0 and any positive number. Given the upward bias in the estimates, it seems that the linear estimator assigns too much weight to changes in the dependent variable from zero to any positive number in high-bite counties due to the minimum wage introduction. Consequently, the log-linear model provides further evidence of the robustness the baseline estimates in terms of effect direction. Additionally, it underscores the conditional fixed-effects Poisson estimator as the preferred econometric model, particularly when the dependent variable includes zeros.

5.2. Employment status, workplace reallocation and internal migration patterns

It is likely that the estimates on the total population are biased due to the fact that the samples include individuals who are unlikely to have been subject to the introduction of the minimum wage. Therefore, I estimate the treatment effects by employment status, namely low-skilled employment, medium-/high-skilled employment and unemployment.[29] The introduction of the minimum wage is likely to have the strongest impact on low-skilled workers and the unemployed, as discussed in section 2. The sample of medium- and high-skilled workers serves as a quasi-placebo group because the internal migration of these workers should theoretically not be affected by the introduction of a minimum wage, as their remuneration is unlikely to be influenced by such a policy change.[30]

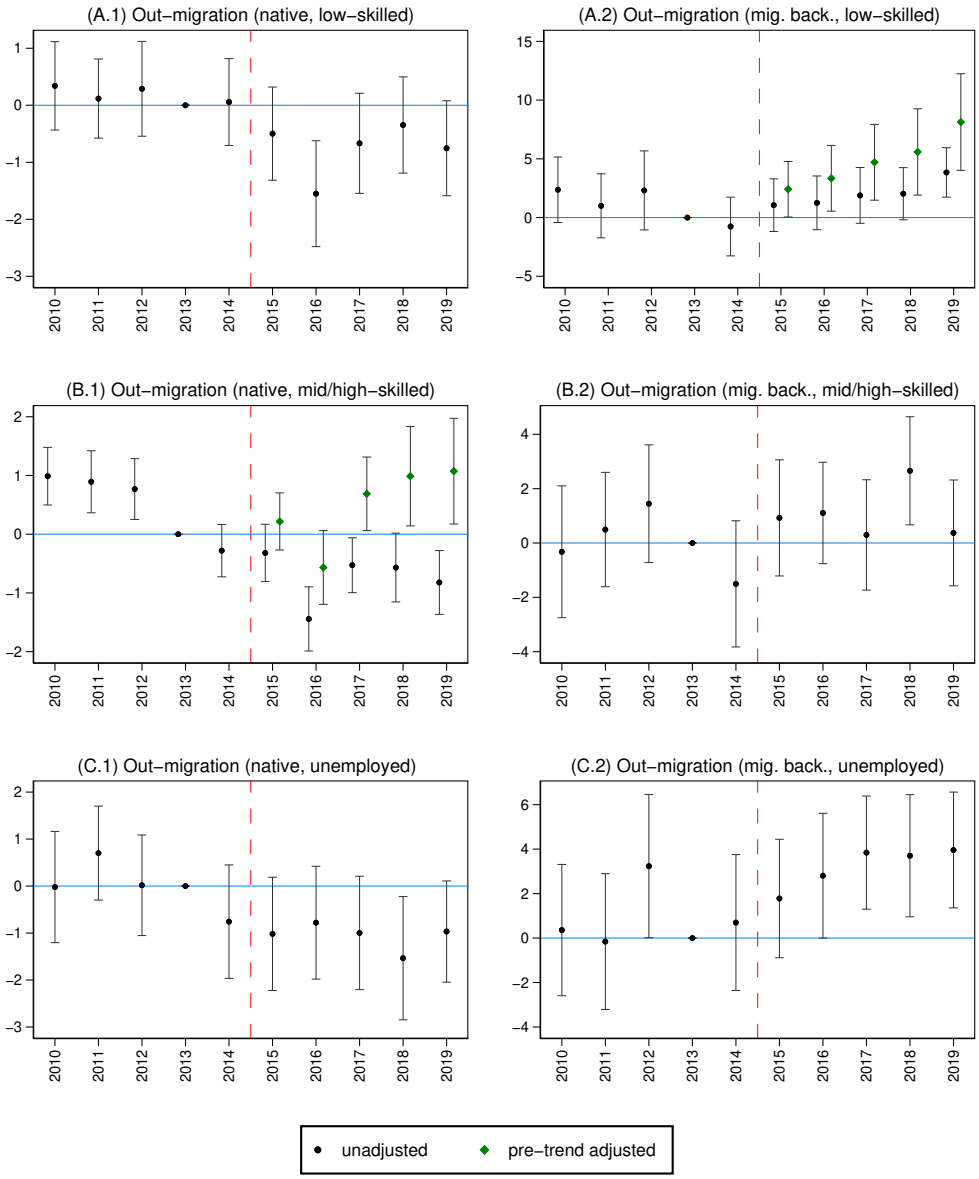
Figure 5 illustrates the average treatment effects on out-migration by employment status. The left-hand column of graphs presents estimates for the native population, while the right-hand column shows estimates for the migrant background sample. For natives, the

[28] I only report and compare non-pre-trend adjusted estimates in table 3, because for the model comparison I am only interested in the magnitude and direction of the estimates.

[29] The SIAB does not include any measure of hours worked, so I use workers in low-skilled employment as a proxy for those subject to the minimum wage.

[30] For comparison, refer to figure 8 in Bossler and Schank (2023). The study indicates that only wages up to the 50th percentile are positively affected by the introduction of the minimum wage, while no effect can be found for wages at higher percentiles. Wages at higher percentiles are likely to correspond to wages for medium- and high-skilled workers, while wages at lower percentiles likely correspond to wages for low-skilled workers.

Figure 5: Treatment effects on out-migration flows by employment status



Notes: Cluster-robust standard errors are estimated and 95% confidence intervals are displayed. $N = 4,000$ over 400 counties. For specifications (A.2), 1 county and (B.2), 2 counties are omitted due to all zero outcomes in the dependent variable. Coefficients shown are $\hat{\gamma}_t$ from estimating a fixed effects Poisson model with the conditional mean specified as in equation (5). The pre-trend Wald test suggests a significant pre-trend for following specifications: (B.1), $p = 0.000$; (A.2), $p = 0.096$. For the respective specifications, trend-adjusted coefficients are estimated by specifying the conditional mean as in equation (6). For all pre-trend corrections, $\hat{\pi}$ and the alternative estimate for the coefficient on $Bite_s \cdot Trend_t$ are very similar – as described in section 4 to check whether equation (6) sufficiently corrects for a linear pre-trend. The magnitude of the average treatment effects should be interpreted by multiplying $\hat{\gamma}_t$ with the average treatment intensity of about 10%. *Source: SIAB, own calculations*

hardly significant positive treatment effect on out-migration diminishes after estimating the model separately by low-skilled workers and unemployed. The findings indicate that the introduction of the minimum wage has no effect on the internal migration of native workers. For workers in low-skilled employment with a migrant background (graph A.2), the pre-trend corrected average treatment effects are initially very similar in magnitude to the overall average effect, showing a significant increase in average out-migration from high-bite counties of 24% in comparison to pre-treatment out-migration flows. Furthermore, the average treatment effect demonstrates a more than threefold increase over time, reaching 81% by 2019. In comparison to the average increase in flows for low-skilled workers with a migrant background of 151%,[31] approximately one-third of the increase can be attributed to the out-migration of the respective population from high-bite counties due to the introduction of a minimum wage. Furthermore, as illustrated in graph C.2, the introduction of the minimum wage has a positive impact on the out-migration of unemployed individuals with a migrant background during the period from 2017 to 2019. The average out-migration flows from high-bite counties increase significantly by approximately 40% in the respective years due to the introduction of the minimum wage. In comparison to the average increase in internal migration flows of 127%, again approximately one-third of this increase can be attributed to out-migration from high-bite counties due to the minimum wage.

Therefore, the aggregate effect of individuals with a migrant background (as in figure 3) can be attributed to low-skilled workers and unemployed, who are directly affected by the minimum wage introduction and therefore increasingly leave high-bite counties due to the minimum wage introduction. This is corroborated by insignificant estimates of γ_t for the quasi-placebo sample of workers in medium-/high-skilled employment with a migrant background.[32]

The results indicate that individuals with a migrant background demonstrate greater flexibility in their residential choice in comparison to natives when local labor market conditions change. This is in line with the findings by Cadena (2013), which indicate that migrants are more responsive to changing labor market conditions, relocating over longer distances than natives in response to changes in minimum wage. In contrast, the difference in sensitivity to changes in local labor market conditions for the German case is evident in migrants who begin to leave high-wage counties in response to the introduction of the minimum wage and natives who do not. Furthermore, the results indicate that natives do not relocate their residences in accordance with the theoretical expectations. Dustmann et al. (2021) do find an increase in commuting distance from high-bite municipalities. Therefore, it is probable

[31] This refers to table 1 where the average increase in flows is calculated as the percentage change in average flows pre- versus post-treatment.

[32] Table E1 to table E4 in appendix E provide robustness checks as in section 5.1 for the low-skilled and unemployed sub-samples which further supports the robustness of this estimates.

that individuals residing in high-bite municipalities are also relocating their place of work. However, this relocation is likely occurring to nearby counties or to municipalities within the same county, rather than to a different county where the individual would have to move.[33]

The difference in internal migration between natives and individuals with a migrant background may be attributed to the stronger personal ties that native individuals have with their home region. For instance, they may give more weight to factors such as proximity to family and friends than to regional wages or expected regional unemployment when evaluating the utility for living in a region. Conversely, workers in low-skilled employment with a migrant background appear to be more flexible in their decision to relocate. This may be due to a lesser attachment to a specific county, potentially influenced by factors such as family living abroad or residing in cities outside of high-bite rural regions, or a personal network scattered across Germany. Therefore, the optimal reallocation mechanism to "better" establishments due to the minimum wage (as described by Dustmann et al. (2021)) may differ between both groups such that natives do relocate to nearby "better" establishments and individuals with migrant background do move to other regions where members of their family or network are living and where respective establishments are located.

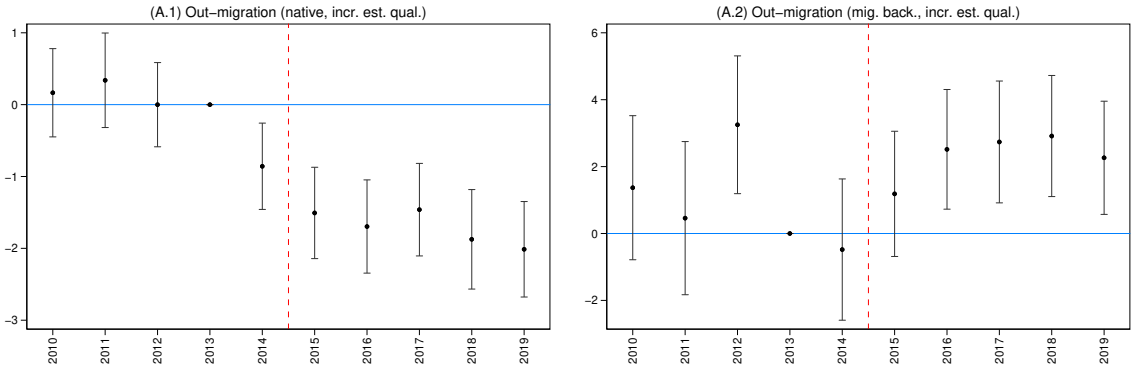
To provide evidence for the optimal reallocation of workers to "better" establishments, I facilitate pre-treatment establishment fixed effects for the years 2007 to 2013, estimated by the AKM model.[34] The establishment fixed effects can be interpreted as a wage premium paid equally to all employees of an establishment, which I use as a proxy for establishment quality. Accordingly, I create a sample comprising individuals who have relocated and subsequently changed to an establishment with a higher value in the respective fixed effects compared to their previous establishment's fixed effects.

Figure 6 illustrates respective estimates in A.1 for native workers and in A.2 for workers with a migrant background. Out-migration from high-bite counties of workers with a migrant background who relocate to "better" establishments due to the minimum wage introduction, increase on average by about 20 to 30%. Therefore, a significant proportion of out-migration due to the minimum wage by workers with migrant background can be attributed to optimal workplace reallocation behavior. However, as only a proportion of workers with a migrant background are relocating for optimal reallocation purposes, it seems probable that the remainder moves either according to theory and/or due to network effects. One likely explanation is that the perceived probability of becoming unemployed within a county or a labor market region increases due the closure of small establishments (as described by Dustmann et al. (2021)). For these workers, this increases the regional perceived probabil-

[33] In this regards, I will show empirical evidence on optimal workplace reallocation across county borders in section 5.3.

[34] The research data center of the IAB provides establishment fixed effects estimated from the AKM model with the full population of German establishments (Lochner, Seth, & Wolter, 2023)

Figure 6: Treatment effects on out-migration flows with improvement in establishment quality



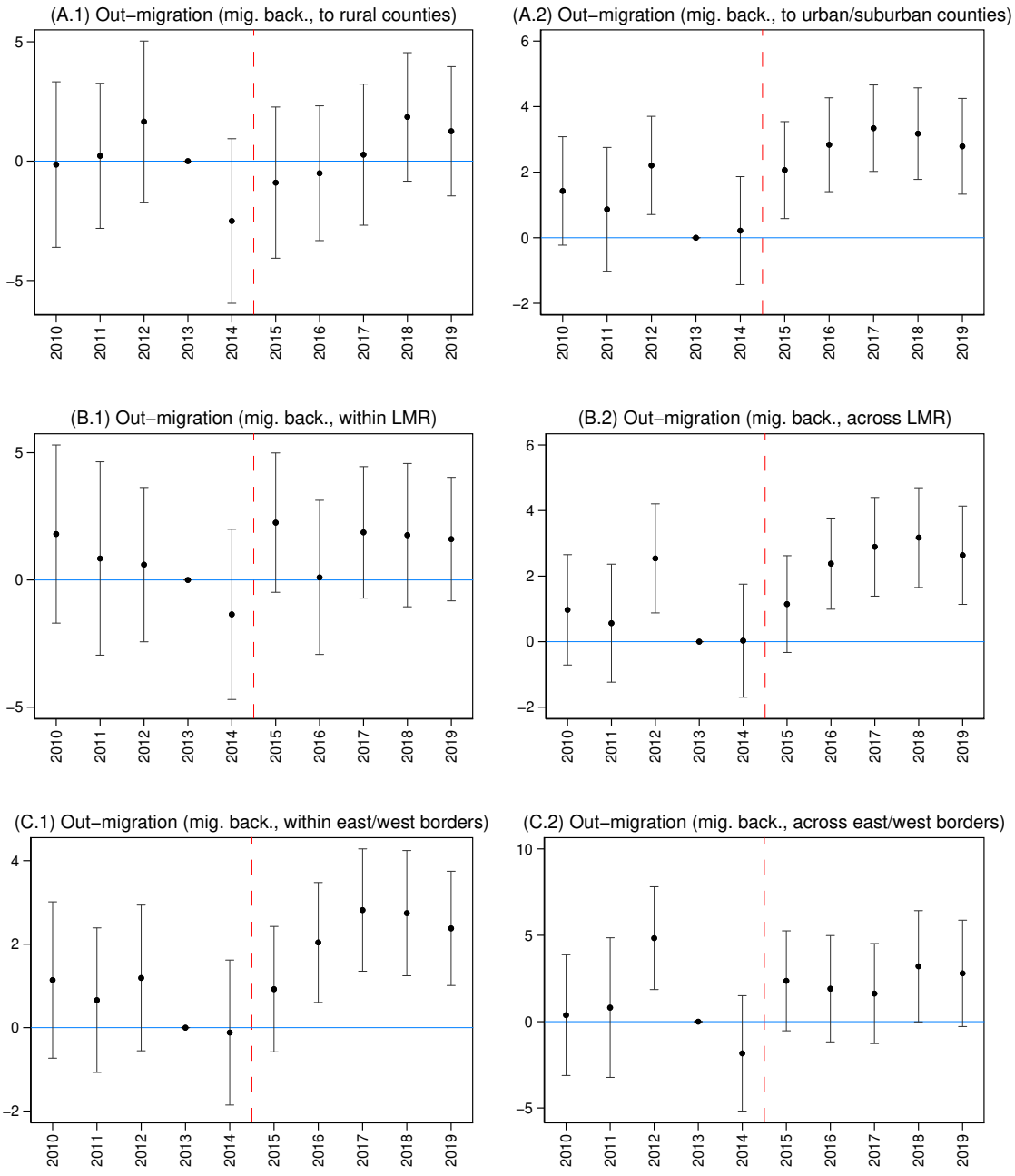
Notes: Cluster-robust standard errors are estimated and 95% confidence intervals are displayed. $N = 4,000$ over 400 counties. Coefficients shown are $\hat{\gamma}_t$ from estimating a fixed effects Poisson model with the conditional mean specified as in equation (5). The magnitude of the average treatment effects should be interpreted by multiplying $\hat{\gamma}_t$ with the average treatment intensity of about 10%. *Source: SIAB, own calculations*

ity of becoming unemployed within a network/community sufficiently enough relative to the regional wage increase such that respective workers begin to out-migrate. Additionally, workers with a migrant background who share networks spread information about "better" workplace quality. As a result, other individuals from the network also out-migrate to regions to which individuals from the same network have migrated. Therefore, the destinations become increasingly attractive over time, with the indirect utility for an individual in the destination rising while the indirect utility perceived in high-bite counties declines. This provides an explanation for both the unexplained aspect in out-migration of individuals with a migrant background and the observed increase in the average treatment effect over time. It is notable that the estimates indicate that native workers reduce out-migration from high-bite counties by 15 to 20% to relocate to "better" establishments. This may suggest a crowding-out of low-skilled workers with migrant backgrounds by natives, which will be discussed in more detail in section 5.3.

The effect on out-migration can also accelerate already existing internal migration patterns, namely migration on the urban-rural sphere or across former East-West German boarders. This may result in higher concentrations of specific groups in distinct geographical areas.

Figure 7 shows respective average treatment effects where the graphs A.1 and A.2 correspond to out-migration to rural or to urban/sub-urban counties, graphs B.1 and B.2 to out-migration within or across labor market regions (LMR) and C.1 and C.2 to out-migration

Figure 7: Treatment effects on out-migration flows by regional variation



Notes: Cluster-robust standard errors are estimated and 95% confidence intervals are displayed. $N = 4,000$ over 400 counties. For specifications (A.1), 3 counties, (B.1), 179 county and (C.2), 5 counties are omitted due to no within-variation. Coefficients shown are $\hat{\gamma}_t$ from estimating a fixed effects Poisson model with the conditional mean specified as in equation (5). The magnitude of the average treatment effects should be interpreted by multiplying $\hat{\gamma}_t$ with the average treatment intensity of about 10%. *Source: SIAB, own calculations*

within or across the former East-West German borders.[35] The average out-migration from high-bite counties to urban/sub-urban counties increases significantly by about 20 to 30% due to the introduction of the minimum wage introduction while a potential effect on out-migration to rural counties is insignificant. Moreover, the relocation across labor market regions appears to be a significant factor in explaining out-migration due to the introduction of the minimum wage for individuals with a migrant background. The average out-migration across labor market regions increases by about 20 to 30% from high-bite counties, while out-migration within labor market regions does not significantly increase due to the minimum wage introduction.[36] Furthermore, the introduction of the minimum wage has led to a notable increase in out-migration within former East-West German borders, averaging about 25%. In contrast, no significant treatment effect on out-migration across respective borders can be observed.

Consequently, the increase in out-migration due to the minimum wage can be attributed to an increase in out-migration to urban/sub-urban counties and across labor market regions, with the majority of moves occurring within former East and West German borders. Therefore, the introduction of the minimum wage does not contribute to an increase in East-West migration patterns. However, the majority of high-bite counties are located in rural areas of former East Germany. Therefore, the results suggest that the introduction of the minimum wage leads to an increased concentration of low-skilled workers with a migration background in eastern German urban labor markets. This is due to the out-migration from high-bite rural counties. This indicates a decreasing share of low-skilled workers with migrant background in rural East German labor market regions which can possibly be explained by the reallocation to urban/sub-urban counties and respective labor market regions, where "better" establishments are more densely located (see for comparison figure 1).

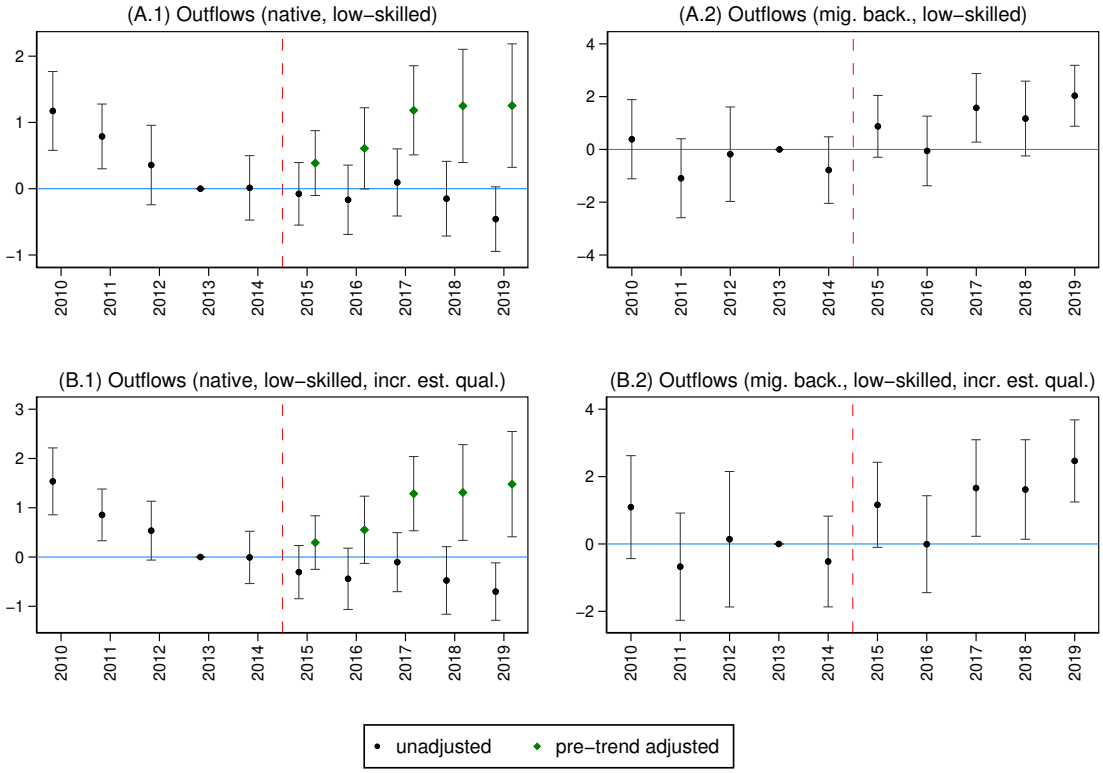
5.3. Workplace reallocation and commuting

After examining the effect of the German minimum wage introduction in 2015 on internal migration, I conduct a subsequent analysis which illustrates whether the minimum wage introduction also affects the optimal reallocation to "better" establishments across county borders, away from high-bite counties without moving. Therefore, another potential channel for workers to relocate to "better" establishments is by simply changing the county in which they

[35] As figure 5 indicates, the minimum wage has mainly affected out-migration flows of individuals with a migrant background. Therefore, I only report treatment effects on internal migration patterns for the migrant background sample in figure 7. Estimates on the native sample are provided in figure C1 in appendix C. For natives the estimates remain insignificant also by distinguishing between internal migration patterns.

[36] The size of the average treatment effects is about the same size as expected from the baseline results. However, the standard errors are very high because the treatment effect is very imprecisely estimated due to 179 counties (1790 Observations) being dropped because of all zero out-migration flows. This indicates individuals with a migrant background are in general rarely moving to counties within the same labor market region which makes the estimates economically less important though similar in size.

Figure 8: Treatment effects on changing the county of work



Notes: Cluster-robust standard errors are estimated and 95% confidence intervals are displayed. $N = 4,000$ over 400 counties. Coefficients shown are $\hat{\gamma}_t$ from estimating a fixed effects Poisson model with the conditional mean specified as in equation (5). The pre-trend Wald test suggests a significant pre-trend for following specifications: (A.1), $p = 0.001$; (B.1), $p = 0.000$. For the respective specifications, trend-adjusted coefficients are estimated by specifying the conditional mean as in equation (6). For all pre-trend corrections, $\hat{\pi}$ and the alternative estimate for the coefficient on $Bite_s \cdot Trend_t$ are very similar – as described in section 4 to check whether equation (6) sufficiently corrects for a linear pre-trend. The magnitude of the average treatment effects should be interpreted by multiplying $\hat{\gamma}_t$ with the average treatment intensity of about 10%. *Source: SIAB, own calculations*

work and then commuting (if not already commuting). I begin the analysis by firstly using the number of individuals who change the county in which they work to a different county, reflecting spatial reallocation across establishments.[37] I again estimate respective variables in a fixed-effects Poisson model with the conditional mean specified as in equation (5).

Figure 8 illustrates the average treatment effects on the number of individuals changing their workplace out of high-bite counties (first row) and those who do simultaneously relocate to "better" establishments (second row). The graphs in the left column illustrate estimates for native workers in low-skilled employment, while the graphs in the right col-

[37] I follow a similar variable generation process as described in section 3 only using the county of an individuals workplace instead of their residency.

umn illustrate estimates for respective workers with a migrant background. The number of low-skilled employed workers with a migrant background who relocate their workplace away from high-bite counties due to the minimum wage increase initially on average by 15% and materializes to 32% until 2019, compared to pre-treatment flows.[38] The results are driven by low-skilled workers who change to a "better" quality establishment. Accordingly, the estimates corroborate my findings in section 5.2 on low-skilled workers with a migrant background who respond to changing labor market conditions by reallocating across establishments while simultaneously moving. The number of native workers in low-skilled employment who change their workplace away from high-bite counties due to the introduction of the minimum wage increase by about 10% on average for the years 2017 to 2019. Therefore, native low-skilled workers also respond to changing local labor market conditions to improve the quality of their workplaces, but only by relocating to different establishments while continuing to reside in their home county. I find no effect of the minimum wage introduction on the reallocation between the county of work for the quasi-placebo group of workers in medium/high-skilled employment, for both natives and those with a migrant background. This further supports the robustness of the estimates in figure 8.

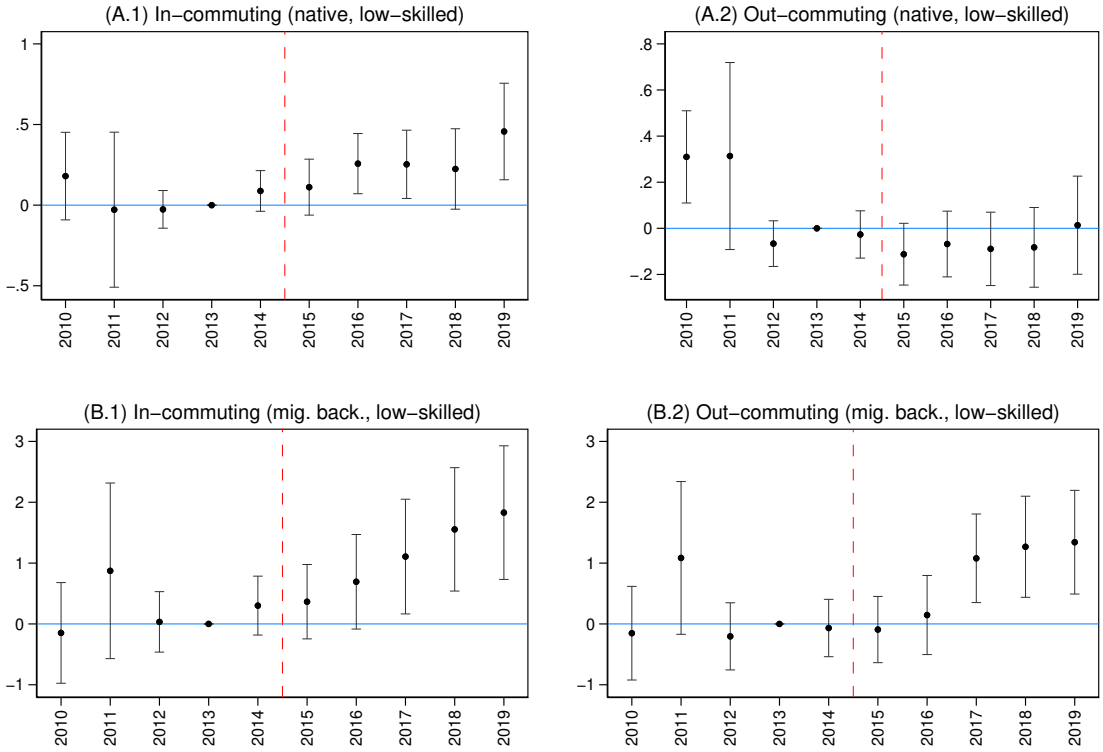
Secondly, I estimate the effect of the minimum wage introduction on the number of out-commuters at the county level to further elaborate on the different reactions of native low-skilled workers and those with a migrant background.[39] In light of the aforementioned findings, it is reasonable to anticipate an increase in out-commuting flows among native low-skilled workers due to the introduction of a minimum wage, while out-commuting flows of workers with a migrant background are expected to remain unaffected.

Figure 9 illustrates average treatment effects on in- and out-commuting flows within a 100 km radius between county centroids, disaggregated by native low-skilled workers in A.1 and A.2 and those with a migrant background in B.1 and B.2. For native low-skilled workers, I find no effect on out-commuting from high-bite counties due to the minimum wage introduction. This indicates that native low-skilled workers who changed their workplace due to the minimum wage, were already commuting to their workplace before the introduction of the minimum wage and simply changed the county in which they work while continuing to commute. However, I find that out-commuting flows for workers in low-skilled employment with a migrant background increased by approximately 10 to 15% in high-bite counties after 2017. This indicates that the reallocation process of low-skilled workers with migrant background is driven by out-migration from high-bite labor market regions in 2015 and 2016. However, in 2017 out-migration continuous, but in addition some low-skilled workers with migrant background do start commuting to reallocate their workplace away from high-bite

[38] To put the estimates into perspective, I report average flows before and after the minimum wage introduction similar to table 1 in table A4

[39] For the calculation of commuting flows refer to appendix F

Figure 9: Treatment effects on out-commuting flows within 100km on county-level



Notes: Cluster-robust standard errors are estimated and 95% confidence intervals are displayed. $N = 4,000$ over 400 counties. Coefficients shown are $\hat{\gamma}_t$ from estimating a fixed effects Poisson model with the conditional mean specified as in equation (5). The magnitude of the average treatment effects should be interpreted by multiplying $\hat{\gamma}_t$ with the average treatment intensity of about 10%. *Source: SIAB, own calculations*

counties. In contrast, in-commuting to high-bite counties appears to increase for workers in low-skilled employment with a migrant background in subsequent periods, while also a slight increase can be observed for natives in the respective employment.

The results for natives are consistent with those of Dustmann et al. (2021), who found that the introduction of the minimum wage led to an increase in commuting distance for optimal reallocation across establishments. I further support these findings by demonstrating that the results remain consistent when analyzed at the broader county level, but only for natives (and for some low-skilled workers with a migrant background starting in 2017[40]). Therefore, the effects on workplace reallocation for these groups are most probably due to the closure of small establishments and a corresponding reallocation to "better" establishments as de-

[40]This part of individuals with a migrant background do react similar to natives most probably to similar reasons, e.g. as they are also tied to their home counties due to their network, family and friends. This hold probably for longer-term migrants. Unfortunately, I cannot distinguish between short- and long-term migrant due to missing information.

scribed by Dustmann et al. (2021). However, workers with a migrant background do not respond to the introduction of the minimum wage in the same way. The other part of individuals with migrant background tend to move to establishments in different labor market regions where commuting is not feasible. This is evidenced by the simultaneous reallocation of their counties of residence and their counties of work. There are a number of potential reasons for the difference in reallocation behavior. One possible explanation is that individuals with a migrant background are more responsive to changing labor market conditions, are less tied to counties, or have stronger network effects within their communities, as discussed in section 5.2. Another potential explanation is that native workers may have an advantage in finding nearby jobs in "better" establishments that are within commuting distance after the closure of small establishments. This is somewhat reflected in the decline in out-migration to reallocate to "better" establishments, as illustrated in figure 6. Subsequently, the labor demand of respective "better" establishments is already saturated. As a result, low-skilled workers with a migrant background do migrate to other labor market regions in infeasible commuting distance to relocate to "better" establishments. To a certain degree this points towards a crowding-out effect of workers with a migrant background from high-bite labor market regions induced by an advantage of native workers to find nearby employment.

6. Conclusion

In this paper, I examine the effect of the statutory minimum wage introduction in Germany in 2015 on geographic labor mobility. In the sample of low-skilled workers with a migrant background, I find an increase in the average out-migration from high-bite counties of about 24% due to the introduction of the minimum wage in 2015. This figure more than tripled by 2019. A significant proportion of this effect is attributable to the optimal reallocation of respective workers from rural counties to better quality establishments which are located urban labor market regions. The other proportion can be attributed to network effects and increases in the perceived probability of becoming unemployed which is probably due to small establishments closure in high-bite regions. In contrast, I find no effect on out-migration for native low-skilled workers while they also do relocate their workplace across counties to better quality establishments due to the minimum wage introduction. Firstly, the findings indicate that individuals with a migrant background respond stronger to changing labor market conditions than natives. This supports the findings of Cadena (2013) also for the German labor market. Secondly, in contrast to Dustmann et al. (2021) who explained the optimal reallocation effect by an increase in commuting distance, I find an increase in out-migration as an additional explanation for the migrant background sample. The differentiation indicates a shift in the socio-demographic characteristics of local labor markets, with a probable increase in the concentration of low-skilled workers with a migrant background in urban labor

market regions, as a consequence of the introduction of the minimum wage.

The findings of this paper demonstrate that the introduction of the statutory minimum wage results in an optimal reallocation process of low-wage workers across establishments, which potentially induce positive welfare effects. Conversely, the findings highlight the importance of considering the potential effects on geographical labor mobility when implementing and evaluating labor market policies. Therefore, policy makers should consider the impact of heterogeneous migration decisions of natives and individuals with a migrant background on local labor markets induced by labor market policies. With regard to statutory minimum wages, my results indicate that rural former East German regions may experience a shift in the socio-demographic profile of the workforce, driven by the introduction of minimum wage policies. This could add to the existing trend of declining numbers of young individuals and individuals with a migrant background in these regions. Especially, migrant workers do more often work in occupations that are already facing labor shortages. These include, for instance, occupations in the health and care sector, as well as in manual labor.[41] Without accounting for the heterogeneous impact of policies on the internal migration decisions of workers, there is a risk of further challenges for local labor markets that are already facing difficulties. Implementing regional minimum wages could offset the out-migration effect on low-skilled workers with migrant backgrounds and may be advantageous for highly affected local labor markets.

[41] For comparison see, e.g. https://www.destatis.de/DE/Presse/Pressemitteilungen/2024/03/PD24_081_125.html.

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Appendix A Further descriptive statistics

Table A1: Sample composition before and after the minimum wage introduction

	Native		Migrant Background	
	2010-2014	2015-2019	2010-2014	2015-2019
Mean age (in years)	41.482	42.508	38.993	38.397
Unemployment	0.115	0.090	0.274	0.260
Low-skill employment	0.289	0.300	0.480	0.542
Imputed daily wage, deflated (2015)	104.559	112.200	86.742	87.947
N (in millions)	2.76	2.85	0.274	0.424

Notes: This table refers to the population of the micro panel dataset after excluding marginally employed, interns, working students, apprentices, family workers, sailors, irregular workers and (part-time) retirees. Censored (top-coded) wages are imputed according to Stüber et al. (2023) who follow a similar procedure as in Dustmann, Ludsteck, and Schönberg (2009) and Card, Heining, and Kline (2013). *Source: SIAB, own calculations*.

Table A1 presents the sample composition in terms of age, unemployment, low-skilled employment and real daily wages of the underlying micro data separately for native individuals and those with a migrant background. The table also shows the averages for both groups separately for five years before and five years after the introduction of the minimum wage. Age is rather stable in both samples over time. Unemployment, however, decreases for both samples after the introduction of the minimum wage, following the general decreasing trend of unemployment in Germany for the respective years. Interestingly, for natives, the share of low-skilled employment increases only slightly, while real daily wages increase on average by 7.3% in the five years after the introduction of the minimum wage compared to the five years before. In comparison, the average share of low-skilled employees with a migrant background increases by about 6.2 percentage points after the introduction of the minimum wage, while the real daily wage increased only marginally by about 1.4%. The increase in the number of low-skilled employees with a migrant background could be due to the migration waves in 2015 and 2016 which can also be observed in the increase in sample size of about 150,000 in the migrant background sample.

Table A2: Average in-migration by sub-sample

	Mean		
	2010-2014	2015-2019	Δ%
In-migration	45.132	45.836	1.56%
In-migration (native-born)	41.176	38.245	−7.11%
In-migration (native-born, within LMR)	9.047	8.456	−6.54%
In-migration (native-born, across LMR)	32.130	29.790	−7.29%
In-migration (native-born, within E/W Germany)	36.035	33.462	−7.12%
In-migration (native-born, across E/W Germany)	5.142	4.783	−6.99%
In-migration (native-born, mid/high-skilled)	27.838	25.800	−7.34%
In-migration (native-born, low-skilled)	8.693	8.527	−1.91%
In-migration (native-born, unemployed)	4.646	3.918	−15.69%
In-migration (native-born, from rural LMR)	11.908	10.215	−14.23%
In-migration (native-born, from urban LMR)	29.269	28.030	−4.24%
In-migration (native-born, from rural county)	12.746	10.922	−14.33%
In-migration (native-born, from urban/suburban county)	28.430	27.323	−3.89%
In-migration (native-born, impr. est. quality)	13.639	14.691	7.71%
In-migration (mig. back.)	3.955	7.590	92.94%
In-migration (mig. back., within LMR)	1.004	1.762	75.57%
In-migration (mig. back., across LMR)	2.951	5.828	97.87%
In-migration (mig. back., within E/W Germany)	3.256	6.017	84.97%
In-migration (mig. back., across E/W Germany)	0.699	1.573	125.04%
In-migration (mig. back., mid/high-skilled)	1.937	2.740	41.53%
In-migration (mig. back., low-skilled)	1.204	2.982	147.12%
In-migration (mig. back., unemployed)	0.815	1.868	128.87%
In-migration (mig. back., from rural LMR)	0.750	1.781	137.47%
In-migration (mig. back., from urban LMR)	3.205	5.809	81.21%
In-migration (mig. back., from rural county)	0.764	1.875	145.83%
In-migration (mig. back., from urban/suburban county)	3.191	5.715	79.05%
In-migration (mig. back., impr. est. quality)	1.933	4.659	141.98%

Notes: In-migration flows $Inf_{s,t}$ and out-migration flows $Out_{s,t}$ measure the number of individuals (given restrictions) who move into our out of counties per year according to equation (2). *Source: SIAB, own calculations*

Table A3: Average out-migration by sub-sample

	Mean		
	2010-2014	2015-2019	Δ%
Out-migration	45.132	45.836	1.56%
Out-migration (native-born)	41.178	38.170	−7.33%
Out-migration (native-born, within LMR)	9.059	8.450	−6.73%
Out-migration (native-born, across LMR)	32.119	29.721	−7.41%
Out-migration (native-born, within E/W Germany)	36.040	33.389	−7.34%
Out-migration (native-born, across E/W Germany)	5.138	4.782	−6.94%
Out-migration (native-born, mid/high-skilled)	27.859	25.794	−7.43%
Out-migration (native-born, low-skilled)	8.711	8.532	−2.05%
Out-migration (native-born, unemployed)	4.607	3.845	−16.58%
Out-migration (native-born, to rural LMR)	10.768	10.264	−4.69%
Out-migration (native-born, to urban LMR)	30.410	27.907	−8.27%
Out-migration (native-born, to rural county)	11.617	11.009	−5.23%
Out-migration (native-born, to urban/suburban county)	29.561	27.161	−8.11%
Out-migration (native-born, impr. est. quality)	13.059	14.291	9.43%
Out-migration (mig. back.)	3.954	7.665	94.51%
Out-migration (mig. back., within LMR)	0.992	1.768	78.53%
Out-migration (mig. back., across LMR)	2.962	5.897	99.33%
Out-migration (mig. back., within E/W Germany)	3.251	6.091	87.47%
Out-migration (mig. back., across E/W Germany)	0.703	1.575	124.44%
Out-migration (mig. back., mid/high-skilled)	1.916	2.746	43.29%
Out-migration (mig. back., low-skilled)	1.185	2.978	151.21%
Out-migration (mig. back., unemployed)	0.853	1.942	127.78%
Out-migration (mig. back., to rural LMR)	0.651	1.604	146.62%
Out-migration (mig. back., to urban LMR)	3.303	6.061	83.94%
Out-migration (mig. back., to rural county)	0.682	1.662	143.65%
Out-migration (mig. back., to urban/suburban county)	3.271	6.003	83.79%
Out-migration (mig. back., impr. est. quality)	1.829	4.762	160.49%

Notes: In-migration flows $Inf_{s,t}$ and out-migration flows $Out_{s,t}$ measure the number of individuals (given restrictions) who move into our out of counties per year according to equation (2). *Source: SIAB, own calculations*

Table A4: Average workplace reallocation flows by sub-sample

	Mean		
	2010-2014	2015-2019	Δ%
Inflow (native-born, low-skilled)	30.415	32.395	6.51%
Inflow (native-born, low-skilled, impr. est. quality)	17.137	19.298	12.64%
Inflow (native-born, mid/high-skilled)	57.752	57.558	−0.34%
Inflow (mig. back., low-skilled)	5.170	10.795	109.36%
Inflow (mig. back., low-skilled, impr. est. quality)	3.457	7.551	118.76%
Inflow (mig. back., mid/high-skilled)	4.707	6.550	39.13%
Outflow (native-born, low-skilled)	30.579	32.564	6.51%
Outflow (native-born, low-skilled, impr. est. quality)	22.215	25.260	13.73%
Outflow (native-born, mid/high-skilled)	57.839	57.543	−0.51%
Outflow (mig. back., low-skilled)	5.006	10.625	112.89%
Outflow (mig. back., low-skilled, impr. est. quality)	3.866	8.858	129.71%
Outflow (mig. back., mid/high-skilled)	4.620	6.565	42.11%

Notes: Inflows and outflows measure the number of workers who reallocate their workplace either into or out of a county per year. Here, I use the workplace location instead of the residency of an individual to calculate according to equation (2). *Source: SIAB, own calculations*

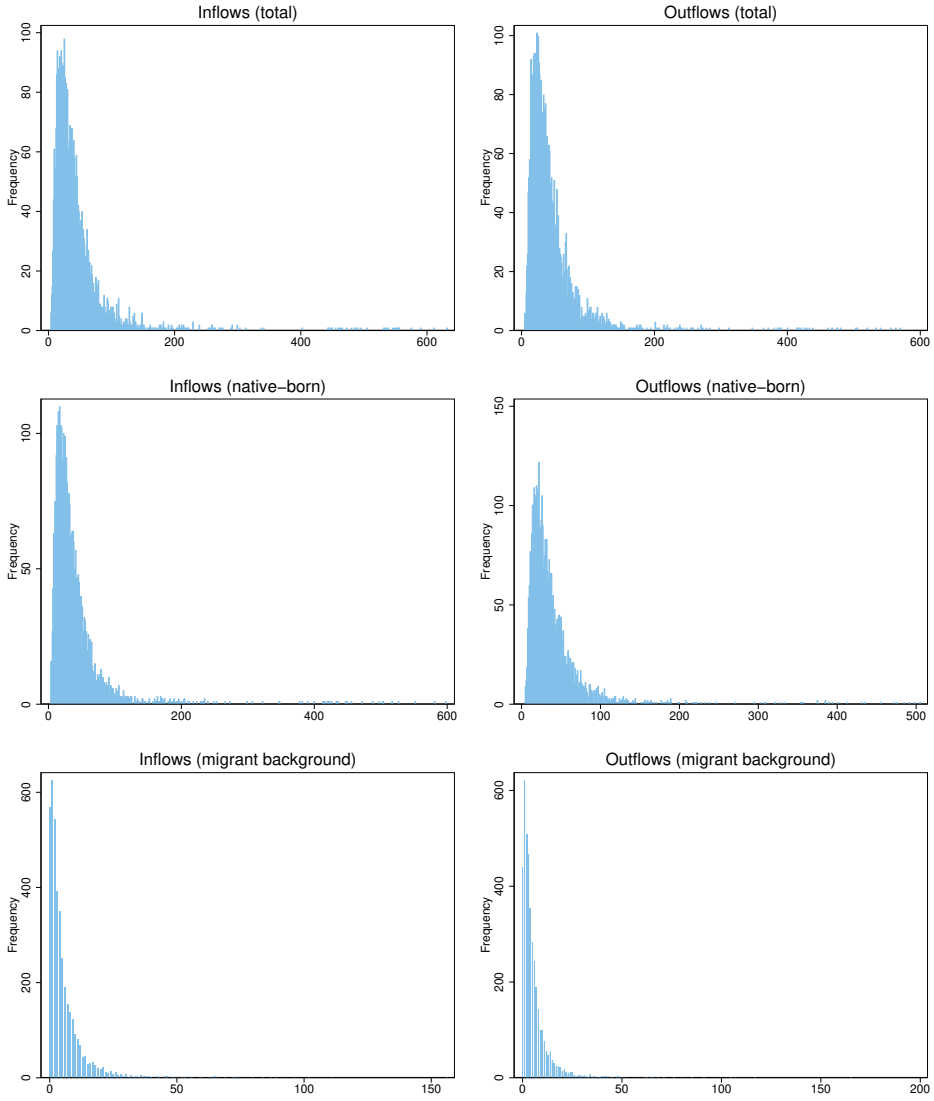
Table A5: Average commuting flows by sub-sample

	Mean		
	2010-2014	2015-2019	Δ%
In-commuting (native-born, low-skilled, <100km)	109.325	120.596	10.30%
In-commuting (migrant background, low-skilled, <100km)	14.288	26.108	82.76%
Out-commuting (native-born, low-skilled, <100km)	109.325	120.596	10.31%
Out-commuting (migrant background, low-skilled, <100km)	14.288	26.108	82.87%

Notes: Commuting measures the number of workers who commute to their workplace per county per year. I differentiate between commuting flows into counties and out of counties. I calculated respective flows as described in appendix F. *Source: SIAB, own calculations*

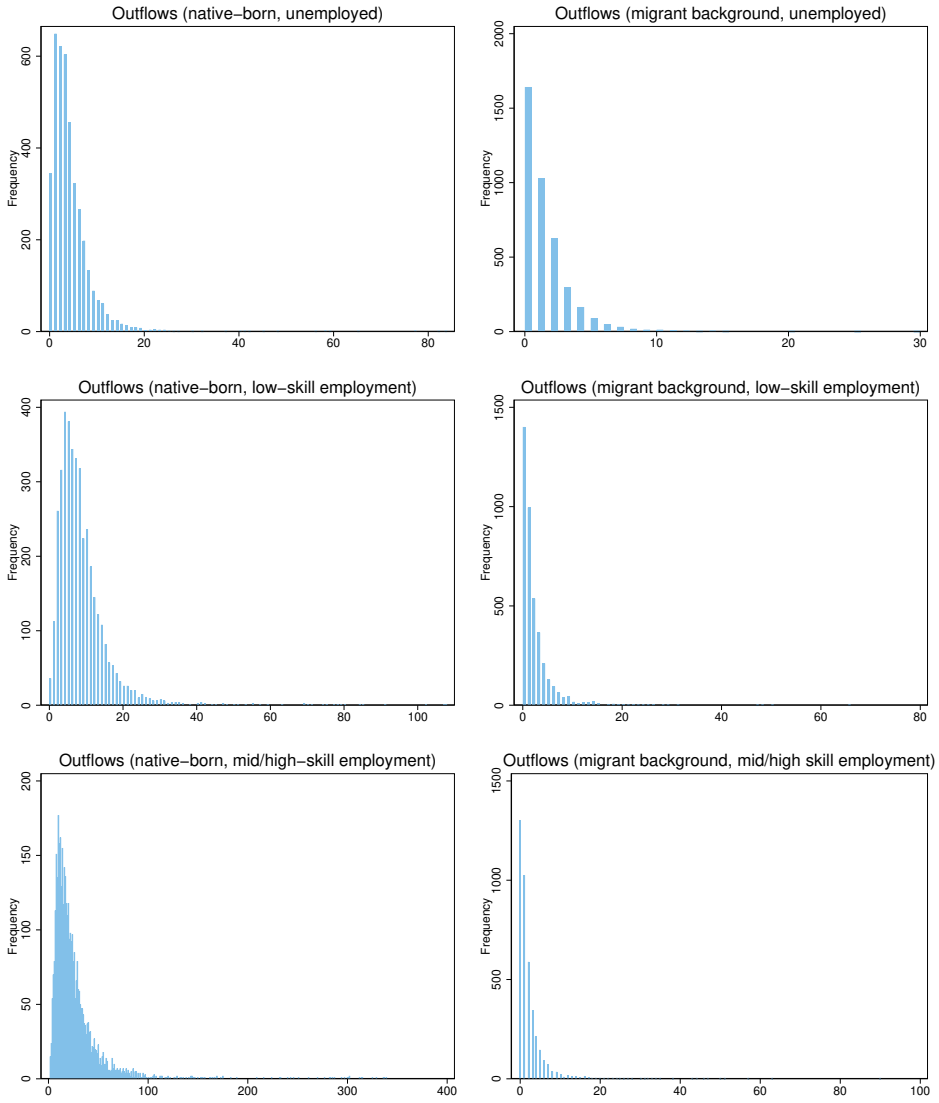
Appendix B Distribution of the main dependent variables

Figure B1: Distribution of inflows and outflows (2010 - 2019)



Notes: This figure shows the distribution of the dependent variables used in figure 3. *Source: SIAB, own calculations*

Figure B2: Distribution of inflows and outflows (2010 - 2019)

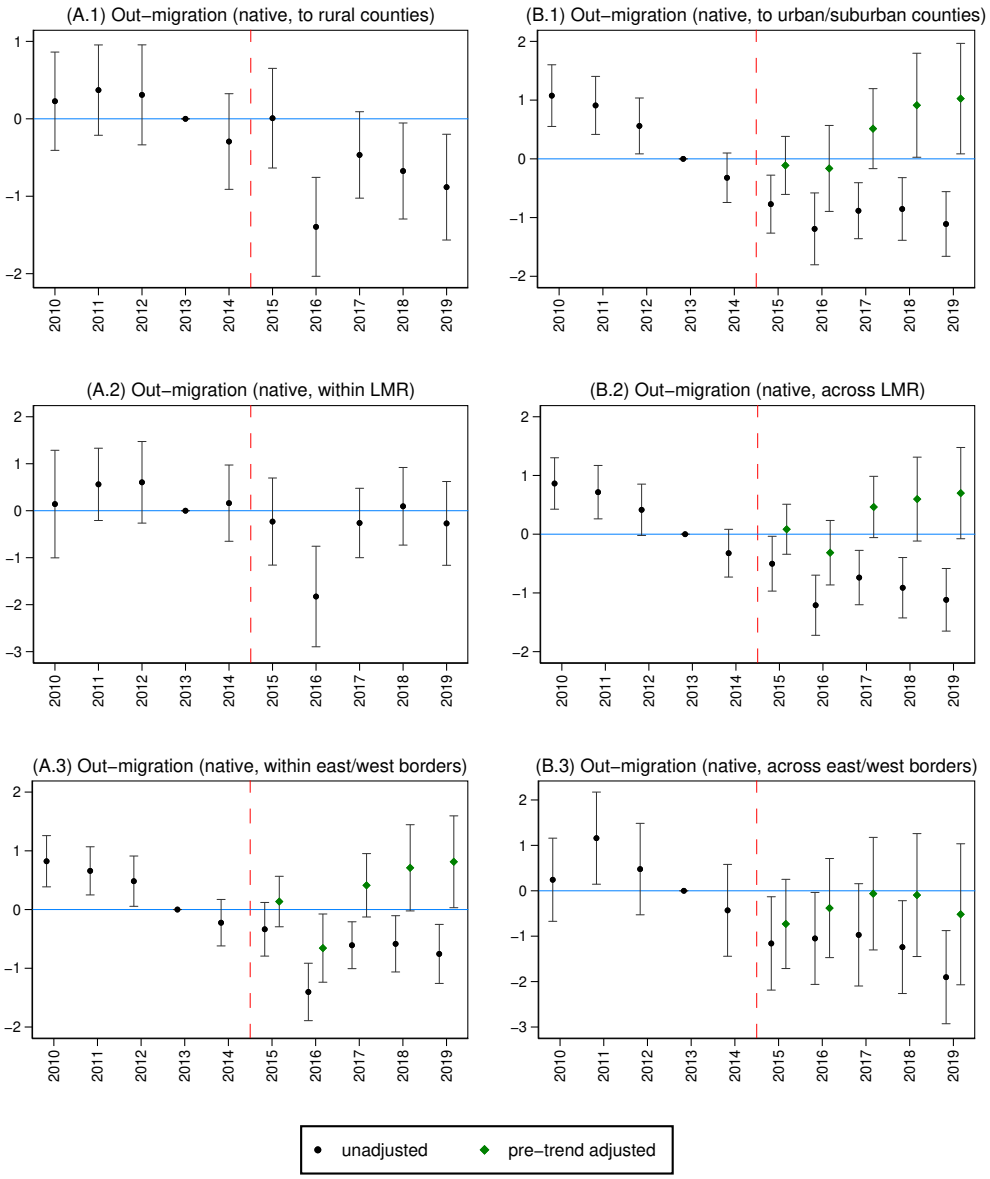


Notes: This figure shows the distribution of the dependent variables used in figure 5. *Source: SIAB, own calculations*

Appendix C Further estimates on internal migration flows

Appendix C provides estimates for additional subsamples in figure C1 according to equation (5) and equation (6).

Figure C1: Treatment effects on outflows by regional variation

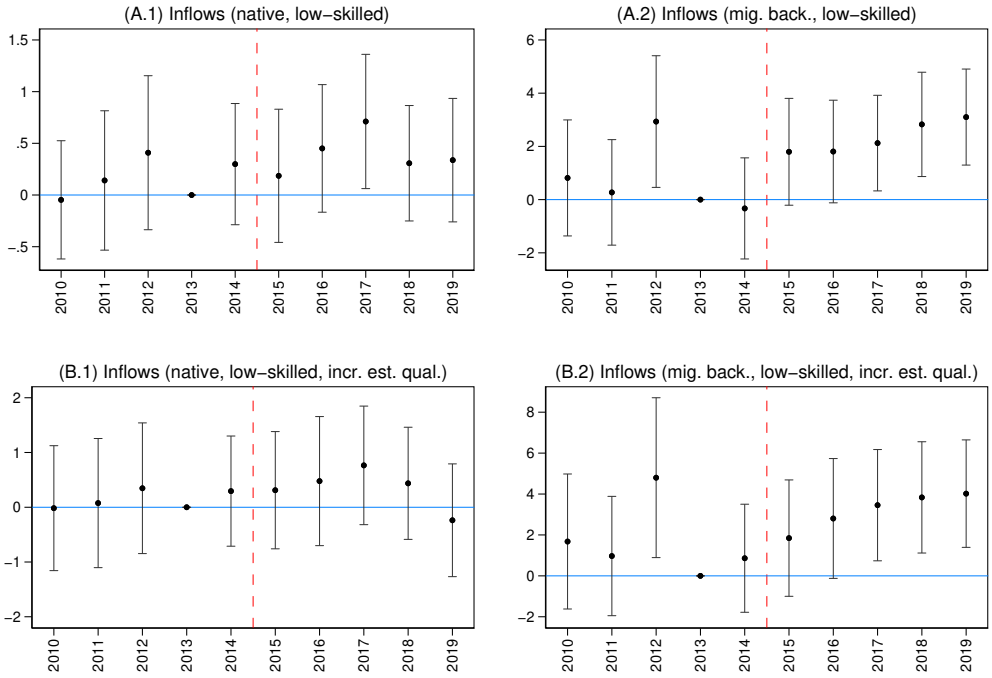


Notes: Cluster-robust standard errors are estimated and 95% confidence intervals are displayed. $N = 4,000$ over 400 counties. For specifications (A.2), 170 counties are omitted due to no within-variation. Coefficients shown are $\hat{\gamma}_t$ from estimating a fixed effects Poisson model with the conditional mean specified as in equation (5). The pre-trend Wald test suggests a significant pre-trend for following specifications: (A.3), $p = 0.000$; (B.1), $p = 0.000$; (B.2), $p = 0.000$; (B.3), $p = 0.039$. For the respective specifications, trend-adjusted coefficients are estimated by specifying the conditional mean as in equation (6). For all pre-trend corrections, $\hat{\pi}$ and the alternative estimate for the coefficient on $Bite_s \cdot Trend_t$ are very similar – as described in section 4 to check whether equation (6) sufficiently corrects for a linear pre-trend. The magnitude of the average treatment effects should be interpreted by multiplying $\hat{\gamma}_t$ with the average treatment intensity of about 10%. *Source: SIAB, own calculations*

Appendix D Further estimates on workplace reallocation

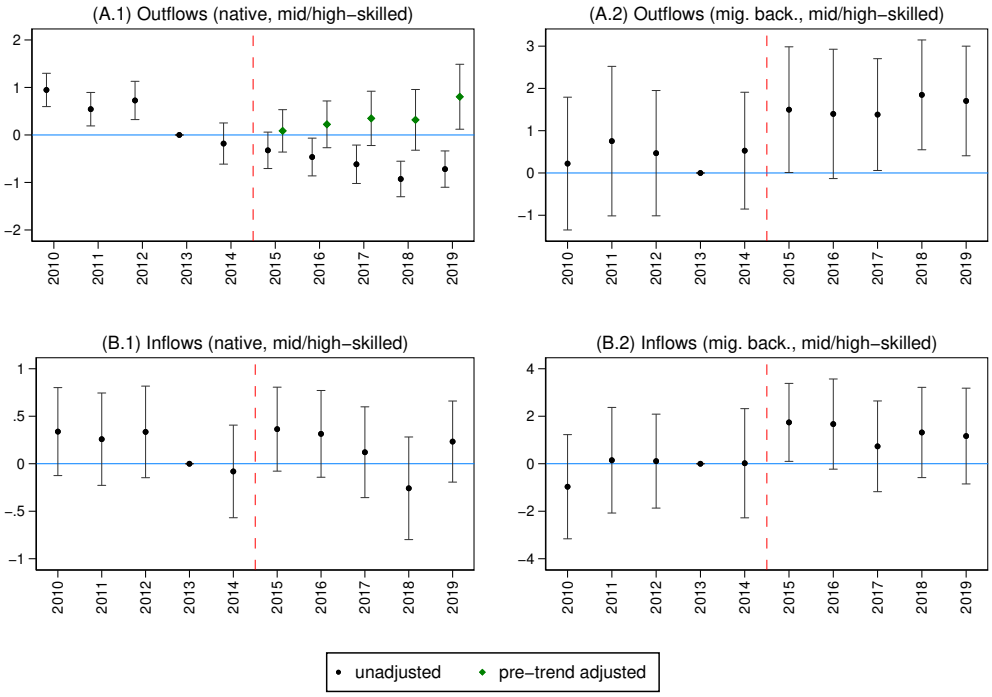
Appendix D provides estimates on inflows in workplace reallocation in figure D1 according to equation (5) and equation (6). Additionally, corresponding estimates on the quasi-placebo group of medium-/high-skilled employed workers are provided in D2.

Figure D1: Treatment effects on inflows of workplace reallocation



Notes: Cluster-robust standard errors are estimated and 95% confidence intervals are displayed. $N = 4,000$ over 400 counties. The magnitude of the average treatment effects should be interpreted by multiplying $\hat{\gamma}_t$ with the average treatment intensity of about 10%. *Source: SIAB, own calculations*

Figure D2: Quasi-Placebo test for workplace reallocation estimates



Notes: Cluster-robust standard errors are estimated and 95% confidence intervals are displayed. $N = 4,000$ over 400 counties. The magnitude of the average treatment effects should be interpreted by multiplying $\hat{\gamma}_t$ with the average treatment intensity of about 10%. *Source: SIAB, own calculations*

Appendix E Further robustness checks

Appendix E provides results in table E1 to table E4 on robustness checks as presented in table 2 and table 3 in section 5 for further relevant sub-samples.

Table E1: Robustness check: Estimates on out-migration including marginal employment for the sample of low-skilled workers

	migrant background		native	
	w/o marg. empl.	w/ marg. empl.	w/o marg. empl.	w/ marg. empl.
$\hat{\gamma}_{2010}$	3.13^{***}	2.77^{***}	0.28	0.73^{*}
$\hat{\gamma}_{2011}$	1.76	1.36	0.06	0.39
$\hat{\gamma}_{2012}$	3.07^{*}	2.61^{*}	0.23	0.39
$\hat{\gamma}_{2013}$	0.76	0.55	-0.06	0.02
$\hat{\gamma}_{2014}$				
$\hat{\gamma}_{2015}$	1.82	0.48	-0.55	-0.38
$\hat{\gamma}_{2016}$	2.02^{*}	1.96^{*}	-1.61^{***}	-1.32^{***}
$\hat{\gamma}_{2017}$	2.65^{**}	2.17^{**}	-0.72^{*}	-0.42
$\hat{\gamma}_{2018}$	2.79^{***}	2.37^{**}	-0.4	-0.07
$\hat{\gamma}_{2019}$	4.6^{***}	3.87^{***}	-0.81^{*}	-0.47

Notes: Estimates for γ_t are provided for the low-skilled employed sub-samples without marginal employment and as a sensitivity analysis with marginal employment. $\hat{\gamma}_t$ are estimated with a conditional fixed effects Poisson model with the conditional mean specified as in equation (5). $\hat{\gamma}_{2014}$ is the base category. Cluster robust standard errors are estimated. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Source: SIAB, own calculations*

Table E2: Robustness check: Estimates on out-migration including marginal employment for the sample of unemployed

	migrant background		native	
	w/o marg. empl.	w/ marg. empl.	w/o marg. empl.	w/ marg. empl.
$\hat{\gamma}_{2010}$	-0.34	-0.68	0.74	0.84
$\hat{\gamma}_{2011}$	-0.85	-1.47	1.46^{**}	1.44^{***}
$\hat{\gamma}_{2012}$	2.54	1.26	0.77	0.78
$\hat{\gamma}_{2013}$	-0.70	-0.98	0.76	0.76
$\hat{\gamma}_{2014}$				
$\hat{\gamma}_{2015}$	1.08	-0.21	-0.26	-0.41
$\hat{\gamma}_{2016}$	2.11	1.17	-0.02	0.06
$\hat{\gamma}_{2017}$	3.15^{***}	2.10^{*}	-0.24	-0.18
$\hat{\gamma}_{2018}$	3.01^{**}	2.06^{*}	-0.78	-0.74
$\hat{\gamma}_{2019}$	3.26^{***}	2.51^{**}	-0.21	-0.13

Notes: Estimates for γ_t are provided for the unemployed sub-samples without marginal employment and as a sensitivity analysis with marginal employment. $\hat{\gamma}_t$ are estimated with a conditional fixed effects Poisson model with the conditional mean specified as in equation (5). $\hat{\gamma}_{2014}$ is the base category. Cluster robust standard errors are estimated. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Source: SIAB, own calculations*

Table E3: Robustness check: Estimates on out-migration varying between count data models for the sample of low-skilled workers

	migrant background			native		
	FE Poisson	pooled Poisson	log-linear	FE Poisson	pooled Poisson	log-linear
$\hat{\gamma}_{2010}$	3.13^{***}	2.87^{***}	16.08	0.28	0.27	-0.34
$\hat{\gamma}_{2011}$	1.76	1.61	16.57	0.06	0.06	-0.08
$\hat{\gamma}_{2012}$	3.07^{*}	2.82^{*}	25.77^{**}	0.23	0.22	1.7
$\hat{\gamma}_{2013}$	0.76	0.69	13.95	-0.06	-0.05	-0.6
$\hat{\gamma}_{2014}$						
$\hat{\gamma}_{2015}$	1.82	1.66	9.54	-0.55	-0.52	-1.31^{*}
$\hat{\gamma}_{2016}$	2.02^{*}	1.84^{*}	22.66^{**}	-1.61^{***}	-1.51^{***}	-3.84
$\hat{\gamma}_{2017}$	2.65^{**}	2.42^{**}	11.1	-0.72^{*}	-0.68^{*}	-5.8
$\hat{\gamma}_{2018}$	2.79^{***}	2.55^{***}	17.18^{*}	-0.4	-0.38	-1.51
$\hat{\gamma}_{2019}$	4.6^{***}	4.24^{***}	33.51^{***}	-0.81^{*}	-0.76^{*}	-3.3

Notes: Estimates for γ_t are provided for the low-skilled employed sub-samples. $\hat{\gamma}_t$ are estimated in column (1) and (4) with a conditional fixed effects Poisson model with the conditional mean specified as in equation (5). In column (2) and (5) $\hat{\gamma}_t$ are estimated with a pooled Poisson model with the conditional mean specified as in equation (3). In column (3) and (6) $hat\gamma_t$ is estimated with a log-linear model as in equation (7). $\hat{\gamma}_{2014}$ is the base category. Cluster robust standard errors are estimated. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Source: SIAB, own calculations*

Table E4: Robustness check: Estimates on out-migration varying between count data models for the sample of unemployed

	migrant background			native		
	FE Poisson	pooled Poisson	log-linear	FE Poisson	pooled Poisson	log-linear
$\hat{\gamma}_{2010}$	-0.34	-0.29	10.33	0.74	0.64	-2.52
$\hat{\gamma}_{2011}$	-0.85	-0.72	15.19	1.46^{**}	1.28^{**}	6.35
$\hat{\gamma}_{2012}$	2.54	2.20	20.49^{*}	0.77	0.68	9.00
$\hat{\gamma}_{2013}$	-0.70	-0.59	14.03	0.76	0.66	3.88
$\hat{\gamma}_{2014}$						
$\hat{\gamma}_{2015}$	1.08	0.93	14.96	-0.26	-0.23	-11.86
$\hat{\gamma}_{2016}$	2.11	1.82	30.74^{***}	-0.02	-0.02	-7.27
$\hat{\gamma}_{2017}$	3.15^{***}	2.73^{**}	28.64^{**}	-0.24	-0.21	-8.90
$\hat{\gamma}_{2018}$	3.01^{**}	2.61^{**}	17.94	-0.78	-0.67	-1.87
$\hat{\gamma}_{2019}$	3.26^{***}	2.84^{***}	37.38^{***}	-0.21	-0.18	-7.13

Notes: Estimates for γ_t are provided for the unemployed sub-samples. $\hat{\gamma}_t$ are estimated in column (1) and (4) with a conditional fixed effects Poisson model with the conditional mean specified as in equation (5). In column (2) and (5) $\hat{\gamma}_t$ are estimated with a pooled Poisson model with the conditional mean specified as in equation (3). In column (3) and (6) $\hat{\gamma}_t$ is estimated with a log-linear model as in equation (7). $\hat{\gamma}_{2014}$ is the base category. Cluster robust standard errors are estimated. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Source: SIAB, own calculations*

Appendix F Calculation of commuting flows

In-commuting flows $Inf(commuting)_{s,t}$ and out-commuting flows $Out(commuting)_{s,t}$ for each county s are calculated given the following equations.

$$Inf(commuting)_{s,t} = \sum_{i}^{N} 1\left[wp_{i,t} = s_t, res_{i,t} \neq s_t\right]_{i,s,t}$$
$$Out(commuting)_{s,t} = \sum_{i}^{N} 1\left[wp_{i,t} \neq s_t, res_{i,t} = s_t\right]_{i,s,t}$$

To capture commuting inflows, I construct an indicator variable that is 1 if an individual's workplace $wp_{i,t}$ is located in county s at year t while their residency $res_{i,t}$ is outside of county s. For commuting outflows the indicator variable is 1 if an individual lives in county s but working outside of respective county. Then I sum the indicator variable over all individuals i where respective conditions hold.