Minimum Wages and Labor Mobility in the European Union*

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Work in progress, all comments welcome!

Abstract

The EU boasts the largest single labor market globally; EU citizens enjoy the freedom to take up work anywhere within the common market. Despite considerably diverse labor market regimes across the EU, little is known about how local labor market settings influence spatial labor mobility within the bloc. By integrating cross-country harmonized labor mobility data from the EU Labor Force Survey with the Kaitz index, a standardized measure of local minimum wage (MW) impact, I investigate the relevance of MWs for low-skilled labor mobility in Europe. Utilizing both a fixed effects model and the Arellano-Bond dynamic panel instrumental variable estimator on a sample of 103 NUTS-2 regions across six EU countries from 2003 to 2019, my analysis reveals that more substantial MWs correspond to elevated local labor inflows: On average, a one percent increase in the Kaitz index associates with a 0.03 percentage point higher worker inflow rate to the given region, indicating a Kaitz index elasticity of low-skilled labor inflow of about 0.18. This results holds for several alternative model specifications and robustness tests. Moreover, I observe substantial cross-country heterogeneity, and find particularly pronounced mobility responses for urban areas and among younger people.

Keywords: Minimum wages, Labor mobility, EU NUTS-2 regions

JEL Classification: J31, J61, R23

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1 Introduction

Minimum wages (MWs) define a lower legal limit of remuneration for labor. Their simple mode of operation and easy implementation makes MWs one of the most widely discussed labor market institutions, often used as flagship policy during election campaigns.[1] About 150 countries around the world have some kind of statutory national MW, and, as of 2023, only 9 out of 49 European countries (including 5 out of 27 EU member states) do not have a legally binding national wage floor.[2] EU directive 2022/2041, demands all EU member states to either set *adequate* statutory MWs by the end of 2024 or, alternatively, to ensure a minimum collective bargaining (CB) coverage rate of 80 percent. A MW is adequate if its value exceeds 60 percent of a country's gross median wage or 50 percent of its gross average wage. At present, less than half the EU countries meet any of these criteria, and most are relatively far from passing the required standard.[3] Accordingly, it is highly likely that applicable statutory MWs in the EU will rise significantly in the near future.

Standard economic theory implies that higher MWs increase labor supply but decrease labor demand (Boeri and van Ours, 2008). The overall impact of MWs on an area's *expected earnings* - i.e., wage level adjusted for the probability of finding employment - is contingent upon the prevailing dominant effect and can either be positive or negative (Harris and Todaro, 1970). Meanwhile, research on worker mobility highlights the importance of expected earnings for mobility decisions (e.g. Sjaastad, 1962, Becker, 1964, Zavodny, 1999, Jaeger, 2007, Kennan and Walker, 2011). EU directive 2022/2041 may therefore have an unintended effect: Affecting labor mobility decisions (and labor flows) across the EU.

The few existing studies on the attraction factor of MWs for spatial worker mobility[4] address the United States labor market and provide somewhat inconclusive results: Cushing (2003) finds poor Americans to be attracted to areas with relatively higher MWs, but both Martin and Termos (2015) and Monras (2019) find US low-skilled workers to leave areas with higher absolute MW levels (Monras, however, emphasizes the importance of local labor market elasticities for this outcome). Literature studying international migrants residing in the US, known for their higher mobility rates compared to native-born Americans, also yields varying findings, with higher state-level MWs either being attracting or deterring (see Von Scheven and Light, 2012, Boffy-Ramirez, 2013, Cadena, 2014, Giulietti, 2014). Across the EU, applicable MWs vary substantially more than across US states.[5] Surprisingly, however, no research has examined the relationship between MWs and labor mobility in the EU.

[1] For instance, MWs were the central topics of the (successful) election campaigns of the UK Labour Party (in 1997) and the Social Democratic Party of Germany (in 2013 & 2021). Olaf Scholz, now German chancellor, acknowledged in 2021 that raising the German MW to 12 EUR (an increase of about 15 percent from the previous level) would be the 'most important law' if he would get elected (Der Spiegel, 2021).

[2] European countries without statutory national MW include the Nordic countries, Italy, Austria, Switzerland and Liechtenstein. A comprehensive global overview is presented by ILO (2020).

[3] See section 2.

[4] Throughout the text, I refer to *spatial* worker mobility.

[5] In 2022, nominal MWs in the EU varied between 2 EUR per hour in Bulgaria and 13 EUR per hour in Luxembourg. MWs in the US ranged from 7.25 USD per hour (the federal MW applicable nationwide) to 15 USD in California and Washington, D.C. (WSI, 2023).

In general, EU countries demonstrate substantial variability in several features potentially relevant for spatial labor mobility, encompassing economic, political and social factors, infrastructure, cultural aspects, and so on. This diversity is not limited to the national level; it also exists within countries on the regional level.[6] Unsurprisingly, research has found both national and regional variations in economic fundamentals influencing labor mobility in the EU (e.g., Beyer and Smets, 2015). Moreover, MW effects are intricately linked to the specific characteristics of local labor markets (e.g., Harris and Todaro, 1970, Dube et al., 2010). Consequently, a comprehensive analysis of the European context necessitates a focus on the regional (i.e. local) level, taking into account not only the mobility of natives but of EU citizens in general: EU citizens, whether natives or from other EU countries, enjoy the freedom to work anywhere within the EU's common market. This freedom implies that they may also be responsive to MW amendments elsewhere in the EU.[7]

Due to the absence of suitable data on harmonized EU labor mobility figures, my analysis starts by establishing regional labor mobility figures. I rely on the EU Labor Force Survey (LFS), a cross-country harmonized and regionally representative survey of the common EU labor market. From this data, I compute annual worker inflow rates for low-skilled individuals — those likely most impacted by MWs — across all the EU NUTS-2 regions.[8] This involves quantifying the regional influx of low-skilled individuals relative to the respective local population. Subsequently, I combine these inflow rates with Hamermesh's (1981) conceptualization of the Kaitz index, a measure indicating the relevance, or *bite*, of the applicable national MW for a given region. My full sample comprises 103 NUTS-2 regions across six EU countries[9], all of which had statutory MWs in place during my observation period from 2003 to 2019.[10]

My baseline specification for regression analysis is a fixed effects panel model at the regional level. It reveals that changes in the Kaitz index correlate substantially with labor mobility in the EU: On average, a one percent increase in the local Kaitz index relates to a 0.03 percentage point higher labor inflow rate of low-skilled individuals into a region, which is equivalent to a Kaitz index elasticity of low-skilled labor inflow of about 0.18. I run several robustness checks and causality tests, including an Arellano-Bond (AB) generalized method of moments (GMM) estimator. The outcome of these exercises enhance the validity of my baseline result and provide support for the assumed causal direction of the relationship between MWs and labor mobility in my sample. Furthermore, a heterogeneity analysis reveals distinct relationships across countries and suggests possible variations in my findings concerning the dimensions of urban/rural settings, natives/EU mobile workers, domestic/cross-

[6]Throughout the text, 'regions' and ' regional' refer to regions within countries.

[7]I refrain from analyzing third-country nationals due to their unequal work rights, dependence on frequently changing visa regulations, and potential limitations in labor mobility.

[8]The *Nomenclature of Territorial Units for Statistics* (NUTS) is an EU geocode standard, referencing administrative divisions within EU countries. Currently, the EU comprises 240 NUTS-2 regions (excluding 37 regions from the former EU member UK, which are part of my data sample).

[9]Throughout the sampling period, the UK was a member of the EU. For simplicity, I categorize it as an EU country in the text, recognizing that this classification may not hold at present.

[10]My sample includes countries with nationwide statutory MWs in place throughout the sampling period, and for which there exists adequate data on regional labor inflows. This selection includes Belgium, France, Greece, Spain, Portugal, and the UK.

border mobility, and by age. Interestingly, there is no indication of heterogeneous results across sexes.

In the upcoming sections, I conduct a detailed examination of the intricate relationship between MWs and labor mobility in the EU. Section 2 offers an overview of the current landscape of MWs across the EU, coupled with some essential insights regarding intra-EU mobility. Section 3 delves into the theoretical underpinnings of the presumed relationship and reviews relevant literature. In section 4, I outline the data and empirical strategy adopted in this study. My baseline finding is presented in section 5, alongside several causality assessments, robustness tests and a thorough heterogeneity analysis.

2 Minimum wages and labor mobility in the EU

2.1 Minimum wages in the EU

MW policies vary widely across EU member states and are subject to ongoing debates and reform efforts. Some countries (Austria, Cyprus, Finland, Italy, and the Scandinavian countries) have hesitated to introduce statutory national MW policies, citing features of their labor market that would make MWs redundant. Other countries have MWs in place for decades (France since 1950, Spain since the 1960s). Figure 1 visualizes EUR-denominated statutory MW levels in place across the EU in 2019 (the final year of my empirical analysis below).

In 2019, statutory nominal MWs in the EU ranged between 1.72 EUR in Bulgaria and 12.08 EUR per hour in Luxembourg. In general, Eastern European countries' MWs are lower than the Western European ones, and MWs in Northern Europe tend to be higher than those in Southern Europe. Despite reflecting diverse economic developments and distinct levels of productivity, these disparities also show divergent (social) policy regimes and contrasting views on the level of the optimal MW (Eurofound, 2020). Figure 2 provides the development of applicable statutory MWs for the countries empirically investigated in this study[11], and contrasts these with national unemployment rates, and with the within-country variation of regional (NUTS-2 level) unemployment rates (reported are the respective national minimum and maximum values).[12]

Among the six sampled countries, (EUR-denominated) nominal MWs varied from 2.14 EUR in Portugal in 2004 to 10.03 EUR in France in 2019. Belgium, France, and the UK consistently maintained MWs exceeding 5 EUR per hour throughout the entire sampling period. Greek and Portuguese MWs never reached this threshold, and the Spanish MW did so only in 2019. Except for Greece, MWs never decreased in nominal terms.[13] Notably, during economic upswings in 2006-2009 and after 2015, most countries witnessed relatively larger MW adjustments.

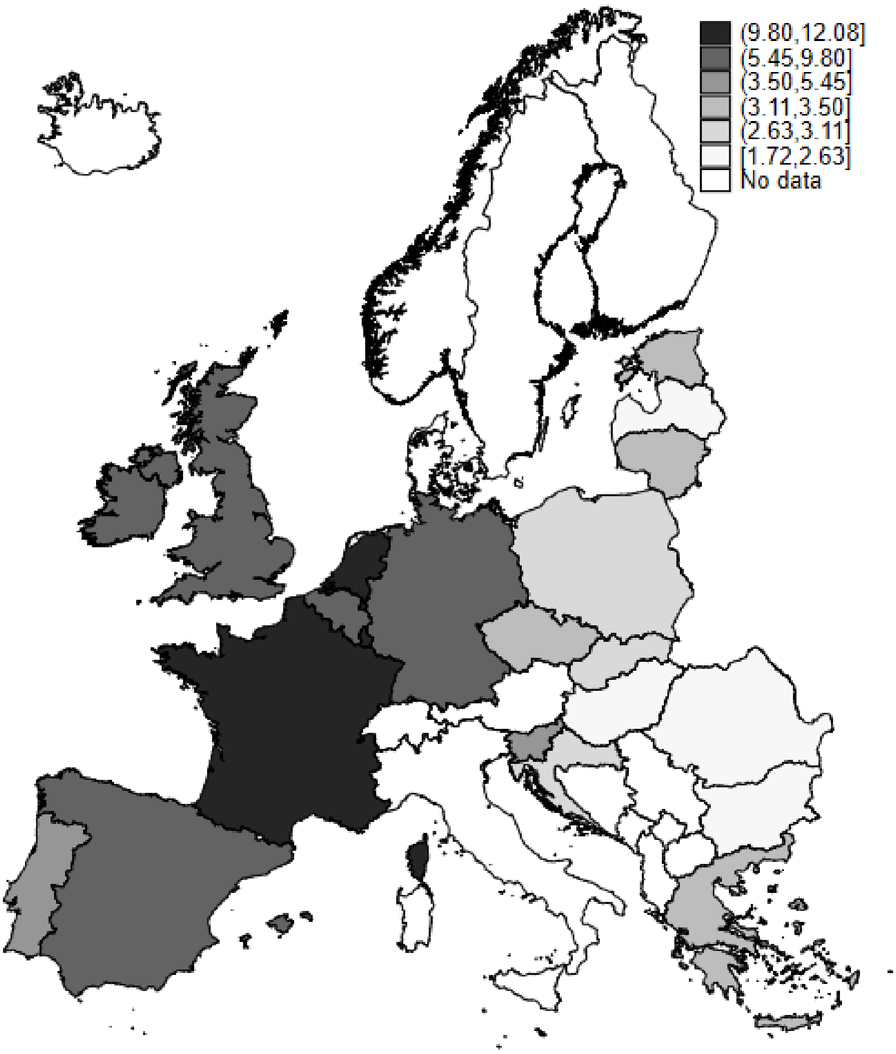
The unemployment rates reveal notable heterogeneity in the resilience of national and local labor markets to economic shocks. Belgium, France, and the UK maintained relatively stable unemployment rates, staying below 10 percent. In contrast, Greece, Spain, and Portugal, initially on par with the others, experienced a sharp

[11] See section 4 for the exact data sample.

[12] A similar graph for the group of EU-15 countries is available in the appendix (Figure A2).

[13] In 2013, as part of a comprehensive economic reform, Greece underwent a one-time reduction in the statutory hourly MW of roughly 1 EUR, representing a decrease of around 22 percent.

Figure 1: EUR-denominated statutory minimum wages in Europe (2019)

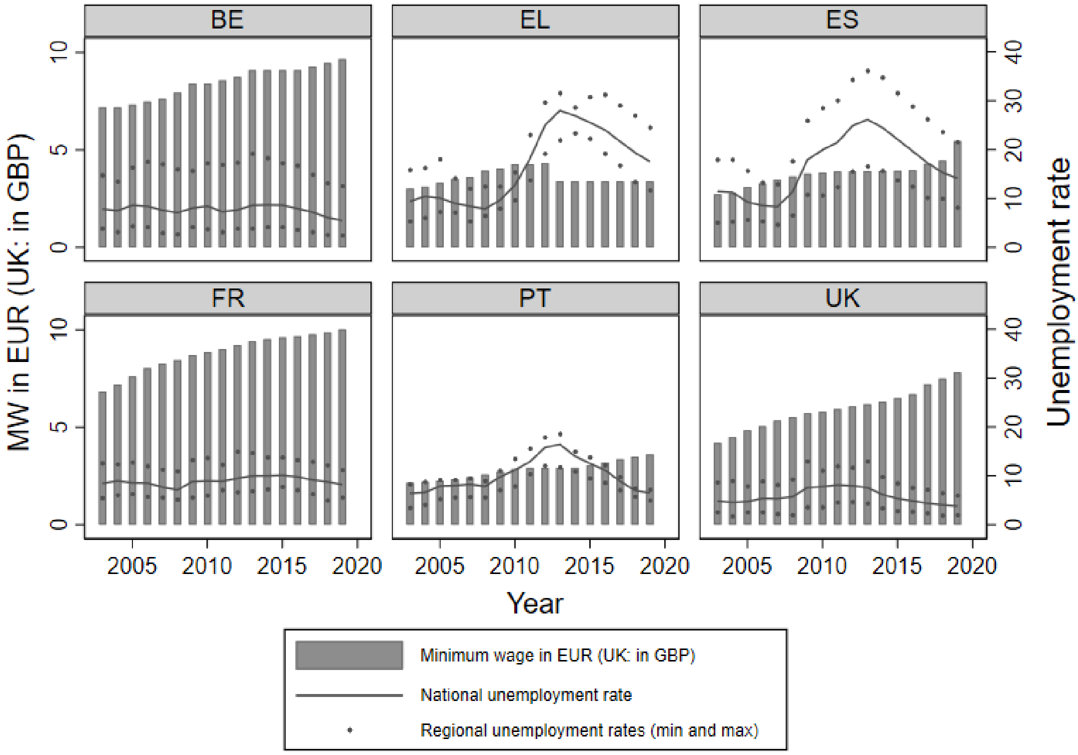


Source: Own elaboration, based on data from WSI (2023). All values denominated in EUR. "No data" indicates that the country has had no statutory national MW in place in 2019. This includes Cyprus, which is not shown on the map. The MWs of non-EU countries, i.e., the EUR-denominated MW levels of Albania (1.21 EUR), North Macedonia (1.63 EUR) and the Republic of Serbia (1.78 EUR) are not shown on the map.

increase in unemployment during the global financial crisis of 2008-2009 and the subsequent sovereign debt crisis. Their national unemployment rates more than doubled between 2008 and 2012, reaching peaks of 27 percent, with relatively long-lasting labor market recoveries thereafter. Regional unemployment also varied significantly within countries. Nations with higher national unemployment rates tended to experience more substantial variations in unemployment across regions (except for Belgium). Additionally, in other dimensions of labor market resilience not detailed here — such as employment and labor market participation rates, youth unemployment, and similar factors — European labor markets displayed notable imbalances within and across countries, predominantly impacting the same set of nations. (e.g. OECD, 2012, Eurofound, 2014).

In 2020, the European Commission initiated a legislative process to enhance the sufficiency and reach of MWs, and to enforce CB as the primary means to guarantee

Figure 2: Nominal minimum wages and unemployment rates



Source: Own elaboration, based on data from WSI (2023) and Eurostat data series lfst_r_lfu3rt and une_rt_a_h. To avoid distorting the picture with exchange rate fluctuations, the statutory MW in the UK is expressed in GBP. Figure A1 (in the appendix) presents the graph for the UK with a EUR-denominated MW.

equitable wages and working conditions throughout all EU countries.[14] MWs and CB legislation in the EU are governed by domestic laws, though. Consequently, the *Directive on adequate Minimum Wages in the European Union* (EU Directive 2022/2041), formally adopted in 2022, mandates member states to align their national regulations with EU-wide minimum standards by the end of 2024. MWs are to be set at a minimum of 60 percent of the gross median wage, 50 percent of the gross average wage, or alternatively, there should be a minimum of 80 percent of workers covered by some form of binding CB agreement. Table 1 reports each EU country's current status with respect to these standards.

Based on these latest available figures (as of December 2023), it appears that only 11 of the 27 current EU members fulfill any of the standards set forth by the directive. The CB coverage rate is met by all the countries without applicable statutory MW in place (with the exception of Cyprus; however, the country introduced a national MW in 2023), and further by Belgium, France, and Spain. France also meets the 60 percent target for the minimum to median wage ratio, as do Bulgaria, Portugal, and Slovenia. The latter country is also the sole EU member meeting the 50 percent target for the minimum wage relative to the mean wage ratio. All other countries are relatively far from reaching any of the specified targets. Remarkably, between

[14]The initiative is part of the *European Pillar of Social Rights* action plan, aiming to establish common living standards across all member states. Its objective is to ensure that EU citizens, irrespective of their place of work within the EU, can enjoy a decent living from their labor income.

Table 1: MW levels and CB coverage in the EU

Country	MW relative to median wage (2021)	MW relative to mean wage (2021)	Collective bargaining coverage rate (latest available)	Directive's target met?
Directive's target:	**60**	**50**	**80**	
Austria	(no MW)	(no MW)	98.0 (2019)	x
Belgium	44.7	40.9	96.0 (2019)	x
Bulgaria	62.7 (2018)	42.8 (2018)	10.8 (2022)	x
Croatia	45.8 (2020)	40.0 (2020)	46.7 (2022)	
Cyprus	(no MW)	(no MW)	43.3 (2022)	
Czech Republic	43.2	37.2	34.7 (2019)	
Denmark	(no MW)	(no MW)	82.0 (2018)	x
Estonia	42.6	36.3	6.1 (2018)	
Finland	(no MW)	(no MW)	88.8 (2017)	x
France	60.9	49.2	98.0 (2018)	x
Germany	51.1	45.1	54.0 (2018)	
Greece	49.8	39.8	14.2 (2017)	
Hungary	45.2	35.3	21.8 (2019)	
Ireland	46.1	35.8	34.0 (2017)	
Italy	(no MW)	(no MW)	100.0 (2019)	x
Latvia	42.3	34.3	27.1 (2018)	
Lithuania	46.7	38.7	7.9 (2019)	
Luxembourg	54.8	43.4	56.9 (2018)	
Malta	43.3 (2018)	35.4 (2018)	41.8 (2022)	
Netherlands	46.3	38.9	75.6 (2019)	
Poland	55.0	45.0	13.4 (2019)	
Portugal	66.2	46.6	73.6 (2018)	x
Romania	54.8	40.1	15.0 (2022)	
Slovak Republic	52.4	39.3	24.4 (2015)	
Slovenia	60.4	50.5	78.6 (2017)	x
Spain	48.4	40.5	80.1 (2018)	x
Sweden	(no MW)	(no MW)	90.0 (2022)	x
United Kingdom	56.9	47.5	26.9 (2019)	

Notes: Own elaboration, based on most recent indicators available. If at least one value reaches its proclaimed norm, the target is met. Information on MW bite (mean and median) by the OECD (data series `MIN2AVE`) or, in the case of Bulgaria, Croatia, and Malta, calculated using Eurostat data series `earn_ses18_19` and `earn_ses_pub2s`. Information on CB coverage comes from the `OECD/AIAS ICTWSS` database.

2015 and 2021, most countries even have moved away from the targets (not shown here, but evident from the underlying data series). Several EU countries already announced to set up policy initiatives to achieve the targeted values within the next 2-3 years (Eurofound, 2023).

2.2 Labor mobility in the EU

Labor mobility is a potential means to facilitate the adjustment of regional labor markets and to offset imbalances caused by economic shocks and regulatory changes, such as MW regulations (Blanchard and Katz, 1992, Kahanec and Zimmermann, 2016, Cadena and Kovak, 2016, Dustmann and Preston, 2019). Yet, a crucial aspect of the unified EU market is the freedom of movement for workers, a fundamental principle of the EU's *acquis communautaire* since 1968: Article 45 of the *Treaty* *on the Functioning of the European Union* (TFEU) guarantees EU citizens' equal treatment across the common EU labor market, i.e., EU citizens possess the right to work anywhere inside the EU under the same principles and regulations as the host country's nationals. This provision enhances EU citizens' job prospects and encourages labor mobility throughout the EU (Ortega and Peri, 2013). And accordingly, it is not only that regional labor market adjustments are influenced by internal worker mobility within a country, but cross-border mobility responses by EU citizens could be another significant factor in this process.

Notwithstanding this consideration, most labor mobility in the EU occurs within countries: A comparative study by the OECD (2012) found inter-regional mobility (NUTS-1) of the working age population *within* EU countries was 1 percent and cross-border mobility 0.3 percent in 2010, i.e., a total of 1.3 percent of the population changed their NUTS-1 region of residence within the EU that year. Cross-state mobility in the United States, in contrast, was reported at 2.4 percent of the population (and even higher in other studies, see for instance Molloy et al., 2011).[15] Moreover, internal mobility in Europe is heterogeneous both across and within countries. Specifically, countries with higher per capita income (most EU15 countries) and northern European countries experience higher per capita internal mobility. These countries also tend to attract more inbound mobility from abroad. In contrast, countries with relatively lower income levels and those in the south of Europe exhibit comparatively lower levels of internal and cross-border mobility: Arpaia et al. (2014) and Liu (2018) find relatively the highest internal mobility figures for the UK, Denmark, France, and Belgium, and the lowest mobility rates in Spain, Portugal, Greece, and Poland. Overall, internal and cross-border labor mobility in the EU increased substantially over the last two decades (Kahanec, 2013, Liu, 2018, European Commission, 2022).

Figure 3 provides an overview of NUTS-2 level net migration rates, i.e. the local change of the resident population not attributable to births and deaths. As such, these figures do not imply absolute mobility counts, but portray whether a country's regions, on average, attract more individuals than they lose.[16] Figure A3 in the appendix shows the respective figure for the full set of EU-15 member countries.

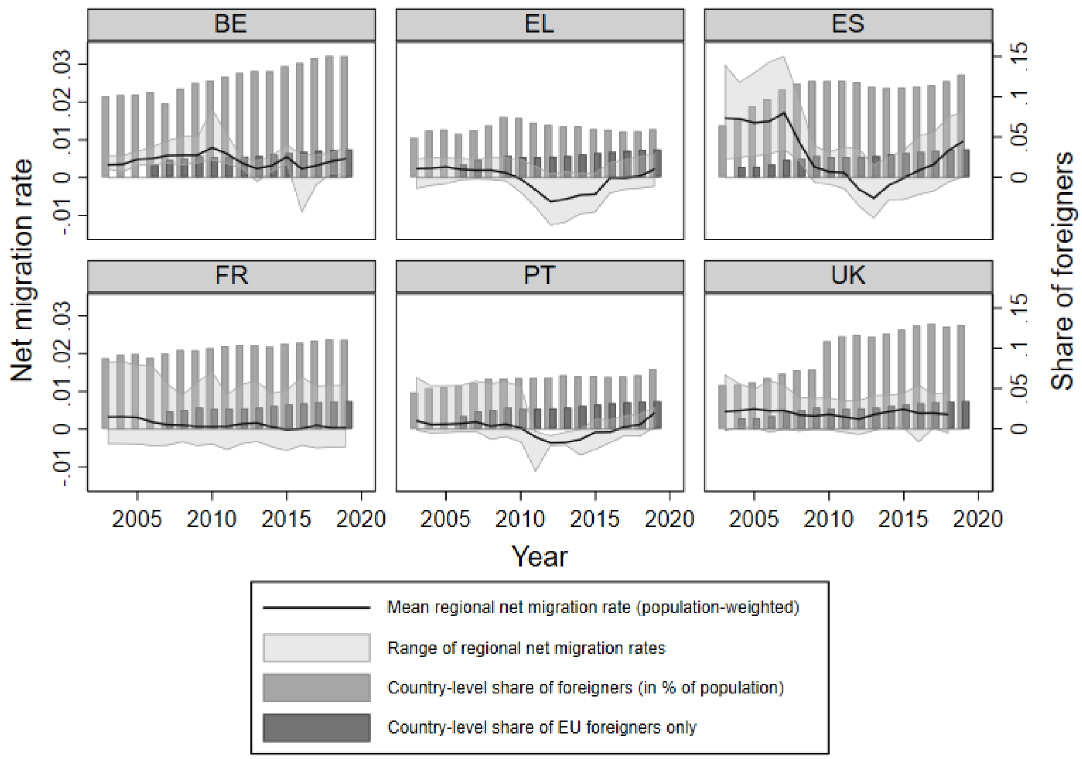
As evident from the graph, the mean net migration rate varies substantially between and within countries, and also over the business cycle. Greece, Portugal, and Spain display significant variability over time (even experiencing net outmigration in the years after the financial crisis), while the mean net migration rates of Belgium, France, and the UK appear relatively more stable. Within-country variability is particularly pronounced in Spain and France.

The diversity in the proportion of foreigners across the countries is considerable as well. With the exception of Greece, the foreign population as a share of the total population increased in all sampled countries over the observed period. Belgium, Spain, France, and the UK have relatively high proportions of foreigners, constituting roughly 10-15 percent of their populations. Conversely, Greece

[15] Similar results on EU labor mobility for other periods can be found, e.g., in Gáková and Dijkstra (2008), Bonin et al. (2008), and Dorn and Zweimüller (2021). For a global comparison of interregional mobility figures, see Bell and Charles-Edwards (2013).

[16] A country might experience substantial mobility while maintaining a relatively low net migration rate if the number of incoming and outgoing individuals effectively offsets each other.

Figure 3: Mean regional net migration rates and share of foreigners



Source: Own elaboration, based on Eurostat data set series lfst_r_lfsd2pwc, demo_r_gind3, and migr_pop1ctz. Note: Many missing data on the stock of EU foreigners in early years for many countries (here for: Belgium, Greece and France until 2008).

and Portugal show notably lower proportions of their population originating from abroad. However, among the foreign population in these countries, there is a higher representation of EU citizens. The share of EU migrants relative to the share of all foreigners increases over time in all the countries shown here, indicating the growing importance of intra-EU labor mobility across the EU, a trend noted in other studies as well (see, e.g., Gáková and Dijkstra, 2008, Eurofound, 2014, European Commission, 2022).[17]

3 Literature

"[D]ifferences in net economic advantages, chiefly differences in wages, are the main causes of migration" (Hicks, 1963, 76-77)

According to Sjaastad (1962) and Becker (1964), moving from one place to another can be described as a rational (investment) decision where individuals compare the expected costs and benefits of a specific move. Mobility takes place whenever the expected benefits exceed the associated expected costs. Likewise, the decision to select one destination over another hinges on the anticipated comparative benefits or gains. Harris and Todaro (1970) formalized these considerations in what is known as the *expected income hypothesis*: Individuals contemplating labor migration consider

[17] Please refer to Figure A4 in the appendix for a broader EU-wide perspective.

not only the potential income achievable in a particular area (local wage levels) but also the probability of finding employment there, which involves taking into account the local unemployment rate.

MWs by design have an influence on an area's entrance wages. Moreover, they potentially also shift the average and median wages of a region, especially if they also trigger labor supply and mobility responses (Grossman, 1983). If a new, elevated MW exceeds the reservation wage of previously inactive members of a population, the increased assured compensation encourages these individuals to join the local workforce. Likewise, working individuals may consider adjusting their number of working hours. On the other hand, firms may be resistant to increasing employment given the higher labor costs per hour. Hence, according to conventional economic theory, MWs in competitive markets are believed to stimulate increased labor supply but reduced labor demand, consequently leading to unemployment (Boeri and van Ours, 2008). Alternative theories propose that in some cases, rather than reducing employment, MWs could boost employment - depending on, for instance, the degree of local market concentration, local market imperfections, and other features of specific (local) labor markets (Card and Krueger, 1993, Manning, 2003). Despite abundant empirical evidence, a universally accepted conclusion on the effect of MWs remains elusive.[18]

Recent studies particularly pointed towards different effects depending on the segment of the labor market one is looking at: For instance, Dolton and Bondibene (2012) found that during economic downturns, it is particularly those at the margin of the workforce that are negatively affected by MWs - young workers are laid off first. Clemens and Wither (2019) provide a similar argument. They show that low-skilled employment declines more than general employment when MWs 'bite'. Episodes of economic unrest expose certain groups to increased vulnerability, and MWs particularly contribute to this effect. In general, Dube and Lindner (2021) demonstrate that MWs typically impact workers at approximately the bottom 30 percentiles of wages, contingent upon the proportional magnitude of the MW relative to local compensation levels. The overall effect of MWs on expected income in an area may thus depend on local market structures (including relative wage levels), the composition of the local workforce, and demand and supply elasticities on the local labor market (Neumark and Shirley, 2022). Following the line of argument of Harris and Todaro (1970), MWs thus exert an influence on the desirability of an area to outsiders by affecting the income to be expected there. MWs' impact, however, can be either positive or negative, contingent upon the relative intensity of the local income and substitution effect triggered, and the segment of the labor market an individual is after.

Several authors argue that MWs are disproportionally more relevant for newcomers compared to established residents: MWs serve as a reference wage value of an area (not necessarily only for the lowest-skilled workers), given that they provide a (worst-case) minimum remuneration for *any* job available at destination (e.g., Sum et al., 2002, Cortes, 2004, Neumark et al., 2014). Moreover, MWs appear more relevant for mobile workers since these tend to be younger than average workers, are typically less experienced and tenured, have lower average education levels,

[18] An encompassing review of the literature goes beyond the scope of this paper. Neumark and Wascher (2008), Dube and Lindner (2021) and Neumark and Shirley (2022) provide extensive summaries of the existing literature.

and initially lack the social capital that could help them in the local labor market (Chiswick, 1986). These characteristics make them lean towards working in low-pay jobs and workplaces with higher job turnover rates, making MWs potentially more relevant. Orrenius and Zavodny (2008) compare the labor market effects of MWs for low-skilled natives with those of low-skilled international immigrants to the United States. They find no substantial differences between the groups, neither in terms of wages nor in employment effects. However, they recognize that their result might be influenced by migrants' higher mobility. Migrants might strategically choose destinations, avoiding regions with notably high MWs where competition with natives is more intense (potentially leading to lower labor market prospects).

Empirical evidence regarding the impact of MWs on labor mobility in the United States is mixed. Cushing (2003) investigates how spatial variation in the level and in the coverage of applicable MWs affects cross-state labor mobility between 1985-1990. He finds that state-level MWs above the federal MW level[19] generally attract Americans from the lower end of the wage distribution; and the absolute difference in MW levels between two states impacts the size of inter-state migration flows. Correspondingly, he finds a higher percentage of employment being covered by MWs positively correlates with the likelihood of low-income Americans deciding to come to this state. Martin and Termos (2015) investigate the mobility response of low-skilled Americans to local MW changes. They find that increases in local MWs lead to more low-skilled emigration away from that area. They calculate that an induced differential of one USD in the real MW between two places correlates with a 3.1 percent increase in the migration of low-skilled workers towards the location offering the lower MW. A similar finding is presented by Monras (2019), who investigates the correlation between state-level applicable MW changes and the inter-state mobility of prime-age (25-35 years old) low-skilled workers in the United States. He shows that, on average, MWs positively affect wages but negatively impact the employment likelihood of affected workers, and that the substitution effect of MWs typically outweighs the income effect in most areas in his sample. However, he observes that this does not significantly increase local unemployment, as numerous low-skilled workers move away from the affected regions, clearing the local market.

Other studies have investigated the influence of MWs on the labor mobility of *international migrants*.[20] Castillo-Freeman and Freeman (1992) find the implementation of the United States federal MW in Puerto Rico (which was significantly higher than the local MW at that time) led to increased out-migration of low-skilled Puerto Ricans to the United States (potentially avoiding unemployment on the home market). Cigagna and Sulis (2015) find for a sample of 15 OECD countries (including nine EU countries) that the existence of MWs (no matter their level) positively influences immigrant counts to a country.

Research on the mobility of international migrants *within* the United States (a group arguably more mobile than natives due to weaker local ties) presents a mixed picture: Von Scheven and Light (2012) show that Latin American immigrants tend not to settle in states that have recently increased their MWs higher than the federal MW in the United States. They argue that states with relatively low MWs maintain larger low-wage sectors, which makes them attractive to immigrants on occupational

[19] The federal MW applies to all individuals working in the United States. States are free to set their own applicable MWs, which can exceed but not fall below the federal standard.

[20] As an unincorporated territory, I do not consider Puerto Rico as part of the United States.

grounds. Similarly, Cadena (2014) finds that low-skilled immigrants arbitrage labor markets by deviating away from high-MW states towards settling in US states with rather stagnant MWs. MW-induced job losses of teens are substantially larger in states with historically low migrant shares, a finding he claims supports the proposed mechanism. Somehow contrasting, Boffy-Ramirez (2013) reveals that some groups of migrants react *positively* to state-level MW changes: Migrants that live in the United States for between 2-4 years already (i.e., migrants not so much settled, and eager to explore their chances on the United States labor market to the largest extent). Meanwhile, he finds no significant response to MWs among more established migrants. Giulietti (2014) assesses the impact of state-level variations in expected wages stemming from increases in the federal MW level (arguing that the income effect is equivalent everywhere, but not necessarily the substitution effect, i.e., the local employment response). He finds that MWs are a sizeable pull factor for recently arrived low-skilled migrants and for inter-state mobility of more established low-skilled migrants (residing in the United States for five years or longer).

Although the overall perspective on the relationship between MWs and labor mobility seems rather inconclusive, certain key aspects emerge from the previously presented studies: First, MWs seem to influence labor mobility. In the United States, they have been observed to attract mobile workers from other states and international migrants. However, certain worker groups have also been found to steer clear of higher MW areas, either relocating or opting for different regions from the outset. The net effect of these channels, i.e. overall mobility counts, have been less studied.[21] Second, and unsurprisingly, it is the individuals at the lower end of the income distribution that have been found to respond to shifts in MWs. There appear, if at all, only little spillover effects to higher skill levels in the United States. Accordingly, the local bite of the MW may be decisive on the overall net effect in an area. And third, several studies pointed out the high relevance of local labor market characteristics for actual mobility responses. Particularly local features affecting labor demand and labor supply have been found to matter for the local mobility response to MWs.[22]

However, Europe may be a different case than the United States for several reasons: The EU's member states exhibit substantial heterogeneity, retaining their unique cultures, legal frameworks, and diverse policy objectives and strategies - including their (local) labor market settings. The EU's principle of free movement of workers significantly impacts member states' labor markets by facilitating skill transfer, fostering competition, and enhancing market efficiency through increased mobility - supporting regional adjustment to imbalances. Overeducation and downskilling of migrant workers are more prevalent in Europe (Nieto et al., 2015), indicating there may be potentially more groups of workers being affected by MWs than just low-skilled workers (Gregory and Zierahn, 2022). The higher level of employment protection across the union contributes to greater job security, reduced job turnover rates, and potentially less in- and out-migration of workers. Furthermore, MW increases correlate with increased selectivity in recruitment (Butschek, 2022).

[21] Exceptions include Boffy-Ramirez (2013), who finds a positive effect of state-level MWs on total state immigrant counts, and Cadena (2014), which finds a negative correlation with the count of immigrants who have arrived in the United States within the last 10 years.

[22] This discovery aligns with similar findings in literature exploring commuting patterns influenced by MWs (e.g. Kuehn, 2016, McKinnish, 2017).

Therefore, the significant variability in applicable MW rates across Europe might result in differing levels of labor market discrimination against outsiders, particularly when coupled with language barriers in cross-border mobility. Accordingly, several country- and region-specific factors may buffer or amplify the potential relationship between MWs and labor mobility in Europe.

Notwithstanding, if Orrenius and Zavodny's hypothesis on the mobility response of workers due MWs holds true, areas with increasing MWs should experience a decrease in labor inflows. With this paper, I test this proposition for mobility within and across EU countries - a unique context that has not been studied yet.

4 Data and empirical strategy

To investigate the impact of MWs on labor mobility in the EU, this section first introduces the data I use. In particular, I highlight my approach to measure cross-country harmonized regional labor inflow figures across regions in the EU, and describe Hamermesh's version of the so called Kaitz index which I use to measure the regional 'bite' of a MW. I then continue to motivate my covariates, explain my empirical model used to analyze the relationship between MWs and labor mobility, and lay out my final data sample.

4.1 Measuring labor mobility

One of the main difficulties in analyzing labor mobility within the EU is the lack of appropriate data on actual worker flows (Raymer et al., 2013, Willekens et al., 2016, Wisniowski, 2017, Willekens, 2019, Fenwick, 2022). All EU countries record harmonized population stock data down to the regional level (also of various subgroups, differentiated, for instance, by working age), but they do not track *movements* of workers in standardized, comparable ways.[23] To overcome this well-known data limitation problem, I calculate regional labor inflow figures from EU LFS microdata.[24] The EU LFS is an individual-level representative household sample survey conducted by all EU member states on a quarterly basis. It offers a consistent methodology and questionnaire, and it has a substantial sample size across all surveyed countries and regions.[25] It is therefore suitable for cross-country comparisons down to regional levels, which makes it Eurostat's primary source for the EU labor market statistics.

I leverage a feature of the EU LFS to derive regional mobility rates: The questionnaire requires individuals to provide their country and region of residence one year before the survey date. Together with other recorded individual-level characteristics, such as differentiating between nationals, EU citizens and third country nationals, it is possible to extract specific macro-level indicators at the regional level. For my purpose, I derive worker inflow rates at the regional level for all EU NUTS-2 regions in the following manner:

[23] Mainly, challenges arise in defining consistent criteria identifying individuals as mobile. Fassmann et al. (2009) review problems associated with measuring mobility in Europe and beyond.

[24] An approach employed previously by Antolin and Bover (1997) to measure inter-regional mobility in Spain, by Bonin et al. (2008) to quantify cross-border mobility in the EU, and by Bloomfield et al. (2017) to assess the cross-border mobility of accounting professionals in Europe.

[25] Typically, the EU LFS sample size ranges between 1-2 percent of the local population.

$$inflow\_rate^s_{i,t} = \frac{m^s_{i,t}}{N_{i,t}}, \quad (1)$$

where $m^s_{i,t}$ is the count of "recent movers" interviewed in region i in year t with characteristic s, who reported living in a different region or country 365 days before the survey date. The subscript s represents individual-level characteristics like nationality, sex, age, and so on. The denominator $N_{i,t}$ signifies the total count of individuals interviewed in region i in year t. To assess actual worker mobility, I narrow down the count data to include only individuals aged 15-65. Additionally, I focus on low-skilled workers only, the group of workers presumably most affected by MW changes. Moreover, it is important to note that not all individuals surveyed in the LFS have equal rights to work in the domestic labor market or move freely between regions across the EU. Consequently, I specifically consider individuals possessing EU citizenship (which inherently includes nationals of the respective country).

However, calculating the regional inflow rate is not equally feasible for all EU countries. Over the years, several countries have changed their regional NUTS breakdown. In my sample, this affects certain regions of France, Greece, and the UK.[26] Adapting these changes isn't always feasible, sometimes necessitating the exclusion of specific regions from the analysis, resulting in an unbalanced sample.[27] Moreover, in some countries (in my sample this pertains to the UK), the lowest surveyed regional breakdown is not at the NUTS-2 level (the UK's county and district level) but only at the NUTS-1 level (the UK' former government office regions). To ensure data availability at my primary analytical level (NUTS-2) for the UK, I adjust the calculated inflow rates from the next higher available level to correspond to the lower level.[28] Later on, I assess the robustness of my baseline regression results against a sample excluding the UK.

Typical problems associated with survey data are non-response, imperfect coverage of subgroups of the population in the sampling frame (and in the post-stratification criteria determining design- and survey weights), and measurement errors related to self-reported data. The extent of these problems in the EU LFS is unknown, making them difficult to address (Bell et al., 2015, Galgóczi et al., 2016, Wisniowski, 2017, Fenwick, 2022).[29] Fortunately, in all the countries of my sample, with the exception of the UK, participation in the EU LFS is mandatory. This design feature limits the potential extent of non-response and suffice the coverage of subgroups. Notwithstanding, the EU LFS only considers people being part of the population, who have registered as permanent residents. Accordingly, short-term mobility (for instance, the presence of seasonal workers) is not covered under my concept of labor inflows. Some authors also claim this negatively affects the

[26] For historical NUTS breakdowns see https://ec.europa.eu/eurostat/web/nuts/history (last accessed 08.12.2023).

[27] For instance, the greater London area (UKI) changed its delineation from NUTS 2010 version to NUTS 2013 version, creating completely new regions (increasing the number of NUTS-2 regions from two to five, with no boundary overlap). Consequently, it was impossible to incorporate the data in or before 2012. I include the London area data only from 2013 onward. Refer to Table 6 in the appendix for details on my full data sample.

[28] For instance, I assign regions *Tees Valley and Durham* (NUTS-2 region UKC1) and *Northumberland and Tyne and Wear* (NUTS-2 region UKC2) the inflow rate calculated for NUTS-1 region *North East England* (NUTS-1 region UKC). See table A1 for the full crosswalk used.

[29] See Heeringa et al. (2017) for an extensive overview of typical problems associated with survey data and potential remedies.

coverage of international migrants (Rendall et al., 2003, Martí and Ródenas, 2007). Yet, in my sample only about 12.5 percent of identified mobile workers are moving across borders.[30] I test the relevance of international mobility for my outcomes in the robustness section of this paper.

A more problematic feature of the EU LFS may be what Martí and Ródenas (2007) labelled as *Problem of Answer Impossible*: In certain countries, the survey design replaces only a fraction of the interviewed individuals each quarter. Consequently, some individuals are surveyed multiple quarters before being replaced, and this time span is sometimes longer than a year.[31] An individual being in the survey sample for longer than a year cannot report having moved in the last 365 days *for mechanical reasons*. The size of the bias introduced is determined by the national survey design and in particular by the survey's replacement rate. While I am unable to test the significance of this issue directly (apart from observing national replacement rates), it certainly downward-biases the mobility rates I derive from the LFS. As this concern pertains to a region-specific matter contingent on the internal survey design, and is likely relatively constant over time, a fixed effects panel model should suffice in capturing the bias (see the discussion of my econometric specification below).

4.2 Regional 'bite' of the minimum wage

My data on the level of statutory national MWs originates from the *WSI Minimum Wage Database International*, which is based on reports by the respective national statistical offices, and supplemented with information from various government agencies and the ILO. This data set provides standardized average MW figures for each country, accounting for country-specific MW policies based on age, occupation, industry, place of residence, etc., and factoring in domestic features like the length of the average work week and the average number of hours worked per month. The data is presented in hourly and monthly formats, denominated in national currency and and euros, and is consistently reported as of January 1st annually.[32]

Nominal MW figures lack information regarding their local market relevance, though. In order to compare MWs' relevance spatially, i.e. across regions or even countries, a local reference value is needed. Kaitz (1970) proposed an index to measure the local 'bite' of the MW: The MW in relation to the typical wage paid in an area. This so called *Kaitz index* is often expressed as the gross hourly MW relative to the gross mean or median hourly earnings in an area (note that the EU's MW directive 2022/2041 similarly demands MW target values in terms of mean and median wages). The Kaitz index score is higher, the higher the nominal level of the MW is, and the lower the average hourly earnings in an area are. Accordingly, a

[30]The empirical evidence from Rendall et al. and Martí and Ródenas is based on LFS samples and survey methodologies predating my sample period, notably before the EU enlargement periods of 2004 and thereafter. Over time, LFS sample sizes have increased substantially, leading to improved coverage of subgroups of society. Meanwhile, EU-wide, the share of migrants (respectively EU mobile citizens) has also increased (see section 2). These developments enhance the likelihood of migrants being sufficiently represented in my sample.

[31]In my sample, this pattern affects all countries, albeit with varying intensity. Yet, the approach chosen by each country typically remains constant over time. An exception is Belgium, where significant changes to the LFS design were implemented in 2006 and 2017. To assess the impact, I test my results against a sample excluding Belgium.

[32]See WSI (2023) for the data set and information on country-specific calculations.

relatively high Kaitz index typically indicates relatively high *real*[33] MWs in an area (and typically more workers being affected), while a low index score implies less relevance of the MW for the local labor market (Boeri and van Ours, 2008).

It is widely acknowledged that MWs not only impact local wage levels but also influence the probability of securing employment, affecting both employment and unemployment rates (see section 3). An essential factor influencing the attractiveness of MWs is the concept of *expected earnings*, which is contingent upon the regional interplay between labor supply and demand (Harris and Todaro, 1970). However, capturing the exact mechanisms of these effects presents a considerable challenge. Recent studies have highlighted that employers respond to MW adjustments not only by altering their labor demand but also through the modulation of employer-provided benefit schemes, which can constitute up to 30 percent of employers' compensation costs (Clemens et al., 2018, Clemens, 2021). My econometric approach aims to account for this aspect and addresses the effects of MWs comprehensively: Traditional metrics like average hourly earnings, utilized in most appliances of the Kaitz index, lack reliability when comparing MW levels across diverse legislatures and different work cultures. Employers potentially consider various costs to adapt to changes in MWs, including payroll taxes, social contributions, bargained earnings components such as paid vacations, bonus payments, and other allowances. Consequently, the total worker compensation could be a more pertinent consideration for employers' labor demand than the average nominal gross wage in a given area.

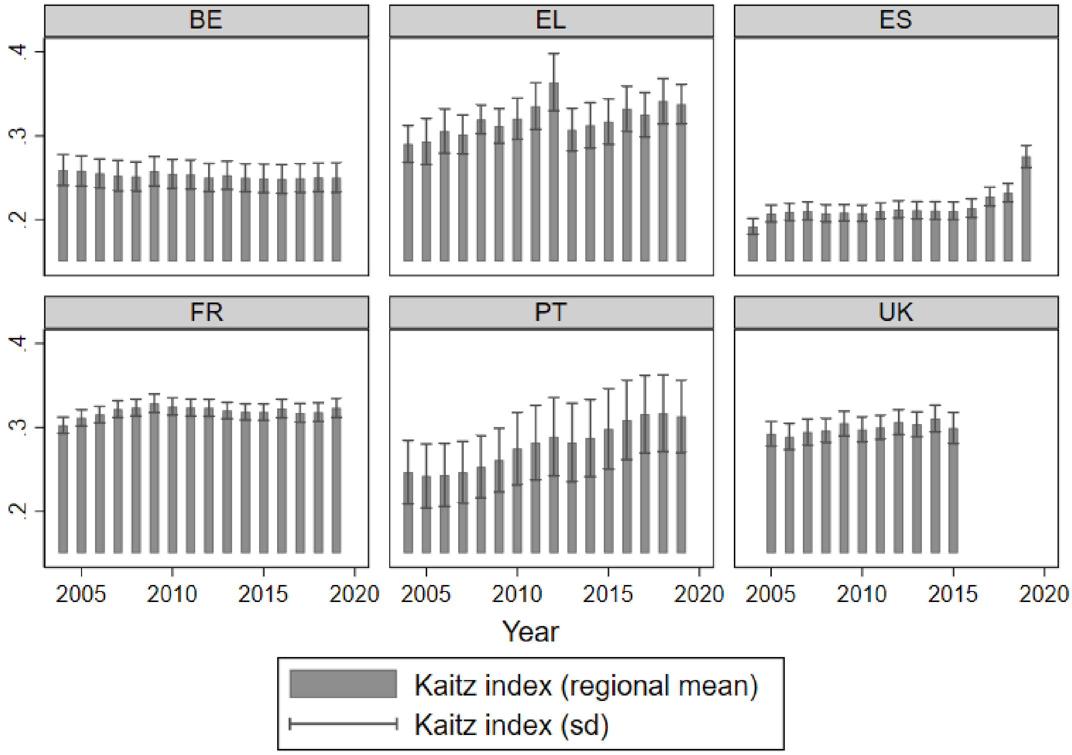
Hamermesh (1981) introduced a Kaitz index variant that takes this argument into account. His Kaitz index considers total compensations instead of gross wages, allowing for comprehensive comparisons across jurisdictions. The measure encompasses nominal local wage levels, similar to the standard Kaitz index, and adapts to the diverse local compensation structures: For instance, it addresses employer-covered tax and social security payments not reflected in gross wages (yet considered in labor demand decisions), and it accommodates regional variations in fringe benefits. In regions with higher non-wage benefits, the MW impact is less intense in Hamermesh's Kaitz index variant, and it rises if employers cut these benefits in response to an MW increase. Building on Hamermesh's Kaitz index concept, I combine the nominal MW figures from the WSI with Eurostat's and the UK's Office for National Statistics (ONS) data on the mean regional compensation of employees per hour. Figure 4 provides the development of this regional-level Kaitz index over time for the countries of interest in this study. Regional-level descriptive statistics on this measure are available from the appendix, table A2.

The regional Kaitz index, i.e., the applicable statutory MW relative to the mean compensation of employees in the NUTS-2 regions in my sample, ranges from around 11 percent to 45 percent.[34] The mean Kaitz index value across all domestic regions of a country is highest in Greece and France, and lowest in Spain. Variability varies notably across countries. Belgium, France, and the UK maintained relatively steady Kaitz index values over the sampling period, contrasting with Portugal and Greece, which exhibited significant fluctuations. Spain shows some substantially low Kaitz values at the beginning of my sample period. The country's mean Kaitz index

[33] The Kaitz index implicitly states the MW in real terms, as it is not susceptible to inflation (provided that the local overall wage level adjusts for inflation).

[34] The lowest Kaitz index value is reported for region UKI3, i.e. inner London area, in 2015. The largest MW bite was detected in 2012 in EL54, the Greek region of Epirus.

Figure 4: Variations in regional Kaitz index



Source: Own elaboration, based on data from WSI (2023) and Eurostat data series nama_10r_2coe. Missing data on the local compensation of employees in the UK in 2004 and 2016-2019.

then considerably increased after 2017 (due to some substantial MW increases in Spain during that period). Portugal and Greece exhibit the most notable regional variation within their countries, with Belgium also demonstrating a relatively higher degree of regional diversity compared to other countries. Notably (but not shown in the graph), in all countries the Kaitz values in major population centers (primarily the capital regions) tend to be relatively low, while they appear higher in more rural regions. This reflects higher labor compensation costs in cities (and, to some extent, the respective higher costs of living). In the results section, I test whether my outcomes are heterogeneous with respect to local population density.

4.3 Covariates

My set of covariates aims to capture the factors influencing labor mobility into a region beyond the potential impact of local MWs. These factors encompass changes in a region's attractiveness for workers over time. Following earlier mobility literature (e.g. Boffy-Ramirez, 2013, Cadena, 2014, Giulietti, 2014), my model specifications include indicators capturing regional employment prospects, indicators of local economic development, and historical trends in attracting foreign labor.

The *total population* of an area is indicative of the size of the local labor market and the associated job opportunities.[35] Moreover, it proxies for general infrastructure, such as the availability of public goods and services (education, healthcare, transportation, and the like), and potential network sizes. I include the regional *gross domestic product per capita* (GDPPC) in EUR terms to account for differences in general economic development, productivity, and income. It provides information concerning the standard of living of individuals within a region. The inclusion of the local *unemployment rate* aims to capture the likelihood of actually finding a job in an area, and serves as a proxy for longer-term shifts in labor demand. Its overall value signifies the local labor market's health and its resilience to labor market shocks. However, the unemployment rate is only indicative of the proportion of the labor force that is actively seeking but unable to find employment. It does not consider individuals not actively seeking work, individuals not immediately available for employment, or those who have dropped out of the labor force altogether. As a result, changes in the unemployment rate may not necessarily reflect changes in employment opportunities for low-wage workers. To address this shortcoming, I also include the *youth employment rate* in an area. Literature identified teenagers as the group of workers typically most affected by MW laws (see e.g. Neumark and Wascher, 2008), which is mainly attributed to their naturally low level of qualification. Changes in the youth employment rate therefore serve as a key indicator of regional developments in the labor market of the low-skilled due to changes in overall job prospects. The relative homogeneity of this group of workers, even across countries, makes it an effective indicator of the local low-skill labor market (Neumark and Wascher, 2004). Finally, I include the region's *share of foreigners* (individuals born outside the country), to proxy for factors such as immigration history, community networks, and social integration dynamics (Beine et al., 2011). Additionally, this variable accounts for labor market diversity, local attitudes towards foreigners and newcomers, and similar factors. All my covariates are sourced from Eurostat.[36]

4.4 Econometric specification

To assess the relationship between MWs and regional labor inflow rates for my sample of EU countries, I broadly adopt methodologies previously used in assessing the United States labor market (Boffy-Ramirez, 2013, Cadena, 2014, Giulietti, 2014, Monras, 2019). In my baseline specification, I apply a fixed effects panel data model at the regional level, nested within the country level. This model is described by the following equation:

$$inflow\_rate^{s}_{i(c),t} = \alpha_0 + \beta_1 lnKaitzIndex_{i,t-1} + \gamma \mathbf{X'}_{i,t} + \lambda_{c,t} + \lambda_t + \epsilon_{i,t}, \qquad (2)$$

[35] NUTS delineations, ranging from 800,000 to 3,000,000 inhabitants, consider population sizes as per regulations. While using total regional population as a covariate is an option, employing constant average regional population figures for weighting in the regression is an alternative. However, my panel's unbalanced nature is partly due to population changes impacting NUTS delineations (like in the London area), i.e. influenced by regional mobility patterns. This necessitates an appropriate control in my estimation strategy. Furthermore, employing average population figures for weighting becomes challenging in unbalanced panel data due to the variation in underlying base years.

[36] The respective variables are derived from Eurostat data series `demo_r_gind3`, `nama_10r_2gdp`, `lfst_r_lfu3rt`, `lfst_r_lfe2en1`, `lfst_r_lfe2en2`, and `lfst_r_lfsd2pwc`.

where the dependent variable, $inflow\_rate^{s}_{i(c),t}$, is the relative inflow rate of recently arrived low-skilled individuals of characteristic s into region i (located in country c) in year t. In my baseline specification, characteristic s exclusively denotes inflows of individuals holding EU citizenship (i.e., natives and EU mobile citizens). My main variable of interest in the specification is $KaitzIndex_{i,t-1}$ (in logarithmic form), which denotes the value of the local Kaitz index in region i in year $t-1$. Using the lagged value is to ensure that MW changes always precede potential mobility responses.[37] $\mathbf{X'}_{i,t}$ denotes a vector of time-varying covariates at the regional level. It includes the covariates presented earlier. All covariates are likewise expressed in logarithmic terms and lagged by one year. Notwithstanding, I lag the covariate on the share of foreigners by three years to minimize potential noise resulting from simultaneous movements with the dependent variable, the inflow rate. Moreover, λ_t captures time fixed effects, and $\lambda_{c,t}$ adjusts for country-specific linear time trends.[38] $\epsilon_{i,t}$ denotes the error term. In my estimations of the mentioned model, I modify the standard errors by clustering them at the regional level. This adjustment is made to accommodate for intragroup correlation, i.e. any interdependence observed within regions.

Note that employing fixed effects in estimating the aforementioned model offers significant advantages - most notably, it effectively eliminates cross-regional differences that are constant over time. For instance, certain regions might be especially attractive to outsiders due to their level of urbanization, easy accessibility, specific cultural appeal, extensive networks of foreign residents, or other (mostly) time-invariant factors. Permanently elevated (or decreased) labor inflows into a region have no influence on the estimated regression coefficients under my setting.[39] In other words, what I am examining with my model specification is how variations in the regional Kaitz index (or any of my other covariates) correspond to the regional labor inflow rate, irrespective of regional specifics such as region-specific labor market responses. This aspect is also crucial in tackling the data constraints I previously outlined: Most of the identified limitations arise from country- and region-specific characteristics, especially reliant on the national survey design and its regional implementation. Employing a fixed effects model setup can aid in mitigating, and ideally eradicating, any systematic biases in the data, provided these biases remain (largely) consistent over time.

Furthermore, all the recognized potential limitations of the data lean towards underestimating the actual labor mobility figures. Technically, in a regression analysis, this makes it more difficult to identify relationship estimates that deviate from zero. Hence, coefficient estimates discovered in my analysis as significant in explaining the relationship are likely to signify the actual direction of the underlying relation-

[37]When an individual reports a move within the last 365 days, this person may have relocated in the previous calendar year: Imagine the survey interview took place on January 1st in year t, then the actual movement date may have been any day back in time until January 1st in $t-1$. The Kaitz index takes into account the MW on January 1st of each year. Accordingly, MW changes precede potential mobility responses in my data. Moreover, this approach alleviates potential endogeneity concerns.

[38]Region-time trends would capture all the degrees of freedom in my model, see section 4.5. Notwithstanding, I test the robustness of my results against such a specification in section 5.3.

[39]The same applies to systematic region-specific deviations among the covariates. Furthermore, since regions are nested within countries, this also includes time-invariant country-specific elements, encompassing legislation, customs, and similar factors.

ship, though not necessarily its precise magnitude (for a detailed examination of this technical aspect, refer to Cohen, 1977). National survey design changes could also influence my model setup and possibly introduce bias into my estimates. I include country-time trends to address changes in the national survey design over time, and also to capture developments in the relative attractiveness of certain countries over others (for instance, due to developments in terms of a country's legal framework, economic developments, and else).[40]

My model inherently encompasses several potential origins of endogeneity. The presented approach establishes statistical correlation, for instance, but it lacks the capability to eliminate the possibility of reverse causality. To tackle this issue, I employ various strategies. One method involves using lag analysis, where I consider lags of two and three years on the Kaitz index rather than just one year. This examination of temporal sequences helps determine whether higher lags consistently show certain patterns, adding robustness to the identification strategy and providing insights into the probable direction of causation. Each additional lag successfully introduced makes a reverse causal relationship less probable. Moreover, in the robustness section of this paper, I perform a reverse causality test to explore if my model, with all other features held constant, can predict changes in the MW using the labor inflow rates (i.e. swapping the dependent variable with the primary independent variable in my model). If the outcome indicates insignificance or a reversal in sign, it provides further support for the credibility of my original model.

Another source of endogeneity arises from the correlation between regressors and the error term, which can result from various factors. These may include omitted variable bias, or be due to factors beyond my control, such as insufficient (erroneous) measurement in the underlying data. Additionally, current measures of labor mobility may be linked to past mobility - following trends like the business cycle, for instance. The examination of EU mobility in section 2 suggested potential correlations in the mean regional net migration rates across consecutive periods, particularly in Spain and Greece. Technically speaking, the underlying structure of my panel data may then be dynamic in the sense that it is first-order serially (auto-) correlated. It is plausible, that my data even contends with a combination of issues. For instance, the current unemployment rate might be influenced by the previous period's labor supply, which in turn could be influenced by the preceding period's labor inflows - and the magnitude of these effects may vary across diverse regions.

My primary approach to addressing these concerns involves testing the outcomes of the fixed effects model against the Arellano-Bond estimator (AB model, hereafter).[41] The AB model is suitable for addressing several endogeneity issues as well as problems associated with autocorrelation and potential heteroscedasticity of data. In essence, it is a dynamic panel data estimator, incorporating lags of the dependent variable as a predictor - a departure that violates the strict exogeneity assumption necessary for fixed effects models (Nickell, 1981). Though basically a random effects model, the AB model applies first differencing to the regression equation. This pro-

[40]Underlying country-time trends may exhibit non-linear characteristics, for instance, due to multiple amendments in survey designs. Therefore, I also test first-order non-linear country-time trends in the robustness section of this paper. Moreover, I test the possibility of region-time trends. However, given that my degrees of freedom are essentially zero in such a model setup, I abstain from using it as my main model - also bearing in mind the high risk of overidentifying the model (Wooldridge, 2010).

[41]See Arellano and Bond (1991), Blundell and Bond (1998), and Roodman (2009).

cess effectively removes time-invariant region-specific factors, methodologically akin to the baseline fixed-effects model I employ. Furthermore, it tackles endogeneity using an instrumental variable (IV) approach by employing longer lags of the dependent variable as instruments for lags of higher order. As a *Generalized Method of Moments* (GMM) estimator, it is more efficient than standard IV estimators and other models in the class of dynamic panel data estimators. And despite the endogenous nature of having the dependent variable (lagged) on both sides of the equation it can be shown to be consistent, also in terms of heteroscedasticity (see Roodman, 2009). However, this class of models is very sensitive, even with regard to the smallest changes in the methodological setup. I therefore only use the model to verify the results of my fixed-effects estimates. As an alternative remedy, I test the robustness of my main results against the heteroskedasticity- and autocorrelation-consistent Newey-West estimator (Newey and West, 1987).

4.5 Data sample

My data sample includes all EU15 regions that maintain statutory MWs throughout the entire 2003-2019 sample period, and for which I have adequate data on my mobility rates sourced from the EU LFS. This leaves me with the NUTS-2 regions of Belgium, Greece, Spain, France, Portugal and the UK. As of 2019, the final year of my sample, the six countries account for slightly more than 52 percent of the entire EU15 population. Unfortunately, however, in some countries across various years, the EU LFS lacks information on an individual's residence 365 days ago. In my sample, this pertains to France (no such information has been reported for the years 2003-2005) and the UK (in 2004 and 2008). Additionally, this issue extends to specific regions in France, Greece, and Spain during certain years, contributing to the unbalanced nature of my panel data set for analysis. Moreover, I refrain from including the French overseas territories, the Greek island regions (except for Crete), the Spanish exclaves of Ceuta and Melilla, and the Portuguese island regions of Acores and Madeira in my analysis. All these regions possess distinctive territorial statuses within their respective countries' legislative frameworks. These statuses result in unique attributes of the local labor markets, including constrained labor mobility and exemptions from statutory MW laws. Finally, there is missing data on the mean compensation of employees and for some covariates for specific regions and years (mainly affecting the UK).

My dependent variable is derived from EU LFS data, which is based on a survey conducted on a population sample. Consequently, potential measurement issues associated with the LFS methodology, coupled with my specific calculation approach, add layers of complexity to this variable. Overall, my derived labor inflow figures closely mirror previous findings in the literature (refer to section 2 and the summary statistics reported in table A3 in the appendix). Yet, certain regions, particularly in Belgium and Greece, exhibit remarkably high labor inflow rates for specific years, a pattern unexpected and unexplained.[42] I adopt the approach outlined by Aggarwal

[42]Especially notable are the Athens metropolitan area of Attica in Greece (EL30), and the Flemish Brabant and Walloon Brabant areas of Belgium (BE24 and BE31), which encircle the Brussels capital region. These three regions contribute to 7 out of the top 10 highest labor inflow rates in my data set, including the three highest values.

(2017) and explore various methods commonly applied in outlier analysis, aiming to assess the severity of the outliers and explore potential remedies.

First, I seek to verify the estimated values of the abnormal observations with other data sources. Specifically, I compare my labor inflow estimates with Eurostat-published net migration rates (refer to section 2). However, I encounter difficulty in validating the accuracy of the extreme percentiles in my sample — the top and lowest 1 percent of values. The correlation with Eurostat's net migration rates is notably weak for these values, yielding a calculated correlation coefficient of around 0.19. Following up, an extreme-value analysis using Tukey fences reveals several *far out* outliers, i.e. values significantly distant from the range statistically to be expected given the overall sample distribution (refer to figure A5 in the appendix). In line with this finding, the Kurtosis measure on the full data set exhibits a highly leptokurtic value exceeding 14.[43] To address these abnormal outliers, I trim my sample by excluding both the highest and lowest 1 percent of values, aiming to preserve the distribution's skewness as much as possible. The trimmed sample demonstrates a value range that is less than half the original. Its Kurtosis measure is approximately 4.6, marking a reduction to less than one third of the previous value. For a visual representation of the samples, my outlier analysis and the adopted measure to trim it, refer to the two *Tukey* box-plots in the appendix (figures A5 and A6).

In table 2, I outline my final (*trimmed*) data sample for analysis. For each country, the table lists the number of regions a country consists of, the potential number of observations (derived by multiplying the number of regions by 17, representing the years covered in my sampling strategy), and the actual number of observations. Moreover, the table details the reasons for missing data entries, whether due to missing information in the underlying LFS data, missing covariates, or as a result of my trimming approach.

Table 2: Final data sample

	# of Regions	# of potential observations	# of actual observations	# of missings (LFS)	# of missings (covariates)	# of missings (trimming)	# of missings (total)	missing quota (total)
Belgium	11	187	167	0	11	9	20	0.107
Greece	10	170	114	44	0	12	56	0.329
Spain	17	289	245	42	0	2	44	0.152
France	22	374	271	77	26	0	103	0.275
Portugal	5	85	84	0	1	0	1	0.012
UK	38	646	339	83	224	0	307	0.475
Total	103	1,751	1,220	246	262	23	531	0.303

Note: Number of potential observations is the number of regions times complete sampling period in years (2003-2019, i.e., 17 years). Missings due LFS signify suppressed information regarding an individual's region of residence 365 days ago within the LFS data set. Missings in covariates pertain to absent data in the respective underlying data sets.

The final data sample comprises 103 NUTS-2 regions, totaling 1,220 observations. As noted earlier, the data is unbalanced, with the percentage of missing data varying significantly across countries. Portugal has the lowest missing quota at 1.2 percent, while the UK exhibits the highest at 47.5 percent. France and Greece also show relatively high missing quotas, surpassing 25 percent of potential observations. Notably, missing data patterns differ among countries. Belgium and Greece are particularly impacted by the trimming procedure. The availability of observations

[43] In such instances, Dixon's Q test would be preferable for outlier detection and as a criterion for their removal. However, it is unsuitable for unbalanced panel data (Aggarwal, 2017).

in Greece, Spain, France, and the UK is affected by suppressed information within the LFS data. France lacks data for the complete LFS years 2003-2005, while the UK has complete data gaps for 2004 and 2008. In the case of the UK, moreover, the high missing data rate is also due to the complete absence of compensation of employees data (required for constructing the main variable, the Kaitz index) for the country's 152 observations in the last four years of the sampling period (coinciding with the period after the Brexit vote, which would have presented analytical challenges anyhow). Moreover, akin to Belgium and France, the UK has 6-7 percent of missing data attributed to gaps in covariate information. Appendix tables A2 and A3 present summary statistics at the regional and country levels, respectively, for my final data sample.

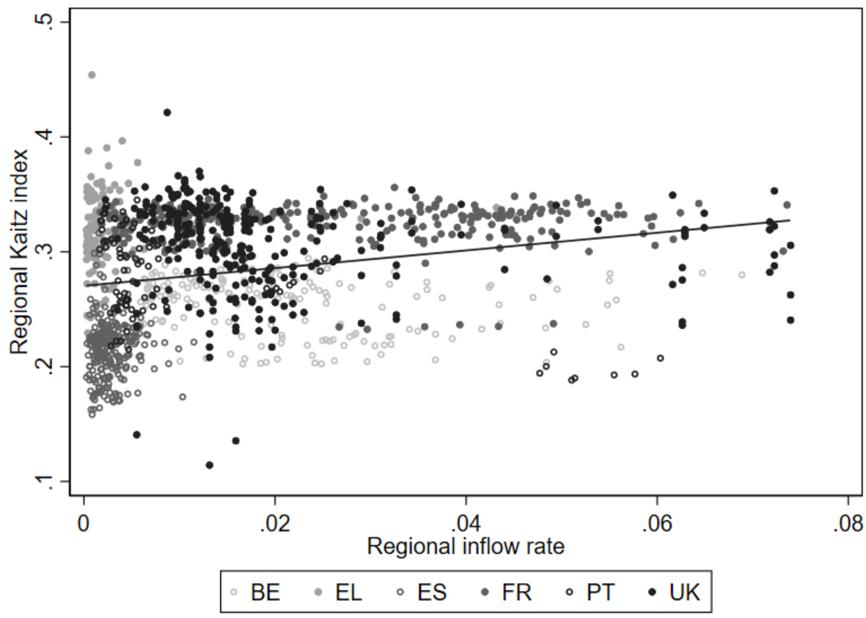
5 Results

The results section begins with descriptive observations from the data, providing an initial overview. It then proceeds to outline the main findings derived from both the fixed effects and AB models. Following this, the analysis tests the resilience of these results against alternative model specifications. Finally, it explores heterogeneous effects among various subgroups, enhancing the depth of the conclusions drawn.

5.1 Descriptive evidence

The introduction of my analysis involves presenting general observations drawn from the data, specifically focusing on the correlation between regional labor inflows and their corresponding Kaitz index scores. Figure 5 presents a simple scatter plot that visualizes the relationship between these two measures.

Figure 5: Scatter plot of regional labor inflow rates versus Kaitz index



Note: The graph plots regional labor inflow rates against the local Kaitz index, with distinct designs and colors representing the respective country where each region is situated. The line represents a linear fit of the data.

The graph displays a positive relationship between a region's inflow rate and its Kaitz index score, which is accentuated by the added linear fit regression line. However, although a visual correlation is evident for the full sample of countries, it notably disappears when analyzed on a country-by-country basis. The graph distinctly emphasizes diverse patterns among countries. France demonstrates relatively high variability in inflow rates but comparatively lower variability in the Kaitz index. Conversely, Greece and Spain exhibit more consistent inflow rates but greater fluctuations in Kaitz index scores. Portugal stands out with a seemingly downward-sloping relationship between the Kaitz index value and labor inflow rate. Notably, Portugal displays three distinct observation clusters: one with high inflow rates and Kaitz values around 20 percent, another with moderate inflow rates aligned with sample-mean Kaitz values, and a third exhibiting low inflow rates along with the highest relative variation in Kaitz scores. Belgium's observations, and even more so, the UK's, appear dispersed across all aspects (yet still implying a positive correlation between the variables).

The overall pattern of a positive relationship between a region's labor inflow rate and its Kaitz index score is also evident when examining a simple correlation table (see in the appendix, table A4). Alongside the positive correlation with the Kaitz index, the labor inflow rate demonstrates positive correlations with GDP per capita and the youth employment rate, while displaying a negative correlation with the general unemployment rate. Interestingly, the Kaitz index exhibits negative correlations with all covariates except for the youth employment rate, to which it correlates positively. Considering that the Kaitz index is typically lower in urban areas — where population, GDP per capita, unemployment rates, and the proportion of foreigners tend to be higher, and youth employment tends to be lower — all the indicated correlations are comprehensible.

5.2 Main result

Section 4 detailed the rationale behind my empirical approach and emphasized the baseline model, defined by equation 2. Table 3 showcases the results of this fixed effects-estimated model. The initial model variant in the table features the baseline model without any covariates. The subsequent model represents the baseline specification with an integration of the comprehensive set of covariates. Additionally, the table demonstrates variations of the baseline specification where the primary variable of interest, the Kaitz index, is lagged by two or three years, deviating from the one-year lag featured in the baseline model.

The outcome of the model without any covariates replicates the result from the (visual) analysis of the scatter plot in figure 5: It suggests a generally positive relationship between the Kaitz index and the regional labor inflow rate of low-skilled workers (significantly estimated at the 5 percent significance level). My baseline model in column (2) confirms this overall pattern in the data: The estimated coefficient for the Kaitz index is 0.029. It is highly significant at the 1 percent level. This main finding suggests that a 1 percent increase in the Kaitz index is associated with a 0.029 percentage point higher labor inflow rate to a given region in my sample, keeping all else equal. This is a sizeable result: The mean level of the Kaitz index in my sample is about 28.2 percent. The mean regional labor inflow rate of low-skilled workers is about 1.6 percent. At the mean, a one-percent increase in the Kaitz

Table 3: Main results - FE model

VARIABLES	(1) FE without covariates	(2) FE with covariates	(3) (2) with Kaitz (lag 2y.)	(4) (2) with Kaitz (lag 3y.)
ln Kaitz (lag 1y.)	0.015**	0.029***		
	(0.006)	(0.006)		
ln Kaitz (lag 2y.)			0.030***	
			(0.006)	
ln Kaitz (lag 3y.)				0.036**
				(0.014)
Constant	-1.155***	-0.695	1.564***	-0.798
	(0.261)	(0.482)	(0.496)	(0.531)
# of observations	1220	1220	1125	1093
Within R2	0.489	0.517	0.500	0.547
Between R2	0.271	0.188	0.120	0.079
Covariates	NO	YES	YES	YES
Year FE	YES	YES	YES	YES
Country-year trend	YES	YES	YES	YES

Note: The dependent variable is the regional inflow rate of low-skilled individuals. Covariates are the population count, GDP per capita, unemployment rate, youth employment rate, and share of foreigners. Covariates estimates are not shown here, a full estimation table is available from the appendix (table A5). The Kaitz index and all covariates are transformed to logarithm. All covariates lagged by one year, the share of foreigners by three years. All models include year fixed effects and country-time trends. Standard errors clustered at the regional level are depicted in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(a 0.282 percentage point index increase) thus corresponds to an increase in the local labor inflow rate of the low-skilled from 1.6 percent to 1.629 percent - which corresponds to an estimated elasticity of roughly 0.18.

To put this result into perspective, I examine the 4.1 percent increase in the national MW in Portugal in 2015, when the nominal MW changed from 2.92 EUR to 3.04 EUR per hour. Portugal's mean Kaitz index score closely aligns with the overall sample mean Kaitz, and the mean MW change in my sample is roughly 4.3 percent, which makes this example illustrative. The MW increase corresponded to an elevation in the country's mean regional Kaitz index from about 28.7 to 29.8, i.e., implying a Kaitz index increase of 3.8 percent.[44] As per the identified relationship between the Kaitz index and local labor inflow rates, the fixed effects model predicts that this increase should have led to an approximately 0.11 percentage point higher average labor inflow rate across the regions in Portugal. Consistent with this prediction, the average regional labor inflow rate in Portugal increased from 0.40 percent in 2014 to 0.54 percent in 2015.

Table 3 additionally includes model variations where the Kaitz index is lagged by two and three years, respectively, aimed at bolstering the proposed direction of causality and verifying the credibility of my results. In both models, the coefficient estimates for the Kaitz index remain consistent with the baseline specification, re-

[44]Spillover effects of MW amendments to the Kaitz index are constrained to be ≤ 1, as the amendment also affects the Kaitz index' denominator (the mean employee compensation). One may be skeptical that MW increases are the actual drivers of the variation in the Kaitz index in my data, though. It could also be changes in the compensation of employees, for reasons unrelated to the MW, that mainly affect the developments of the Kaitz index. Calculating the Pearson correlation coefficient between the Kaitz index and its components, the nominal MW level, and the mean compensation of employees in an area, reveals that the MW is substantially higher correlated ($\rho \approx +0.45$) than the compensation measure ($\rho \approx -0.03$) with the Kaitz index.

inforcing its reliability. However, the coefficient estimate for the three-year lag is relatively less precise, likely due to increased noise in the estimation process, compromising its accuracy. Nonetheless, the overall findings from both models support the suggested direction of causality.

5.3 Robustness

As outlined in the empirical section, it is crucial to consider potential methodological limitations that may restrict my findings in several ways. Endogeneity, such as the potential impact of reverse causality on result interpretation, cannot be disregarded, and perfect exogeneity of regressors cannot be guaranteed. Moreover, the region-specific nature of labor market responses to changes in MWs and the Kaitz index may result in correlated residuals within regions. Additionally, labor mobility patterns might exhibit trends, leading to a dynamic setting with underlying autocorrelation. A fixed effects model could potentially be susceptible to bias and inefficiencies stemming from the identified methodological issues. The following tests are intended to verify the robustness of my baseline results.

Arellano-Bond dynamic panel estimator

My main approach to test the robustness of the baseline results is the Arellano Bond estimator. It addresses several potential sources of endogeneity in my setting; adjusting for potential underlying dynamic processes (autocorrelation), and integrating instrumental variables to mitigate biases from the correlation of regressors with the error terms, thereby establishing a quasi-causal relationship. However, the AB model's complexity and sensitivity emphasize the critical need for accurate model specification: I essentially replicate the fixed effects model configuration by employing an identical set of variables (including time dummies and country-year trends). In my AB model estimations, the majority of covariates are considered strictly exogenous.[45] Only the Kaitz index and the lag of the labor inflow rate are categorized as (potentially) endogenous. For this purpose, I apply the one-step system GMM estimation, assuming that my orthogonality-adjusted instruments are uncorrelated with the fixed effects (Arellano and Bover, 1995, Blundell and Bond, 1998).[46] To address instrument proliferation (which is particularly pertinent in system GMM-estimated AB models), I restrict the number of lags used as instruments for the endogenous regressors to be strictly between 2 and 5. This approach avoids problems associated with overfitting the endogenous variables.[47] As with the fixed effects model, I cluster standard errors at the regional level (Arellano and Bond, 1991, Blundell and Bond, 1998, Roodman, 2009). The first column of table 4 repli-

[45]This contrasts somewhat with my earlier discussion regarding control variables as a potential source of endogeneity; however, it substantially simplifies the model (which is crucial for demonstrating my fixed effects model's robustness) and reduces the number of instruments.

[46]Rather than employing first-differencing by subtracting the previous observation from the contemporaneous one, I apply forward orthogonal deviations (as recommended by Roodman (2009) when dealing with unbalanced panel data). This involves subtracting the average of all future available observations of a variable.

[47]The discussion in Roodman (2009, pp. 98) aids determining an appropriate number of lags utilized as instruments. Upon reducing the number of lags further, I find my results remain largely unchanged.

cates the results from my baseline fixed effects model (as reference). The second column provides the outcome from the AB model.

Table 4: Baseline model versus Arellano Bond

	(1) FE model	(2) AB model	(3) Newey-West estimator
ln Kaitz (lag 1y.)	0.029***	0.026**	0.029***
	(0.006)	(0.013)	(0.008)
Labor inflow rate (lag 1y.)		0.157***	
		(0.053)	
Constant	-0.695	-0.044	-6.151***
	(0.482)	(0.037)	(0.620)
N	1220	1220	1220
R^2	0.517		0.710
# of instruments		165	
Sargan statistic		620.906	
Sargan p-value		0.000	
Hansen J statistic		101.529	
Hansen p-value		0.988	
AR1		-5.095	
AR1 p-value		0.000	
AR2		-0.558	
AR2 p-value		0.577	

Note: The dependent variable is the regional inflow rate of low-skilled individuals. Column (1) reports the results of the baseline FE model, column (2) of the AB model, column (3) of the baseline FE model that additionally includes the lagged dependent variable. Standard errors clustered at the regional level are depicted in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The AB model confirms the outcomes observed in the baseline fixed effects model. It bolsters confidence in the presumed causal link, suggesting that rises in minimum wages lead to increased labor inflow rates among low-skilled workers in a region. The magnitude of the estimated coefficient for the Kaitz index is in line with my baseline estimate. Yet, it is less precisely estimated. Both the Sargan and the Hansen J statistics indicate no overidentification by the number of 165 instruments used in the model.[48] Including the lagged dependent variable as a regressor further exposes an inherent dynamic relationship within the data. The respective coefficient is estimated as highly significant, demonstrating a relatively large positive magnitude (which is consistent across several alternative model specifications not displayed here). The observed autocorrelation is primarily of first-order; the test for second-order autocorrelation is rejected.

Incorporating dynamic processes, as identified with the AB model, into fixed effects models presents methodological challenges, though. In particular, lagged values of the dependent variable are correlated with the error term in such a setting, which violates the Gauss-Markov theorem (Nickell, 1981). To gauge the potential impact of omitted dynamic processes in my baseline fixed effects model, I draw on the Newey-West estimator (Newey and West, 1987), which adjusts estimates for

[48] The Hansen J statistic comes with a very high p-value, though. Upon reducing the number of lags further, I find my results remain largely consistent while decreasing the Hansen p-value substantially.

autocorrelation and heteroscedasticity in the error terms. I estimate an OLS model with region-fixed effects using the Newey-West method, everything else alike my baseline fixed effects model. The outcomes of this analysis is detailed in column (3), aligning with the earlier models presented in the table and thus affirming the consistency of my overall findings (even in the potential presence of dynamic processes underlying in the data). From this exercise I conclude that the induced bias by dynamic processes, if indeed existing and relevant, is not severely affecting my baseline estimates.

Reverse causality and placebo tests

The analysis of both the lag structure (as depicted in table 3) and the findings from the AB model (as presented in table 4) concurred in supporting the existence of the proposed causal direction within the identified relationship between Kaitz index changes and labor mobility. To reinforce the causality argument further, I proceeded with several supplementary tests. First, I examine the potential presence of reverse causality within my context by conducting two additional model variations where I reverse the roles of the dependent and main independent variable. I explore two distinct lag structures of the regional labor inflow rate to elucidate its influence on current realizations of the Kaitz index: one with no lag and another with a one-year lagged inflow rate. The respective outcomes of these analyses are detailed in table A6 in the appendix. Notably, the labor inflow rate does not demonstrate statistical significance in explaining the regional Kaitz index in either of the proposed settings - indicating further support for the presumed direction of causality.

Alternatively, I run a placebo test. The MW is likely pertinent primarily to those directly affected by it, or earning wages relatively close to the MW (see also section 3). MW amendments should be rather irrelevant for mobility decisions of high earners. Unfortunately, the EU LFS lacks specific information on the surveyed workers' actual income levels. Nevertheless, higher skill levels typically align with higher wages, and vice versa. The LFS does allow for accurate screening of individuals' skill levels, a feature I use for the following exercise. Table 5 presents the results of a placebo test, of a model using the regional inflow rate of *high-skilled* workers as the dependent variable, contrasting with the usual focus on low-skilled workers. Due to its theoretical irrelevance, the estimated coefficient of the Kaitz index on high-skilled workers' mobility rates should be negligibly small or insignificant.

As evident from column (2) in the table, the coefficient on the Kaitz index is, as expected, insignificant: I fail to detect a statistically significant relationship between the local Kaitz index score and the labor inflow rate of high-skilled workers to a region. The standard error of the estimated coefficient is even larger than the coefficient itself. Note, however, that the number of observations is substantially lower for this sample compared to my baseline result, attributable to a considerable reduction in the domain size when focusing solely on high-skilled workers with recent mobility backgrounds (of which only relatively few exist in the data). Accordingly, the results from this model cannot be compared directly to the reference model presented in column (1). In order to rule out that there are sample composition effects that drive this result, I re-run my baseline model, but restrict it to the sample underlying the model in column (2). This model variation is reported in column (3). I still find a robust result of somewhat comparable magnitude to the

Table 5: Placebo test: High-skilled individuals

	(1) FE (baseline)	(2) (1) for high-skilled only	(3) Model (1) for the sample used in (2)
ln Kaitz (lag 1y.)	0.029***	0.095	0.038**
	(0.006)	(0.112)	(0.016)
Constant	-0.695	2.286	-1.433
	(0.482)	(3.059)	(0.944)
# of observations	1220	545	545
Within R2	0.517	0.105	0.682
Between R2	0.188	0.001	0.300
Covariates	YES	YES	YES
Year FE	YES	YES	YES
Country-year trend	YES	YES	YES

Note: The dependent variable is the regional inflow rate of low-skilled individuals in columns (1) and (3). In column (2), the dependent variable is the regional inflow rate of high-skilled individuals. The model in column (3) differs from (1) in the way that it applies the main model only to the sub-sample used in model (2). All other model specifications are as in table 3. Standard errors clustered at the regional level are depicted in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

original baseline model in column (1), but with a slightly increased p-value (which is plausible given the massively reduced sample size). In essence, the placebo test strongly supports the proposed causal mechanism behind my baseline result.

Other robustness tests

I run several further robustness tests to fortify the reliability of the findings and to check for the credibility of my estimates. First, I check my model against the importance of single countries for my overall outcome. While the sample sizes of the individual countries are too small to be estimated separately, I estimate my model by excluding each country one-at-a-time, i.e., I estimate a so called leave-one-out (L1O) approach. I report the results in table A7 in the appendix; none of the countries is dominant in explaining my overall result, and any country of my sample may be dropped without significantly changing the basic result - that increases in the Kaitz index seem to attract inward low-skilled labor mobility at the regional level.

Moreover, and methodologically somehow similar, I run a Jackknife resampling estimation (testing the importance of single regions), and also use bootstrapping (employing 1000 replications) to check the stability of the results. Both these exercises yield results in line with my baseline finding. Expanding the scope of assessment, I further evaluated my baseline findings by adjusting for *region-time trends* rather than country-time trends. While this alternate approach might seem preferable initially, it also takes away all the degrees of freedom in my model. Thus, it excludes the possibility of various statistical testing against my models, such as assessing the overall significance of the model. Notwithstanding this drawback, the model including region-time trends yields similar coefficient estimates - both in terms of magnitude and significance - to those in my baseline model. Finally, I scrutinize the nature of the country-time trends utilized in my analysis. Given variations in the LFS sampling design across different periods within certain countries, there's a possibility of time-varying impacts on the estimates. To address this, I implement a model incorporating first-order non-linear country-time trends. This adjustment aims to account for any potential time-varying effects at the country level, impacting all regions within a country. Once more, this test results in a robust estimate, akin to the findings derived from the baseline model. All the robustness tests mentioned are accessible in the appendix, specifically detailed in table A8.

5.4 Heterogenous effects

[*Some short intro text...*]

Heterogenous effects across countries

Figure 5 visually highlighted potential variations in the relationship between the Kaitz index and regional inflow rates across countries. To delve into this aspect more comprehensively, I enhance my model by introducing an interaction term between the primary variable of interest, the Kaitz index, and a categorical variable identifying the country in which a region is located. This modification allows me to capture and report the distinct relationship between the Kaitz index and the labor inflow rate for each country within my sample.[49] The corresponding results are available from the appendix, table A9.

The outcomes from this exercise highlight substantial heterogeneity across the countries in my sample. I detect variation in both magnitude and significance levels. The estimated coefficient magnitudes reach up to five times higher than the mean estimate identified in the baseline specification (reiterated in column (1) of the table for easy comparison). Belgium shows the largest country-specific coefficient in my sample with an estimated coefficient magnitude of 0.153, followed by France at 0.082 and Portugal at 0.056. All these three coefficients are significant, albeit not highly significant (having p-values of around 1-7 percent each). The UK's coefficient of 0.034 aligns closest with the baseline model's estimate, showing high significance at the 1 percent level. In contrast, Greece and Spain's coefficients do not demonstrate any significant coefficient estimates.

The significant coefficient for Belgium is likely influenced by the interplay of substantial economic imbalances across its regions over time, the uniform MW throughout the country, and notable regional differences in labor mobility. The scatter plot in Figure 5 visually supports this interpretation. The substantially higher economic power per capita of Flanders and in the Brussels capital region may result in relatively smaller local Kaitz index fluctuations in response to national MW changes. Meanwhile, the southern regions of Wallonia historically exhibit larger labor mobility rates and variations, among the highest in Europe.[50] Similarly, the notable effects detected for France and Portugal may be influenced by the considerable differences in the costs of living, mean employee compensations, and consequently, the

[49] Given the limited number of observations, it is not practical to sample and analyze individual countries separately, as this would compromise the statistical reliability of the results.

[50] There exists substantial cross-border labor mobility in the area, in particular with France and Luxembourg. The European Employment Service, EURES, provides an overview on the diverse local labor market features of the Belgian regions: https://eures.europa.eu/living-and-working/labour-market-information/labour-market-information-belgium_en (last accessed: 12.12.2023).

Kaitz index, between urban agglomeration regions (especially the capital regions) and other regions in the countries. This is further compounded by uniform domestic MW policies. Considering the appeal of urban centers to many individuals, even slight alterations in relative affordability can result in significantly increased labor inflows (Harris and Todaro, 1970), a phenomenon that may be evident in this context. Spain and Greece exhibit the lowest average labor inflow rates in my sample (see table A3). In both these countries, people place a higher cultural value on family ties compared to other regions in Europe. Even in the presence of financial incentives (such as MWs), individuals have been found to be less inclined to relocate from their local communities (Alesina et al., 2015).

Heterogenous effects in population density, citizenship, and domestic mobility

If my theoretical rationale for cross-country variations holds, I anticipate substantial differences between rural and urban areas in my dataset. More specifically, owing to the higher mean compensation levels in urban areas, greater adjustments in the MW are necessary to induce Kaitz shifts of similar magnitude — implying that similar-sized shifts in the Kaitz should lead to more substantial mobility responses (if my argument holds). To explore this hypothesis, I divide my sample into areas with higher and with lower population density, and estimate these subsets separately. Additionally, section 2 demonstrated that the countries in my sample have historically encountered diverse migration legacies, evident in their varying stocks of foreigners, net migration rates, and intensities of worker inflows from abroad. I assess the significance of these patterns in two ways: First, by exploring the distinct mobility responsiveness exclusively of natives[51]; and second, by evaluating whether restricting my mobility measure to domestic mobility yields different results. I report the respective results in table A10 (in the appendix).

The first exercise reveals that the estimated coefficient magnitude of 0.034 for urban areas surpasses the baseline estimate and is higher than the estimated coefficient for rural areas, which shows a coefficient estimate of 0.018.[52] Though these estimates appear to suggest that MWs indeed hold relatively greater appeal in urban areas, they are not statistically significantly different from each other, in part due to the reduced numbers of observations in this setting. The evidence is thus limited; nonetheless, the finding lends some indicative support for the earlier argument concerning cross-country heterogeneity.

Furthermore, the analysis presented in table A10 reveals that a sample comprising only natives (of the respective country) produces results roughly comparable to the baseline scenario estimates, with a highly significant coefficient estimate of 0.025. Considering that approximately 90 percent of mobile workers in my sample are natives, and that the slightly higher baseline estimate represents an average score of both natives and EU mobile citizens, I speculate that EU mobile citizens exhibit a relatively higher responsiveness to MWs than natives. This interpretation gains some further support when examining the relationship between the Kaitz index and domestic labor mobility: the corresponding estimated coefficient is esti-

[51]Unfortunately, the LFS's limited domain size for testing exclusively EU citizens (except for natives) prevents independent analysis.

[52]The mean Kaitz index values and the mean labor inflow rates in both urban and rural subsamples closely align with those in the baseline setting.

mated smaller than the baseline, standing at 0.020, though not significantly different to the baseline. As mentioned earlier, about 12.5 percent of mobility in my sample involves crossing borders. Consequently, if domestic mobility is associated with relatively less responsiveness to MWs, cross-border mobility (which typically also encompasses more EU mobile citizens than natives) likely exhibits relatively greater responsiveness to MWs. These interpretations also aligns with earlier findings in the literature, suggesting migrant workers exhibiting higher mobility and are less restricted in their choice of locations (see section 3), though in my data these findings lack statistical precision.

Heterogenous effects across sex and age

The influence of MWs on labor inflow rates may vary between males and females - not only due to distinct average characteristics of male versus female workers (for instance, in terms of education) but also due to heterogeneous mobility patterns exhibited by each sex. Similarly, age may play a significant role in shaping the examined relationship: It has been observed that both inter-regional and cross-border mobility tend to be more prevalent among younger individuals compared to the overall population in the EU (e.g., Eurofound, 2014, European Commission, 2022). Furthermore, a considerable body of literature focuses on investigating the labor market impacts of MWs by specifically studying young workers and teenagers. This demographic is presumed to be most affected by MWs due to their inherently lower levels of education (also refer to the closely related arguments regarding my selection of covariates in section 4). I explore potential heterogeneity by using different sets of dependent variables under my main specification - specifically focusing on the labor inflow rates of females, of males, and of individuals aged 27 years or younger. Table A11 reports the corresponding results.

From this analysis, I observe only marginal differences between low-skilled male and female workers; no statistically significant variations are apparent. The results for both sexes closely align with those discovered in my baseline model. In contrast, young low-skilled workers appear having a higher responsiveness to MWs: A 1 percent increase in the Kaitz index is estimated to correspond with a 0.47 percentage point increase in the labor inflow rate to a region for young individuals — a coefficient magnitude approximately 50 percent higher than the one derived from my baseline specification. However, given the elevated standard error combined with the lower number of observations in this specification, the coefficient estimate is statistically not significantly different than the baseline result.[53]

6 Conclusion

Numerous studies have examined the impact of MWs on local labor markets. By altering entrance level wages and job market prospects, MWs potentially affect the attractiveness of regions to outsiders, particularly for low-skilled workers. Consequently, changes in MWs may influence regional labor mobility. The EU presents

[53] It is important to reiterate that estimating subgroups of the population with my data may be susceptible to domain size problems. In practical terms, this leads to a reduction in the number of observations relative to the baseline model in this instance.

a particularly intriguing case due to the freedom of movement of workers across the union, the significant diversity in domestic institutional settings, and substantial regional differences in economic fundamentals, labor market settings, customs, industry and workforce compositions, and various other factors that are crucial for the local impact of MWs. The study of MWs in the EU recently gained increased attention when EU directive 2022/2041 was passed, calling for adequate MWs in all member states by 2025. Currently, less than half of the member countries meet this demand. Therefore, the directive can be anticipated to generate significant dynamics in European MW policies in the near future. Changes in labor mobility may be an unintended consequence.

In this work, I studied the impact of MW changes on regional labor mobility across NUTS-2 regions in the EU. Specifically, I analysed the impact of changes in the Kaitz index, defined as the MW relative to the mean local compensation of employees, acknowledging the varying local relevance of MWs. For my analysis, I obtained cross-country harmonized regional mobility figures from the EU LFS; my dependent variable being the relative number of low-skilled workers who relocated to this region in the last 365 days. My baseline fixed effects model demonstrates a significant association between the Kaitz index and regional labor mobility in the EU. In my sample, a one percent increase in the Kaitz index corresponds to a 0.03 percentage point higher regional inflow rate of low-skilled EU citizens. While this correlation may seem modest, it holds significance - the result implies an elasticity of approximately 0.18; at the mean, a one percent change in the Kaitz index relates to a labor inflow rate change of about 0.18 percent. This main result has proven robust across various alternative model specifications and robustness tests. Furthermore, an AB dynamic GMM panel estimator, along with multiple other tests, provided additional support for the identified relationship being causal.

Heterogeneity analysis uncovered significant cross-country variations in the observed relationship. For Belgium, France, Portugal, and UK regions I find coefficient estimates on the Kaitz index higher than in my baseline estimation, while I did not identify any discernible relationship for Spain and Greece. This variation is likely tied to substantial regional heterogeneity in terms of Kaitz index and labor mobility rates within the countries of the first group, coupled with culturally driven constraints on spatial mobility in Spain and Greece. Additional analyses provide some support for this argument. Furthermore, there are indications that natives may be relatively less responsive in their spatial mobility behavior compared to EU mobile citizens, although the statistical precision is insufficient to draw conclusive answers. An examination of potentially varying impacts between sexes showed no differences among male and female low-skilled workers. Interestingly, there is some indication that young individuals may be more responsive to alterations in the Kaitz index.

Hence, my paper suggests that EU directive 2022/2041 may have unintended effects: An EU-wide increase of MWs may redirect low-skilled labor mobility flows away from those regions with already established adequate MWs, and towards regions with previously inadequate MWs. The relative attractiveness of increased MWs will be the highest, where these 'bite' the most - where they most substantially affect the local labor force in terms of relevance. [*to be cont.*]

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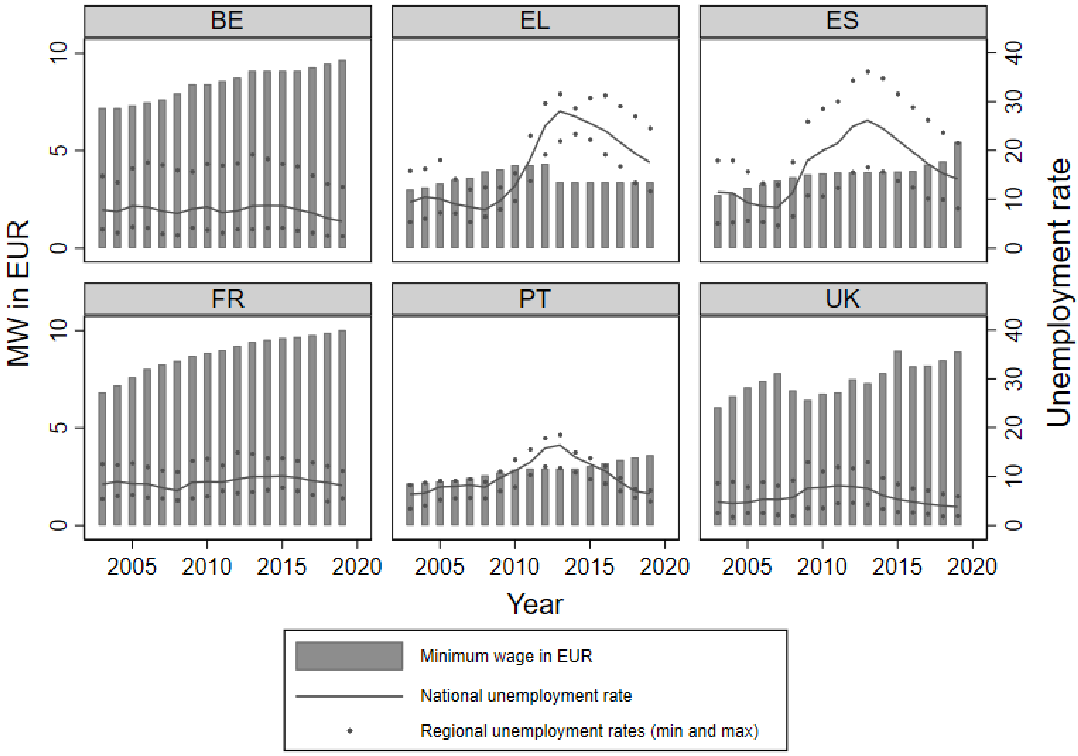
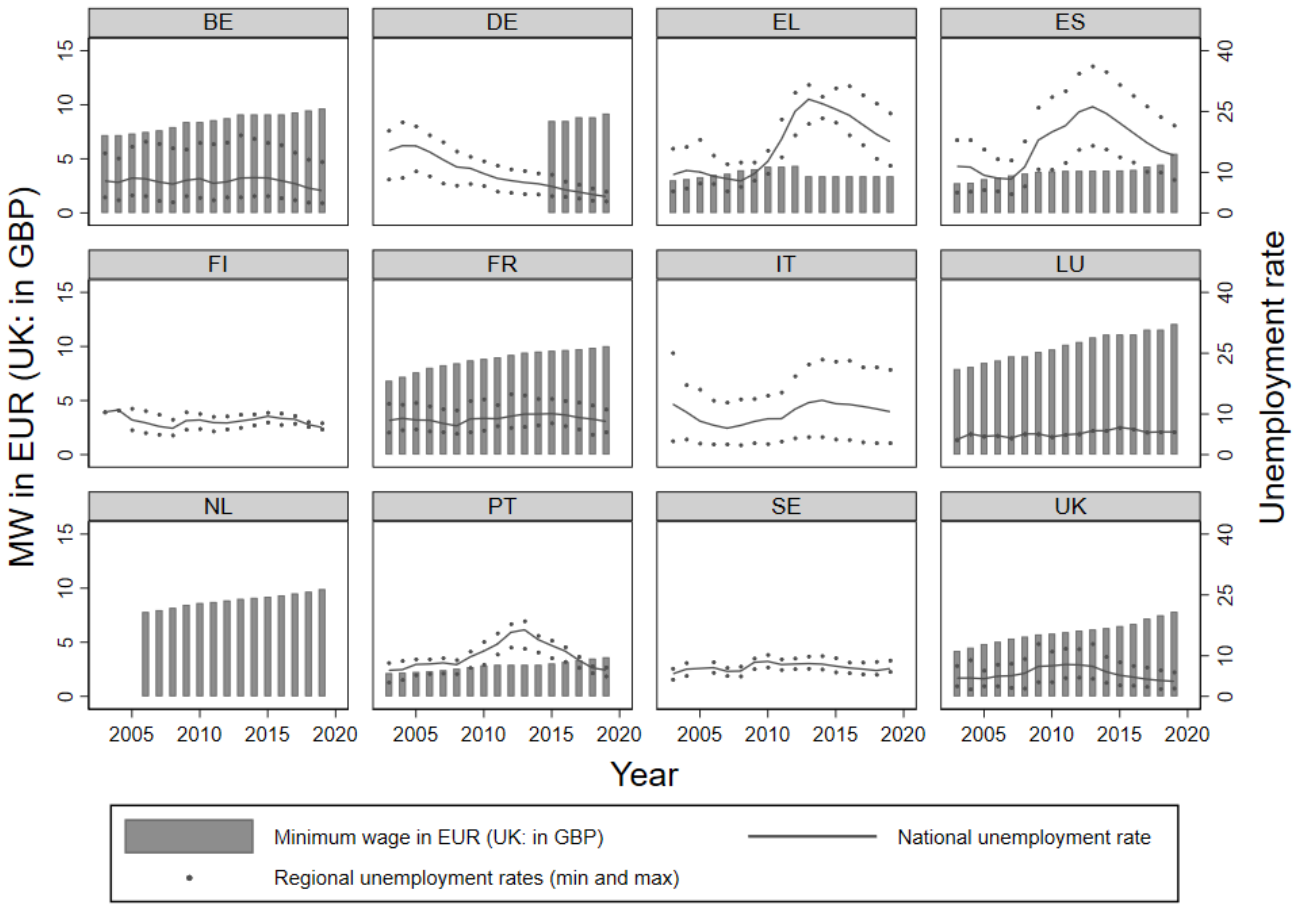
Appendix

Figure A1: EUR-denominated nominal MWs and unemployment rates



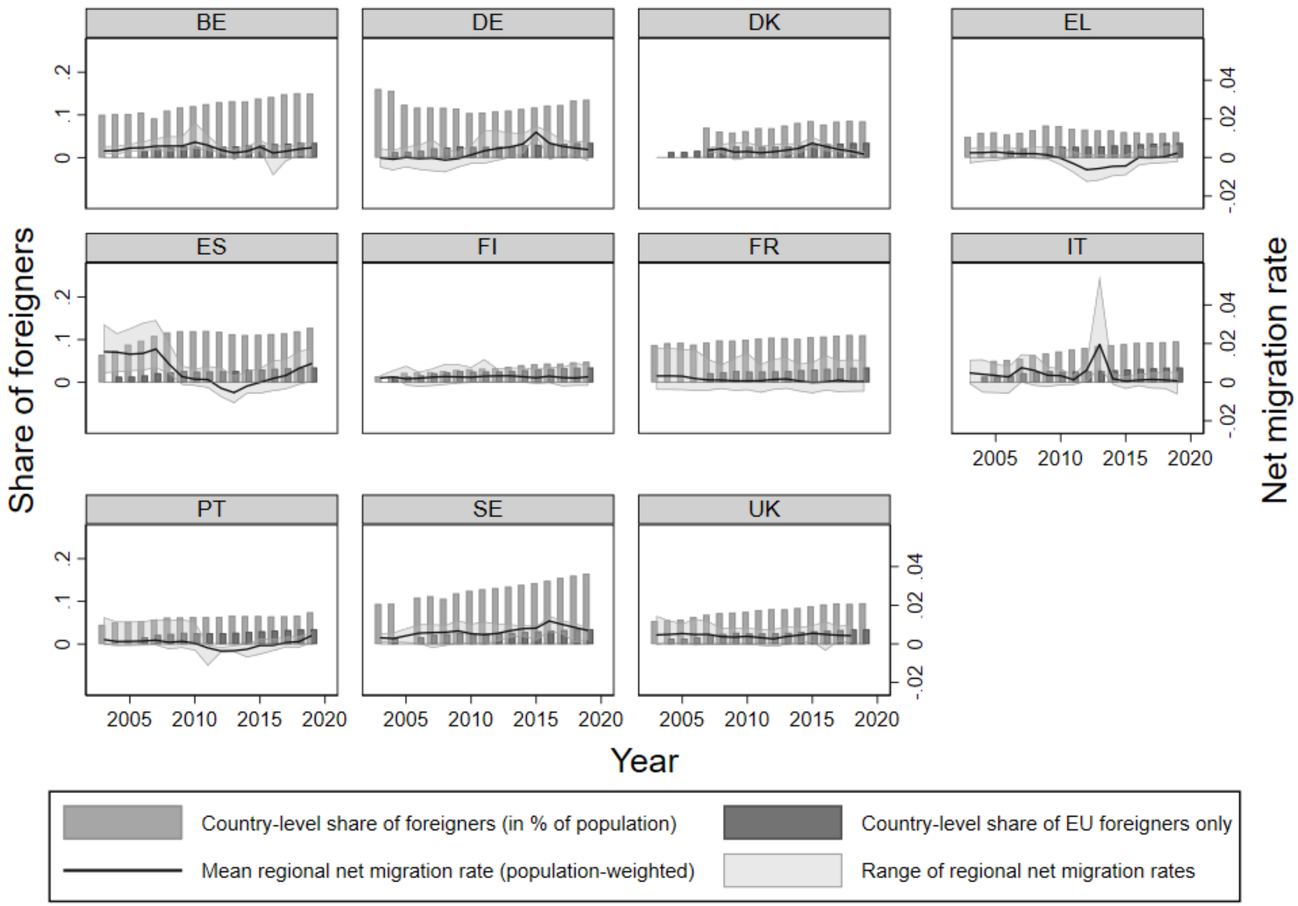
Note: Same graph as depicted in Figure 2, with the exception that the UK MW is presented in EUR-denominated terms (reflecting exchange rate fluctuations).

Figure A2: EU-15: MWs and unemployment rates



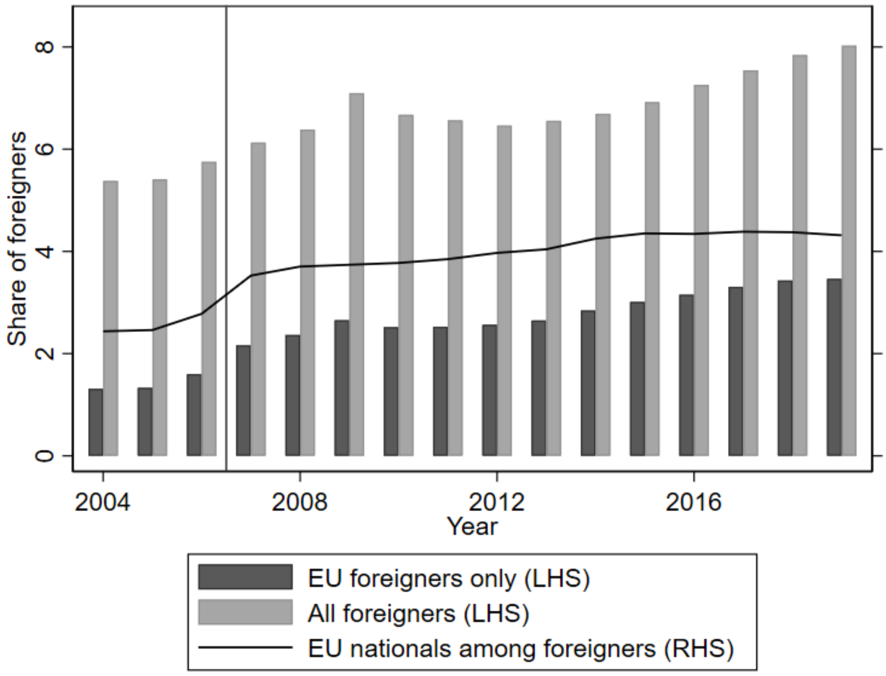
Source: Own elaboration, based on data from WSI (2023) and Eurostat data sets `lfst_r_lfu3rt` and `une_rt_a_h`.
Note: MW levels indicated by the bars. Missing bar means that there is no statutory nationwide MW in that year existing. Data for Austria, Denmark and Ireland not included due missing data on regional unemployment rates. For all countries contained in the chart: Blank spaces on unemployment rates indicate missing data.

Figure A3: Share of foreigners and net migration rates



Source: Own elaboration, based on Eurostat data set series `lfst_r_lfsd2pwc`, `demo_r_gind3`, and `migr_pop1ctz`.
Note: Data for Luxembourg not included in the chart (extreme outlier in terms of share of foreigners, which is roughly between 30-40 percent during my entire sampling period). Data on Austria and the Netherlands not included due missing data. For all countries contained in the chart: Blank spaces indicate missing data.

Figure A4: EU-wide share of foreigners



Source: Own elaboration, based on Eurostat data series migr_pop1ctz.
Note: The chart shows in bars the proportion of foreigners in the EU and the proportion of EU citizens living in a country other than their own ("EU foreigners"), indicated on the left-hand scale (LHS), and by means of the line the ratio of EU foreigners to all foreigners (on the right-hand scale, RHS). All figures refer to the current composition of the EU in the year indicated. Note further that there is some missings in the underlying data; Romania is therefore only considered from 2012 onwards, Malta from 2009 onwards, Poland is not considered in 2009, Greece not in 2008, Bulgaria not in 2007. Further, Estonia, Ireland, Greece, France, and Portugal are only considered from 2007 onward, which is marked by the vertical line in the graph.

Table A1: UK - NUTS-2 to NUTS-1 regions crosswalk

	NUTS-1		NUTS-2	
Country	Region	Code	Region	Code
England	North East	UKC	Tees Valley and Durham	UKC1
			Northumberland and Tyne and Wear	UKC2
	North West	UKD	Cumbria	UKD1
			Cheshire	UKD6
			Greater Manchester	UKD3
			Lancashire	UKD4
			Merseyside	UKD7
	Yorkshire and the Humber	UKE	East Riding and North Lincolnshire	UKE1
			North Yorkshire	UKE2
			South Yorkshire	UKE3
			West Yorkshire	UKE4
	East Midlands	UKF	Derbyshire and Nottinghamshire	UKF1
			Leicestershire, Rutland and Northamptonshire	UKF2
			Lincolnshire	UKF3
	West Midlands	UKG	Herefordshire, Worcestershire and Warwickshire	UKG1
			Shropshire and Staffordshire	UKG2
			West Midlands	UKG3
	East of England	UKH	East Anglia	UKH1
			Bedfordshire and Hertfordshire	UKH2
			Essex	UKH3
	London	UKI	Inner London - West	UKI3
			Inner London - East	UKI4
			Outer London - East and North East	UKI5
			Outer London - South	UKI6
			Outer London - West and North West	UKI7
	South East	UKJ	Berkshire, Buckinghamshire, and Oxfordshire	UKJ1
			Surrey, East and West Sussex	UKJ2
			Hampshire and Isle of Wight	UKJ3
			Kent	UKJ4
	South West	UKK	Gloucestershire, Wiltshire and Bristol/Bath area	UKK1
			Dorset and Somerset	UKK2
			Cornwall and Isles of Scilly	UKK3
			Devon	UKK4
Wales	Wales	UKL	West Wales and The Valleys	UKL1
			East Wales	UKL2
Scotland	Scotland	UKM	North Eastern Scotland	UKM5
			Highlands and Islands	UKM6
			Eastern Scotland	UKM7
			West Central Scotland	UKM8
			Southern Scotland	UKM9
Northern Ireland	Northern Ireland	UKN	Northern Ireland	UKN0

Notes: Table provides the crosswalk used between NUTS-1 and NUTS-2 regions in the UK (NUTS version 2016), based on historical NUTS data by Eurostat (see https://ec.europa.eu/eurostat/web/nuts/history, last accessed 08.12.2023).

Table A2: Regional level summary statistics

Region	# of observations	mean N	mean inflow rate	s.d. inflow rate	mean Kaitz Index	s.d. Kaitz Index	mean Population	mean GDPpc	mean UR	mean Youth Empl. Rate	mean Share Foreigners
BE10	16	7716	0.0385	0.0130	0.2059	0.0028	1118409	64135	0.1627	0.1737	0.3696
BE21	16	6444	0.0171	0.0123	0.2383	0.0024	1767956	40964	0.0550	0.2891	0.1066
BE22	16	5051	0.0176	0.0106	0.2708	0.0029	844192	28301	0.0514	0.3176	0.1063
BE23	16	6416	0.0225	0.0149	0.2569	0.0033	1445809	31481	0.0408	0.3102	0.0591
BE24	14	5991	0.0318	0.0095	0.2216	0.0030	1082315	36260	0.0445	0.2459	0.0886
BE25	16	6059	0.0169	0.0104	0.2788	0.0046	1166554	33245	0.0358	0.3306	0.0464
BE31	13	3537	0.0392	0.0050	0.2279	0.0045	379996	37132	0.0743	0.1760	0.1226
BE32	15	5788	0.0191	0.0097	0.2697	0.0039	1316609	22057	0.1251	0.1948	0.1261
BE33	16	6518	0.0161	0.0101	0.2629	0.0041	1076170	25035	0.1094	0.2181	0.1432
BE34	15	3842	0.0300	0.0149	0.2849	0.0042	271330	22122	0.0735	0.2578	0.0972
BE35	14	3858	0.0302	0.0112	0.2657	0.0056	474758	23478	0.0909	0.2235	0.0742
EL30	7	40478	0.0015	0.0013	0.3088	0.0094	3857174	23873	0.1983	0.1570	0.0882
EL43	10	12021	0.0021	0.0016	0.3571	0.0285	622246	15318	0.1640	0.2068	0.0563
EL51	13	11210	0.0059	0.0030	0.3197	0.0174	602368	13165	0.1425	0.2178	0.0504
EL52	16	24176	0.0089	0.0109	0.3411	0.0153	1895851	14286	0.1739	0.1589	0.0586
EL53	12	5084	0.0035	0.0017	0.2444	0.0223	283334	17221	0.2157	0.1284	0.0273
EL54	11	10938	0.0042	0.0020	0.3586	0.0354	344005	13458	0.1405	0.1761	0.0299
EL61	14	9337	0.0033	0.0020	0.3074	0.0146	737927	13724	0.1599	0.1876	0.0323
EL63	13	10885	0.0030	0.0016	0.3235	0.0223	684775	13851	0.1745	0.1653	0.0294
EL64	10	10248	0.0026	0.0014	0.2953	0.0175	556977	16661	0.1661	0.2235	0.0459
EL65	8	10453	0.0015	0.0009	0.3023	0.0338	587188	14641	0.1329	0.2031	0.0491
ES11	17	8630	0.0041	0.0012	0.2250	0.0170	2736848	20056	0.1455	0.2389	0.0612
ES12	11	3068	0.0041	0.0021	0.2062	0.0222	1054064	20417	0.1247	0.2299	0.0482
ES13	13	2503	0.0042	0.0027	0.2133	0.0176	579072	21509	0.1305	0.2265	0.0644
ES21	14	4722	0.0036	0.0021	0.1753	0.0165	2151930	29077	0.1086	0.2435	0.0593
ES22	8	2720	0.0042	0.0020	0.1902	0.0208	616426	28326	0.0894	0.2895	0.0973
ES23	12	1638	0.0093	0.0051	0.2229	0.0214	311531	24748	0.1263	0.2584	0.1154
ES24	15	4219	0.0043	0.0022	0.2032	0.0108	1305787	24728	0.1176	0.2895	0.1037
ES30	16	5198	0.0048	0.0019	0.1810	0.0161	6249384	31157	0.1252	0.2816	0.1473
ES41	15	9446	0.0051	0.0022	0.2124	0.0194	2500150	21043	0.1404	0.2488	0.0591
ES42	17	6905	0.0061	0.0019	0.2289	0.0190	2010048	18293	0.1838	0.2637	0.0833
ES43	17	3695	0.0044	0.0027	0.2371	0.0203	1084095	16055	0.2268	0.2205	0.0320
ES51	14	9574	0.0032	0.0011	0.1966	0.0184	7298320	27630	0.1340	0.3219	0.1361
ES52	17	7641	0.0039	0.0015	0.2248	0.0191	4846678	20464	0.1763	0.2817	0.1424
ES53	16	2396	0.0055	0.0022	0.2229	0.0183	1065672	25086	0.1448	0.3204	0.1969
ES61	17	16810	0.0032	0.0009	0.2312	0.0208	8165873	17360	0.2418	0.2293	0.0757
ES62	11	3334	0.0038	0.0009	0.2464	0.0245	1412914	19256	0.1685	0.3009	0.1383
ES70	15	5323	0.0043	0.0020	0.2274	0.0219	2012625	19826	0.2186	0.2407	0.1474
FR10	13	47325	0.0335	0.0220	0.2321	0.0053	11950142	54194	0.0851	0.2601	0.1941
FR21	13	9217	0.0407	0.0202	0.3371	0.0040	1334275	27854	0.0989	0.2998	0.0672
FR22	12	9414	0.0330	0.0163	0.3285	0.0034	1921481	24463	0.1025	0.2967	0.0609
FR23	12	9454	0.0374	0.0212	0.3140	0.0026	1844453	28274	0.1023	0.3039	0.0551
FR24	13	10668	0.0353	0.0175	0.3334	0.0039	2560665	27162	0.0845	0.3113	0.0670
FR25	13	7843	0.0380	0.0176	0.3392	0.0036	1473434	25901	0.0795	0.3360	0.0338
FR26	13	7823	0.0425	0.0172	0.3337	0.0034	1637748	27106	0.0879	0.3137	0.0681
FR30	13	20994	0.0290	0.0195	0.3204	0.0028	4054731	26417	0.1272	0.2591	0.0485
FR41	12	10515	0.0334	0.0201	0.3311	0.0037	2341000	24462	0.1022	0.3210	0.0876
FR42	12	9268	0.0318	0.0184	0.3092	0.0036	1863162	30007	0.0840	0.3379	0.1102
FR43	13	7205	0.0345	0.0205	0.3319	0.0052	1174028	25109	0.0825	0.3213	0.0717
FR51	13	16652	0.0369	0.0171	0.3312	0.0038	3652633	28768	0.0792	0.3458	0.0412
FR52	13	13948	0.0439	0.0193	0.3387	0.0037	3248918	27269	0.0709	0.3096	0.0353
FR53	13	8237	0.0387	0.0176	0.3457	0.0046	1785626	26150	0.0858	0.3329	0.0499
FR61	13	13305	0.0424	0.0147	0.3253	0.0080	3310871	28727	0.0885	0.2976	0.0905
FR62	13	11374	0.0521	0.0262	0.3142	0.0056	2948783	29215	0.0795	0.2961	0.0965
FR63	13	6392	0.0429	0.0211	0.3344	0.0051	737412	24267	0.0708	0.3570	0.0574
FR71	13	26330	0.0357	0.0199	0.3046	0.0038	6385541	32662	0.0776	0.3251	0.1035
FR72	11	6053	0.0439	0.0215	0.3321	0.0049	1355103	25786	0.0775	0.3368	0.0574
FR81	13	10807	0.0437	0.0185	0.3294	0.0056	2715057	24808	0.1215	0.2314	0.1356
FR82	13	19195	0.0348	0.0179	0.3094	0.0055	4961786	30430	0.0970	0.2735	0.1599
FR83	4	988	0.0255	0.0177	0.2984	0.0075	328973	26413	0.0863	0.3853	0.1143

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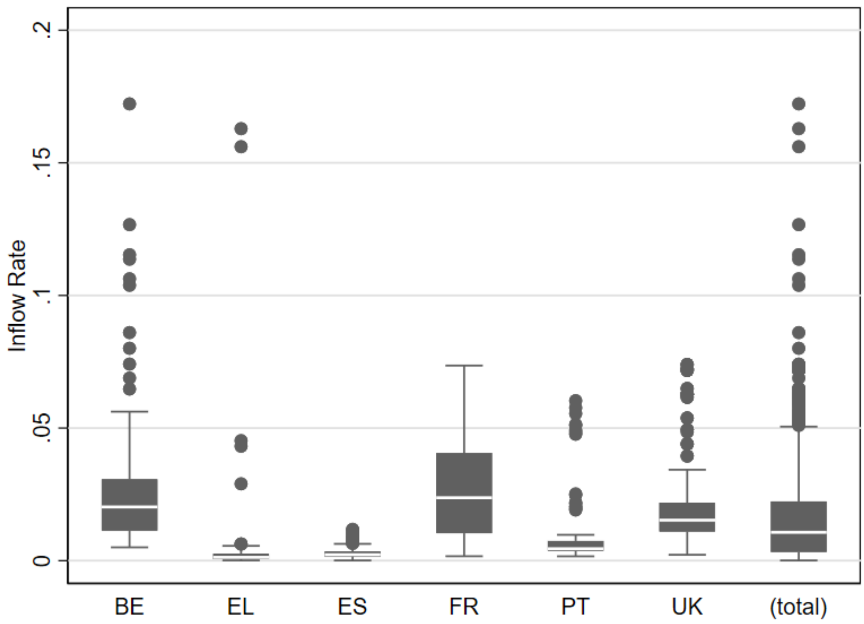
Region	# of observations	mean N	mean inflow rate	s.d. inflow rate	mean Kaitz Index	s.d. Kaitz Index	mean Population	mean GDPpc	mean UR	mean Youth Empl. Rate	mean Share Foreigners
PT11	17	27792	0.0114	0.0091	0.2974	0.0255	3668549	13835	0.1093	0.3145	0.0355
PT15	17	9532	0.0073	0.0022	0.2969	0.0325	435324	17839	0.1001	0.2838	0.1093
PT16	17	14515	0.0063	0.0020	0.2876	0.0270	2307453	14404	0.0742	0.2907	0.0508
PT17	17	15839	0.0280	0.0232	0.2168	0.0223	2790236	23374	0.1094	0.2647	0.1045
PT18	16	11468	0.0062	0.0022	0.2875	0.0302	748765	15672	0.1097	0.2632	0.0315
UKC1	10	2722	0.0238	0.0177	0.3291	0.0131	1171475	23417	0.0881	0.4432	0.0354
UKC2	10	2722	0.0238	0.0177	0.3264	0.0129	1417876	26524	0.0796	0.4899	0.0456
UKD1	7	6146	0.0169	0.0037	0.3181	0.0093	499221	29358	0.0544	0.5478	0.0313
UKD3	10	6790	0.0233	0.0158	0.3211	0.0104	2665176	29375	0.0754	0.4790	0.1027
UKD4	10	6790	0.0233	0.0158	0.3502	0.0130	1458246	26459	0.0577	0.5126	0.0609
UKD6	7	6146	0.0169	0.0037	0.2969	0.0123	908416	39349	0.0471	0.5228	0.0527
UKD7	7	6146	0.0169	0.0037	0.3294	0.0061	1514138	26042	0.0819	0.4405	0.0504
UKE1	10	5609	0.0293	0.0186	0.3367	0.0176	913797	26528	0.0747	0.5051	0.0479
UKE2	10	5609	0.0293	0.0186	0.2966	0.0109	793621	29974	0.0435	0.5410	0.0486
UKE3	10	5609	0.0293	0.0186	0.3370	0.0193	1335743	23543	0.0839	0.4977	0.0628
UKE4	10	5609	0.0293	0.0186	0.3257	0.0118	2212462	28706	0.0739	0.4671	0.0962
UKF1	10	4558	0.0334	0.0155	0.3232	0.0130	2099994	26583	0.0643	0.5044	0.0644
UKF2	10	4558	0.0334	0.0155	0.3145	0.0103	1700083	29629	0.0571	0.5219	0.1169
UKF3	10	4558	0.0334	0.0155	0.3347	0.0174	709523	23701	0.0539	0.5473	0.0641
UKG1	10	5207	0.0247	0.0143	0.2978	0.0147	1290560	30480	0.0453	0.5170	0.0571
UKG2	10	5207	0.0247	0.0143	0.3259	0.0086	1562153	25175	0.0564	0.5453	0.0438
UKG3	10	5207	0.0247	0.0143	0.3282	0.0146	2724822	27410	0.0957	0.4016	0.1416
UKH1	10	5673	0.0327	0.0168	0.3101	0.0116	2372425	30169	0.0512	0.5589	0.0851
UKH2	10	5673	0.0327	0.0168	0.2507	0.0117	1727318	34905	0.0503	0.4997	0.1261
UKH3	10	5673	0.0327	0.0168	0.2757	0.0103	1723156	27342	0.0562	0.5362	0.0700
UKI3	4	5713	0.0287	0.0040	0.1304	0.0140	1130366	201589	0.0580	0.4026	0.4064
UKI4	4	5713	0.0287	0.0040	0.2438	0.0138	2271574	57429	0.0803	0.4015	0.3766
UKI5	4	5713	0.0287	0.0040	0.2680	0.0071	1840011	26072	0.0752	0.4040	0.2887
UKI6	4	5713	0.0287	0.0040	0.2293	0.0104	1269209	32295	0.0552	0.4610	0.2648
UKI7	4	5713	0.0287	0.0040	0.2247	0.0144	2029546	44520	0.0628	0.4034	0.3864
UKJ1	10	8063	0.0359	0.0176	0.2498	0.0081	2258467	46575	0.0441	0.5374	0.1360
UKJ2	10	8063	0.0359	0.0176	0.2410	0.0112	2728488	35472	0.0448	0.5454	0.0988
UKJ3	10	8063	0.0359	0.0176	0.2854	0.0081	1889946	34259	0.0492	0.5515	0.0781
UKJ4	10	8063	0.0359	0.0176	0.2741	0.0137	1717896	27791	0.0627	0.5224	0.0763
UKK1	10	4945	0.0356	0.0209	0.2920	0.0091	2340991	34834	0.0468	0.5570	0.0790
UKK2	10	4945	0.0356	0.0209	0.3100	0.0123	1268802	26923	0.0457	0.5878	0.0658
UKK3	10	4945	0.0356	0.0209	0.3410	0.0182	534630	22036	0.0512	0.5270	0.0393
UKK4	10	4945	0.0356	0.0209	0.3344	0.0084	1134160	25510	0.0515	0.5258	0.0504
UKL1	10	2905	0.0250	0.0173	0.3409	0.0118	1924125	21255	0.0701	0.4760	0.0344
UKL2	10	2905	0.0250	0.0173	0.3221	0.0122	1119931	29216	0.0574	0.4747	0.0628
UKM5	9	5044	0.0195	0.0175	0.2615	0.0122	475084	48511	0.0400	0.6651	0.0834
UKM6	9	5044	0.0195	0.0175	0.3448	0.0339	463179	29200	0.0467	0.5622	0.0492
UKN0	10	2456	0.0223	0.0181	0.3249	0.0345	1798184	26149	0.0609	0.4205	0.0533

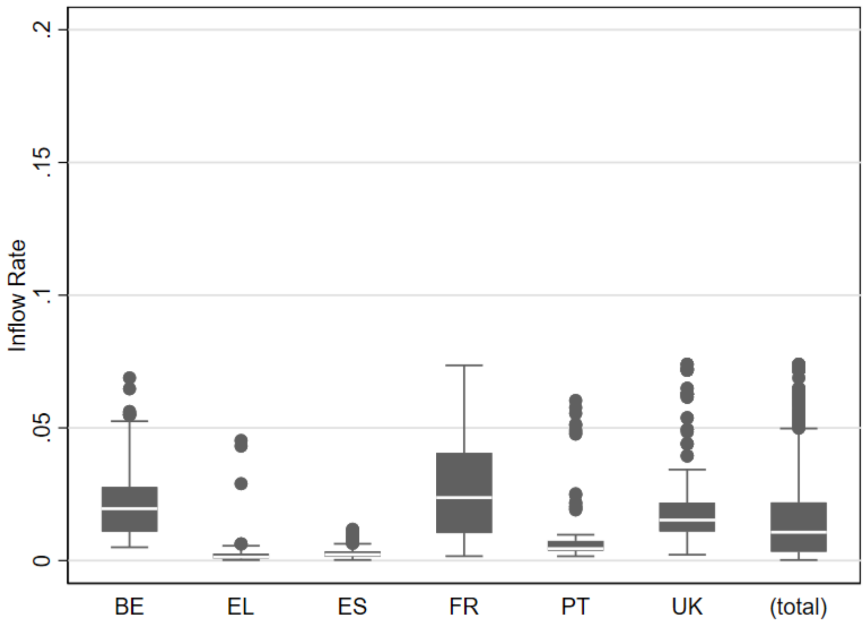
Notes: Own elaboration, based on historical NUTS data by Eurostat (see https://ec.europa.eu/eurostat/web/nuts/history, last accessed 17.03.2023). Table provides the crosswalk between NUTS-1 and NUTS-2 regions in the UK (NUTS version 2016).

Figure A5: Boxplot of inflow rates - *raw* sample



Note: The graph provides boxplots on the derived regional inflow rates by country (raw sample, non-trimmed). The skewness is 2.5719, the kurtosis is 14.4322.

Figure A6: Boxplot of inflow rates - *trimmed* sample



Note The graph provides boxplots on the derived regional inflow rates by country for the trimmed data sample (the raw sample without the highest and lowest 1 percent of values). The skewness for the trimmed sample is 1.4409, the kurtosis is 4.5945.

Table A3: Country level summary statistics

Country	indicator	# of obs.	mean	std.dev.	min	max
	Labor inflow rate	167	0.0217	0.0134	0.0050	0.0688
	Kaitz index	167	0.2544	0.0250	0.2025	0.2945
	Population	167	1,007,138	439,208	252,295	1,849,523
Belgium	GDP per capita	167	32,401	12,131	17,445	69,873
	Unemployment rate	167	0.0797	0.0406	0.0260	0.1920
	Youth employment rate	167	0.2519	0.0581	0.1425	0.3994
	Share of foreigners	167	0.1149	0.0829	0.0208	0.4087
	Labor inflow rate	114	0.0027	0.0063	0.0002	0.0452
	Kaitz index	114	0.3157	0.0383	0.2217	0.4543
	Population	114	949,341	894,701	273,843	3,999,457
Greece	GDP per capita	114	15,165	3,163	11,189	29,247
	Unemployment rate	114	0.1602	0.0742	0.0540	0.3160
	Empl. Rate of Youth	114	0.1896	0.0643	0.0623	0.3454
	Share of foreigners	114	0.0408	0.0190	0.0131	0.0961
	Labor inflow rate	245	0.0027	0.0019	0.0002	0.0118
	Kaitz index	245	0.2104	0.0211	0.1585	0.2646
	Population	245	2,836,513	2,399,517	277,989	8,410,095
Spain	GDP per capita	245	21,886	4,673	11,594	35,241
	Unemployment rate	245	0.1558	0.0728	0.0510	0.3620
	Empl. Rate of Youth	245	0.2697	0.0906	0.1274	0.4679
	Share of foreigners	245	0.0868	0.0504	0.0055	0.2130
	Labor inflow rate	271	0.0261	0.0173	0.0017	0.0736
	Kaitz index	271	0.3216	0.0235	0.2222	0.3563
	Population	271	2,986,787	2,417,840	309,693	12,213,447
France	GDP per capita	271	28,137	6,130	22,662	59,749
	Unemployment rate	271	0.0895	0.0193	0.0500	0.1500
	Empl. Rate of Youth	271	0.3079	0.0401	0.1997	0.5103
	Share of foreigners	271	0.0772	0.0413	0.0216	0.1986
	Labor inflow rate	84	0.0107	0.0147	0.0016	0.0603
	Kaitz index	84	0.2733	0.0403	0.1885	0.3454
	Population	84	2,006,317	1,234,606	400,937	3,719,898
Portugal	GDP per capita	84	16,618	3,833	11,001	25,974
	Unemployment rate	84	0.0995	0.0377	0.0290	0.1860
	Empl. Rate of Youth	84	0.2902	0.0621	0.1867	0.4618
	Share of foreigners	84	0.0607	0.0347	0.0156	0.1260
	Labor inflow rate	339	0.0199	0.0151	0.0022	0.0739
	Kaitz index	339	0.3064	0.0393	0.1145	0.4216
	Population	339	1,549,525	639,713	444,381	2,827,820
UK	GDP per capita	339	30,910	19,351	16,876	222,201
	Unemployment rate	339	0.0624	0.0208	0.0260	0.1300
	Empl. Rate of Youth	339	0.5090	0.0705	0.3430	0.6920
	Share of foreigners	339	0.0782	0.0702	0.0153	0.3970
	Labor inflow rate	1,220	0.0158	0.0161	0.0002	0.0739
	Kaitz index	1220	0.2820	0.0523	0.1145	0.4543
	Population	1220	2,028,362	1,848,263	252,295	12,213,447
Total	GDP per capita	1220	26,231	13,123	11,001	222,201
	Unemployment rate	1220	0.1012	0.0594	0.0260	0.3620
	Empl. Rate of Youth	1220	0.3361	0.1303	0.0623	0.6920
	Share of foreigners	1220	0.0800	0.0604	0.0055	0.4087

Note: Summary statistics based on the final sample laid out before.

Table A4: Variable correlations

	inflow rate	Kaitz index	population	gdppc	unemployment rate	youth empl. rate
Kaitz index	0.257***	1				
population	-0.0316	-0.207***	1			
gdppc	0.192***	-0.237***	0.119***	1		
unemployment rate	-0.376***	-0.220***	0.163***	-0.259***	1	
youth empl. rate	0.258***	0.249***	-0.0966***	0.181***	-0.675***	1
share of foreigners	0.0203	-0.368***	0.212***	0.598***	0.154***	-0.175***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Correlation statistics based on the final sample laid out before. Variables gdppc and UR are the regional GDP per capita and the regional unemployment rate, respectively. The correlations of *inflow rate* and *share of foreigners* with its own are 1 (not shown here).

Table A5: Main results - FE model (showing covariates estimates)

VARIABLES	(1) FE without covariates	(2) FE with covariates	(3) (2) with Kaitz (lag 2y.)	(4) (2) with Kaitz (lag 3y.)
ln Kaitz (lag 1y.)	0.015**	0.029***		
	(0.006)	(0.006)		
ln Kaitz (lag 2y.)			0.030***	
			(0.006)	
ln Kaitz (lag 3y.)				0.036**
				(0.014)
ln population (lag 1y.)		0.003	0.001	-0.010
		(0.018)	(0.017)	(0.019)
ln GDP per capita (lag 1y.)		0.041***	0.037***	0.043***
		(0.007)	(0.008)	(0.009)
ln unemployment rate (lag 1y.)		0.004	0.010***	0.008**
		(0.003)	(0.003)	(0.003)
ln youth employment rate (lag 1y.)		-0.012***	-0.006*	-0.013***
		(0.003)	(0.003)	(0.004)
ln share of foreigners (lag 3y.)		-0.002	-0.001	-0.006**
		(0.002)	(0.002)	(0.003)
Constant	-1.155***	-0.695	1.564***	-0.798
	(0.261)	(0.482)	(0.496)	(0.531)
# of observations	1220	1220	1125	1093
Within R2	0.489	0.517	0.500	0.547
Between R2	0.271	0.188	0.120	0.079
Covariates	NO	YES	YES	YES
Year FE	YES	YES	YES	YES
Country-year trend	YES	YES	YES	YES

Dependent variable is the regional inflow rate of low-skilled individuals. The Kaitz index and all covariates (not shown here) in logarithm. Standard errors in parantheses.

Table A6: Robustness - Reverse causality test

VARIABLES	(1) Main model	(2) Reverse causality (no lag)	(3) Reverse causality (lag 1y.)
ln Kaitz (lag 1y.)	0.029***		
	(0.006)		
labor inflow rate		0.047	
		(0.092)	
labor inflow rate (lag 1y.)			0.047
			(0.090)
Constant	-0.695	2.001	1.989
	(0.482)	(1.703)	(1.709)
# of observations	1220	1182	1182
Within R2	0.517	0.662	0.662
Between R2	0.188	0.144	0.144
Covariates	YES	YES	YES

Note: The dependent variable in column (1) is the regional inflow rate of low-skilled individuals. The dependent variable in columns (2) and (3) is the logarithm of the regional Kaitz index. All other model specifications as in table 3. Standard errors clustered at the regional level are depicted in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Leave-1-Out country-by-country

	(1) FE (baseline)	(2) (1) w/o Belgium	(3) (1) w/o Greece	(4) (1) w/o Spain	(5) (1) w/o France	(6) (1) w/o Portugal	(7) (1) w/o UK
ln Kaitz (lag 1y.)	0.029***	0.022***	0.039***	0.031***	0.025***	0.029***	0.023***
	(0.006)	(0.006)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	-0.695	0.436	-0.377	-0.289	-2.181***	-1.077***	-1.433
	(0.482)	(0.545)	(0.492)	(0.910)	(0.564)	(0.310)	(1.472)
# of observations	1,220	1,053	1,106	975	949	1,136	881
Within R2	0.517	0.554	0.550	0.566	0.496	0.547	0.500
Between R2	0.188	0.563	0.094	0.180	0.000	0.228	0.152
Covariates	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Country-year trend	YES	YES	YES	YES	YES	YES	YES

Note: The dependent variable is the regional inflow rate of low-skilled individuals. Column (1) provides results from my baseline model, the other specification always take the full sample but without regions from the country indicated. All other model specifications as in table 3. Standard errors clustered at the regional level are depicted in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Robustness - Other approaches

VARIABLES	(1) Main model	(2) Jacknife approach	(3) Bootstrap approach	(4) Region-trends (linear)	(5) Non-linear country-trends
ln Kaitz (lag 1y.)	0.029***	0.029***	0.029***	0.034***	0.028**
	(0.006)	(0.007)	(0.007)	(0.008)	(0.012)
Constant	-0.695	-0.695	-0.695	-1.206*	469.224
	(0.482)	(0.708)	(0.659)	(0.712)	(2300.249)
# of observations	1220	1220	1220	1220	1220
Within R2	0.517	0.517	0.517	0.584	0.526
Between R2	0.188	0.188	0.188	0.160	0.058
Covariates	YES	YES	YES	YES	YES

Note: The dependent variable is the regional inflow rate of low-skilled individuals. The model in column (2) is estimated using jacknife resampling technique, the model in column (3) using bootstrapping (with 1000 replications). The model in column (4) uses region time-trends (rather than the country time-trends utilized in the baseline model), the model in column (5) applies non-linear country time-trends. All other model specifications as in table 3. Standard errors clustered at the regional level are depicted in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Country-specific results

	(1) FE with covariates	(2) (1) with country-specific effects
ln Kaitz (lag 1y.)	0.029***	
	(0.006)	
BE # ln Kaitz (lag 1y.)		0.153**
		(0.072)
EL # ln Kaitz (lag 1y.)		0.011
		(0.009)
ES # ln Kaitz (lag 1y.)		0.006
		(0.019)
FR # ln Kaitz (lag 1y.)		0.082*
		(0.044)
PT # ln Kaitz (lag 1y.)		0.056**
		(0.022)
UK # ln Kaitz (lag 1y.)		0.034***
		(0.011)
Constant	-0.695	-0.855*
	(0.482)	(0.477)
# of observations	1220	1220
Within R2	0.517	0.520
Between R2	0.188	0.181
Covariates	YES	YES
Year FE	YES	YES
Country-year trend	YES	YES

Note: The dependent variable is the regional inflow rate of low-skilled individuals. All model specifications as in table 3, except that in column (2) the Kaitz index is interacted with a categorical variable identifying the country in which a region is located. Standard errors clustered at the regional level are depicted in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Urban vs. rural areas, nationality, within-country mobility

	(1) FE (baseline)	(2) (1) only for urban areas	(3) (1) only for rural areas	(4) (1) with natives only	(5) (1) restricted to domestic mobility
ln Kaitz (lag 1y.)	0.029***	0.034***	0.018**	0.025***	0.020***
	(0.006)	(0.013)	(0.007)	(0.006)	(0.006)
Constant	-0.695	-0.791	-0.662	-0.076*	-1.448***
	(0.482)	(0.374)	(0.737)	(0.433)	(0.501)
# of observations	1220	617	603	1220	1220
Within R2	0.517	0.677	0.483	0.530	0.363
Between R2	0.188	0.010	0.432	0.293	0.002
Covariates	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Country-year trend	YES	YES	YES	YES	YES

Note: The dependent variable is the regional inflow rate of low-skilled individuals, but with the subgroup restrictions indicated at the top. All model specifications as in table 3. Standard errors clustered at the regional level are depicted in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Heterogenous effects across gender and age

	(1) FE (baseline)	(2) (1) for females only	(3) (1) for males only	(4) (1) for young (<28y.) only
ln Kaitz (lag 1y.)	0.029***	0.032***	0.033***	0.047***
	(0.006)	(0.009)	(0.008)	(0.016)
Constant	-0.695	-0.405	-0.822	-2.336***
	(0.482)	(0.528)	(0.553)	(0.654)
# of observations	1220	1136	1161	1095
Within R2	0.517	0.465	0.486	0.498
Between R2	0.188	0.173	0.223	0.347
Covariates	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Country-year trend	YES	YES	YES	YES

Note: The dependent variable is the regional inflow rate of low-skilled individuals, but with the subgroup restrictions indicated at the top. All other model specifications as in table 3. Standard errors clustered at the regional level are depicted in parentheses:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.