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David Zuchowski[1]

Migration Response to an Immigration Shock: Evidence from Russia's Aggression against Ukraine

Abstract

Russia's attacks against Ukraine have triggered massive and unexpected migration movements. In this paper, I examine the impact of the inflow of Ukrainians that resulted from Russia's aggression in 2014 on local migration patterns in Poland. For identification, I use an instrumental variable approach drawing on unique historical data on the forced resettlement of Ukrainians in Poland after World War II. The results show that the regional inflow of immigrants decreases both internal and international out-migration of the Polish population. I provide supportive evidence that the decrease in out-migration is due to the upscaling of local labor markets.

JEL-Codes: F22, J61, O15

Keywords: Migration; immigrant workers; Poland; Ukraine

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1 Introduction

Massive and unexpected migration flows emerged due to Russia's attacks against Ukraine. The migration surge began with the annexation of Crimea in 2014 and reached unprecedented dimensions after the full invasion of Ukraine in February 2022, when more than 8 million people fled to neighboring countries (UNHCR, 2023). Central and Eastern European countries such as Estonia, the Czech Republic, Poland, and Lithuania are the largest per capita recipients of Ukrainian refugees among OECD countries (OECD, 2022a).[1] Those post-communist countries in transition are not typical immigration countries. On the contrary, since the fall of the Iron Curtain, they have experienced long-standing high emigration, mainly of young and well-educated citizens who saw no professional prospects in their own country (IMF, 2014, 2016).

In this paper, I examine the impact of the inflow of Ukrainians that resulted from Russia's aggression in 2014 on local migration patterns in Poland. It is the first study evaluating the impact of an immigration shock on local migration patterns in a post-communist country in transition. In particular, I take advantage of the fact that Poland, the country currently hosting the largest absolute number of Ukrainian refugees (UNHCR, 2023), has been the primary destination of conflict-induced temporary labor migration from Ukraine for nearly a decade. The annexation of Crimea by Russia in 2014 and the ongoing conflict in the Donbas region destabilized the Ukrainian economy, forcing many Ukrainians to look for work abroad. As a result, the Polish labor market has experienced a massive and unexpected conflict-induced labor supply shock.

The analysis in this paper focuses on migration outcomes, which are particularly interesting as Poland, like other post-communist countries, has for decades been a country of high labor emigration, especially of well-educated citizens. The education boom during the socio-economic transition and the lack of demand for highly educated workers led to graduates of Polish universities being employed as *"cleaners in Europe, dishwashers in*

[1] See also Figure A1 in the Appendix. Overall, the country with the highest per capita inflow of Ukrainian refugees is Moldova (United Nations, 2022), the last European country to overthrow the communist government (Barsbai *et al.*, 2017).

London, and caregivers for the elderly in Germany" (Radio Poznan, 2011). Furthermore, with around 2 million temporary foreign workers in 2019, the vast majority of whom were Ukrainians, Poland underwent a rapid transformation from a traditional emigration country to a host country (Statistics Poland, 2020). This sudden and massive inflow of temporary workers could potentially further increase Polish emigration, for example, by intensifying competition in local labor markets. However, with the inflow of Ukrainian workers after the Russian aggression in 2014, Polish emigration decreased (Statistics Poland, 2020), and at the same time the share of highly skilled emigrants among all Polish emigrants also decreased (Giesing and Schikora, 2023).

To examine the impact of the inflow of Ukrainian workers caused by Russia's aggression in 2014 on the migration behavior of the local population, this paper exploits the spatial variation across Polish counties in the intensity of exposure to this labor supply shock. I use administrative data on internal and international migration to measure changes in migration patterns in Poland and administrative records on firms' statements on the employment of foreigners to measure the intensity of the local exposure to the labor supply shock.

The main challenge is the endogeneity of immigrant workers' location decisions. Despite the labor supply shock's exogenous timing, the location of Ukrainian workers across Polish counties is, at least to some extent, determined by the prospects of the local labor markets, which are also determinants of changes in the migration behavior of natives (Peri, 2016). Thus, counties attracting more immigrant workers could have experienced higher in-migration trends even in the absence of the inflow of Ukrainian workers.

To address this issue, I propose a novel instrument based on unique historical records on the forced resettlement of Ukrainians in Poland in the aftermath of World War II. This mass displacement took place as part of a military operation called Vistula, during which around 140,000 Ukrainians were forcibly relocated. The instrument draws on the commonly used distance instrument. However, instead of instrumenting the contemporary distribution of Ukrainian workers with the distance to the border of immigrants' country of origin, I use the distance to historical hotspots of Ukrainian networks in Poland that emerged due to Operation Vistula.[2] First, I define the historical hotspots as places where the share of forcibly resettled Ukrainians exceeded 10% of the local population in 1950.[3] Second, I instrument the contemporary location of Ukrainians with the distance in kilometers to the nearest hotspot point. The constructed distance instrument is predictive of the contemporary location of Ukrainians and thus relevant. Furthermore, it does not predict changes in migration patterns or any other socio-economic characteristics in the pre-treatment period, which suggests that the exclusion restriction is satisfied.

The findings show that the immigrant inflow decreases both internal and international out-migration. On average, the inflow of 1000 Ukrainian workers into local labor markets lowers internal out-migration by around 19 inhabitants and international out-migration by about 5 inhabitants. I find evidence of upscaling, that is, an enlargement of local labor markets as a potential driver of the results. As descriptive evidence suggests complementarity between Ukrainian workers and Polish emigrants, this may indicate the absorption of local workers into the local labor market who would otherwise emigrate. Furthermore, I find evidence of crowding-out in-migration as an initial response to the shock. This effect decreases in magnitude and becomes statistically insignificant for international in-migration after two and for internal in-migration after four years, showing a reduction of this effect in the long run.

I run several robustness checks. The results are robust to a number of different specifications and the exclusion of potential outliers. Furthermore, I find no evidence of pre-treatment trends in migration outcomes between counties with different exposure to the inflow of Ukrainians, which suggests that the parallel trend assumption holds.

The findings have important policy implications, especially in light of the escalation of Russian aggression against Ukraine in 2022 and the subsequent decision to invoke the Temporary Protection Directive in the European Union. The latter provided Ukrainian refugees unprecedented free access to host countries' labor markets and thus led to a significant labor supply in several post-communist countries. Estimates suggest that the

[2] For example, Dustmann *et al.* (2016) and Aksu *et al.* (2022) use the distance to the border of immigrants' country of origin as an instrument in their studies on the effects of immigration.

[3] The results are robust to alternative definitions of the threshold.

inflow of Ukrainian refugees increases the labor force in the Czech Republic, Poland, and Estonia by around 2%, and many other countries in Central and Eastern Europe by 1 to 1.5% (OECD, 2022b). This sudden labor supply shock could pose a particular challenge for post-communist countries, which, despite their transition to capitalist economies, still have relatively weak labor market institutions and no established immigration structures. However, the present study finds that in transition economies with a surplus of highly educated workers, an immigration shock can result in positive effects for host communities.

This article relates to the broad debate on the impact of immigration on host counties' labor markets, in particular, to the growing literature analyzing the impact of immigration on the migration behavior of the local population.[4] Several recent studies provide evidence on the effects of conflict-induced immigration and find mixed results. Batut and Schneider-Strawczynski (2022) find a decline in the in-migration to municipalities hosting refugees in France. Elmallakh and Wahba (2023) examine the impact of the inflow of Syrian refugees on Jordanians' migration behavior and find an increase in internal out-migration from affected regions but an increase in job-related in-migration into the camp areas. On the contrary, in a similar analysis for Turkey, Akgündüz *et al.* (2021) find a decrease in inter-regional job-related in-migration to provinces hosting Syrian refugees but no evidence of an increase in out-migration. However, in the context of conflict-induced internal displacement in Colombia, Morales (2018) finds an increase in out-migration from affected communities, in particular of high-skilled workers. Moreover, empirical findings in the setting of immigration to highly developed countries are also not homogenous and indicate that the effects depend on the immigration policy and the type of migration.[5]

This paper contributes to the literature by providing evidence from a unique and highly policy-relevant context. As forced migrants typically seek protection either in

[4]For a broad literature survey on the impact of immigration in OECD countries see for example Edo *et al.* (2020). Furthermore, Verme and Schuettler (2021) provide a recent review on the impact of forced displacement on host countries. Most literature studying the impact of immigration on host countries has focused on the impact of immigration on wages and employment. See Edo (2019) or Dustmann *et al.* (2016) for an extensive literature review.

[5]See for example Card (2001) and Borjas (2006) for evidence for the US, Hatton and Tani (2005) for UK, Mocetti and Porello (2010) for Italy, Beine and Coulombe (2018) for Canada, Moraga *et al.* (2019) for Spain, Ortega and Verdugo (2022) for France, and Han *et al.* (2022) for South Korea.

neighboring developing countries or in high-income OECD countries (Devictor *et al.*, 2021), little is known about the impact of conflict-related immigration in other settings. The case of Poland is also unique in that it is a post-communist country with long-standing high emigration. Moreover, at the time of the immigration shock, Polish citizens enjoyed the freedom of migration within the European Union (including labor migration), which allowed for a potentially strong migration response. Finally, unlike most previous studies, my data allows me to examine both the internal and the international migration response of the local population.

The remainder of this paper is organized as follows. Section 2 provides background information on the inflow of Ukrainians to Poland. Section 3 describes the underlying data. Section 4 discusses the empirical strategy. Section 5 presents and discusses the empirical results. Section 6 concludes.

2 Background Information

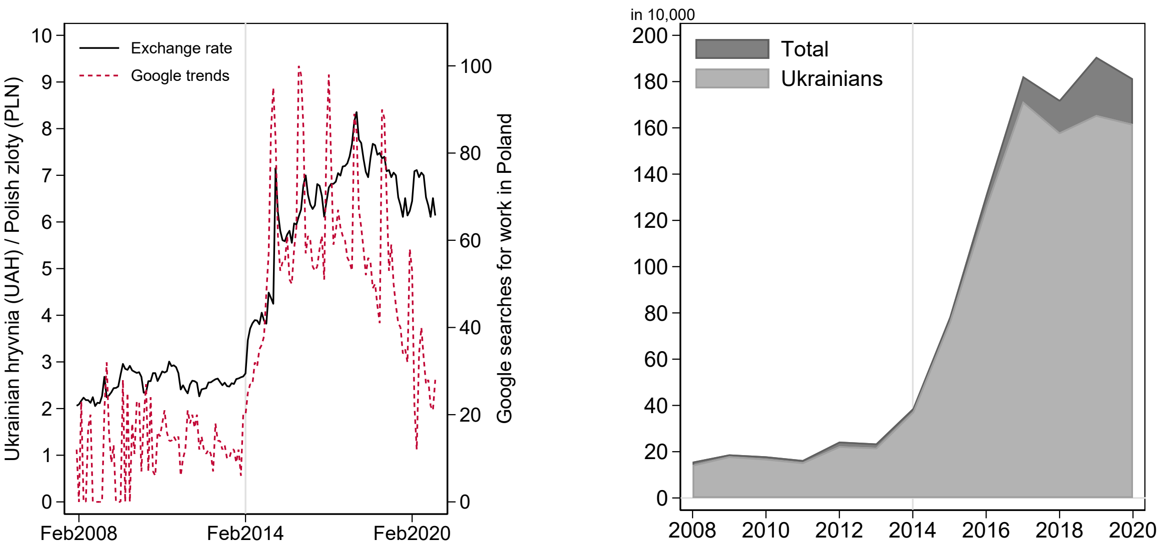
2.1 Destabilization of Ukraine and Labor Migration to Poland

After the collapse of the Soviet Union in 1991, Ukraine became an independent state in its current borders. The newly established Ukraine was divided on whether it should be more economically and politically aligned with the West or with Russia. Two decades later, however, when former Ukrainian President Viktor Yanukovych refused to sign the European Union - Ukraine Association Agreement, massive protests emerged on Kyiv's Independence Square. The protests from November 2013 to February 2014, later called Euromaidan, became a symbol of Ukrainians' support for closer relations with the West. Following the escalation of protests, the pro-Russian President Yanukovych fled Kyiv and later Ukraine (Plokhy, 2016).

Taking advantage of the internal crisis in Ukraine, Russia took control of the Crimean Peninsula. Furthermore, the subsequent fights and the emergence of pro-Russian self-proclaimed "people's republics" in the eastern Ukrainian territories of Donetsk and Lugansk further intensified the political and economic destabilization of Ukraine (Plokhy, 2016).

The destabilization of the Ukrainian economy following the Russian aggression has forced many Ukrainians to search for work abroad. The solid line in Figure 1a shows a sharp depreciation of Ukraine's national currency after February 2014. This sharp fall in the exchange rate of the Ukrainian hryvnia against the Polish zloty increased the economic incentives for Ukrainians to work in Poland, as the depreciation amplified the purchasing power of the earnings in Polish zloty when converted to Ukrainian hryvnia. The devaluation of the Ukrainian currency aligns with the increase in interest in labor migration from Ukraine to Poland.[6] This trend is illustrated by the dashed line, which shows the sudden rise in Google queries in Ukraine for "work in Poland" after the Russian aggression.

Alongside the income prospects, the existence of networks in the destination country



(a) UAH/PLN and Google trends **(b)** Foreign employment

Figure 1: Inflow of Ukrainians to the Polish Labor Market

Notes: Panel (a): Polish zloty to Ukrainian hryvnia exchange rate based on official data from the National Bank of Poland and relative intensity of google searches in Ukraine for "work in Poland" (in Ukrainian) provided by Google Trends. Panel (b): Number of firms' statements on the employment of a foreigner over time. In both panels, the vertical gray lines indicate the period before and after the Russian aggression against Ukraine.

[6]According to Statistics Ukraine (2017), between 2015 and 2017, over 73% of Ukrainian labor migrants in Poland originated from Western Ukraine, not directly affected by the war. This suggests that the migration shock was primarily driven by the economic and currency shock resulting from Russian aggression.

is a driver of migration (Docquier *et al.*, 2014). Ukrainian networks in Poland as well as relatively small geographical and linguistic distance, which also play a role in the choice of destination (see e.g., Adsera and Pytlikova (2015), and Bredtmann *et al.* (2020)), make Poland a natural destination country for Ukrainians.[7] Thus, after the Russian aggression against Ukraine in 2014, the Polish economy experienced an unexpected and massive inflow of Ukrainian workers reaching almost two million in 2019 as illustrated in Figure 1b. The next section discusses their geographic location within Poland.

2.2 Ukrainians in Poland: Historical Background and Geographic Dispersion

Figure 2 shows the geographic dispersion of Ukrainian workers across Polish counties in 2019. Ukrainians are more likely to work in areas of Poland far from the Ukrainian border for historical reasons.

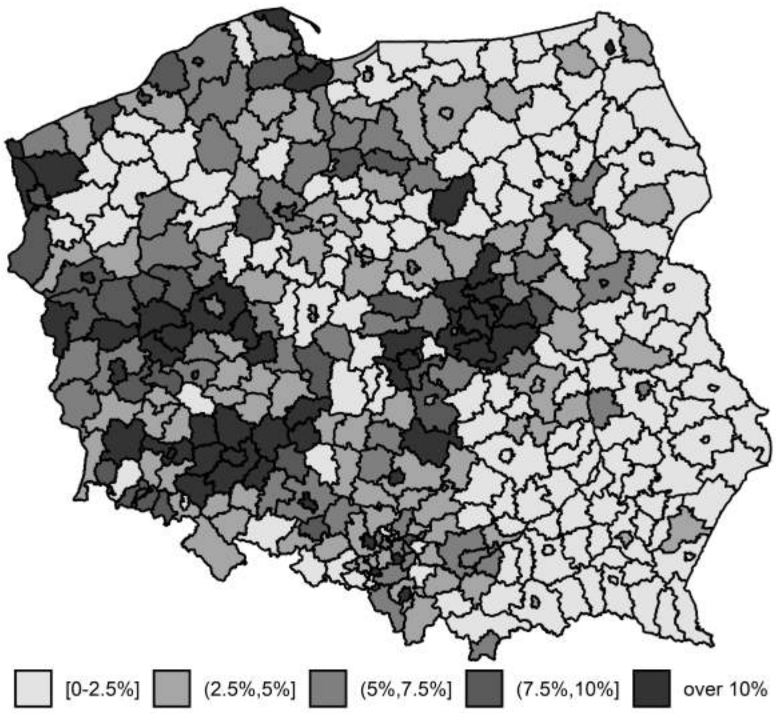


Figure 2: Geographic dispersion of Ukrainian workers in 2019

Notes: This figure presents the spatial distribution of the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013 across Polish counties.

[7]For literature on the role of migrant networks in determining migration and location decisions, see for example McKenzie and Rapoport (2010), Beine and Coulombe (2018), and Giulietti *et al.* (2018).

After World War II, most Ukrainians living within Poland's new borders were resettled to the Soviet Union. The remaining Ukrainian minority, living primarily in the southeast of the Polish territory, was forcibly resettled by the Polish People's Army in April 1947. Overall, around 140,000 Ukrainians were relocated during the military operation called Vistula. The official goal of this forced resettlement was to prevent the recruitment of new members of the Ukrainian Insurgent Army (UPA) and suppress any potential collaboration with this Ukrainian nationalist paramilitary formation (Nasz Wybir, 2016; Plokhy, 2016; Misiło, 2013).

During the military operation Vistula, Ukrainians living in southeastern Poland were to be *"scattered among the Polish population so that they do not pose any danger [to the Polish People's Republic]"* (Misiło, 2013). Entire families identified by the local government as Ukrainian, along with mixed families, were forced to leave the areas they had historically inhabited. To undermine the national, cultural, and familial ties within the Ukrainian community in Poland, people originating from the same locality were supposed to be separated, and the total number of resettled Ukrainians was not to exceed 10% of the local population. These guidelines often went unmet due to two primary reasons: delayed arrival of information to the authorities or receiving it only after resettlement, as well as the initial underestimation of the Ukrainian population's size, resulting in a much larger resettlement than expected. As a result, the allocation of Ukrainians to counties was influenced by the extent of post-war destruction and thus by the availability of housing. The crucial factor, however, was the availability of train stations, since the resettlement was primarily carried out using trains (Misiło, 2013).

Furthermore, Polish authorities' efforts to create a unitary state and suppress Ukrainian national identity led to the prohibition of the Ukrainian language and culture in the early 1950s (Nasz Wybir, 2016). The dispersion of the Ukrainian population and further persecution made it difficult to preserve the Ukrainian language and cultivate culture. Therefore, only if the resettled Ukrainian community was large enough to resist the forced cultural assimilation, the Ukrainian identity could survive.

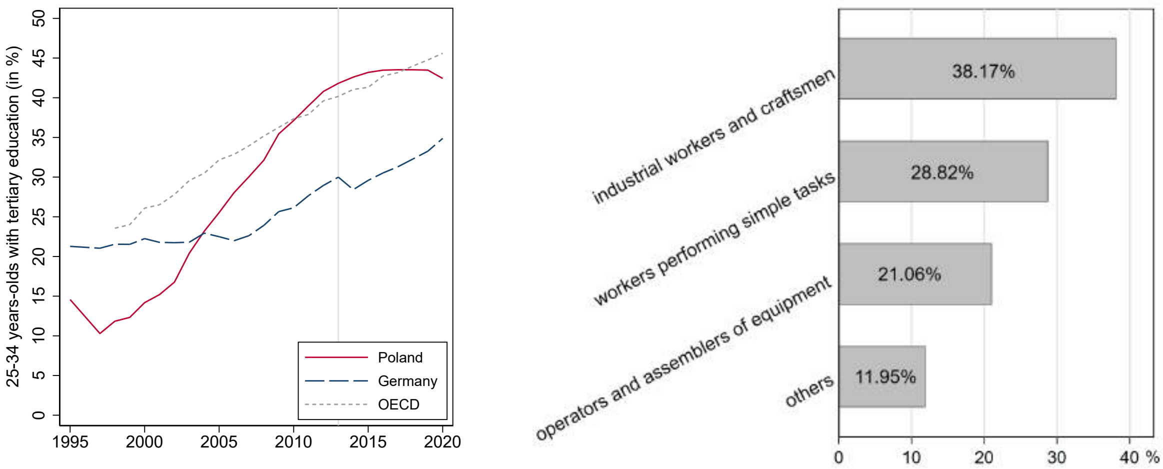
As restrictions on the cultivation of Ukrainian culture were gradually eased over time, Ukrainian institutions emerged in large Ukrainian centers, that had formed as a consequence of Operation Vistula. Establishments such as Ukrainian churches or schools helped to preserve Ukrainian culture and language despite earlier dispersion and repression.[8] The existence of such Ukrainian establishments and networks that attracted contemporary migrant workers from Ukraine explains their current distribution far from the Ukrainian border in places not populated by Ukrainians before World War II.

2.3 Complementarity of Polish Emigrants and Foreign Workers

Well-established immigration countries, as the United States, Canada, or Germany, seek to alleviate labor shortages through immigration. In contrast, before the inflow of temporary workers from Ukraine, Poland was a country of emigration. Over 2 million Poles emigrated from Poland in the decade after the country's accession to the European Union in 2004 (Financial Times, 2014). Similar to trends in other post-communist countries, Polish emigrants were on average younger and more educated than the overall population. In fact, the proportion of Polish emigrants with tertiary education was approximately twice as high as that within the Polish population (IMF, 2016).

The positive selection of educated emigrants is related to the saturation of the Polish labor market with university graduates. After the fall of the Iron Curtain, Poland began a transition from a communist to a free-market country, which led to a surge in demand for university education. The desire for better living conditions and a social advancement has led to a massive increase in the number of people with higher education (Onet, 2012a). Figure 3a shows that the share of young people with tertiary education in Poland increased from around 10-15% in the 1990s to almost 45% in 2014.

[8] Ukrainian religious ceremonies were allowed to be cultivated, first at Polish Roman Catholic parishes and later also in newly established Ukrainian Greek Catholic and Orthodox churches. See Figure A2 in the Appendix for examples. Further liberties were introduced after social protests in the 1980s and the subsequent collapse of communism in Poland (Nasz Wybir, 2016). For example, schools with education in the Ukrainian language were established in the 1990s. Figure A3 in the Appendix shows two examples of such schools.



(a) Youths with tertiary education **(b)** Types of work Ukrainians perform

Figure 3: Complementarity of Poles entering labor market and Ukrainian immigrants

Notes: Panel (a): Percentage of 25 to 34 years old with tertiary education over time. Data source: OECD (2023) The vertical gray line indicates the periods before and after the treatment. Panel (b): Distribution of the share of statements on the employment of a Ukrainian in 2019 by occupation groups according to the Polish Classification of Occupations and Specializations.

Despite experiencing steady economic growth, the Polish economy was not able to absorb the excessive number of young people with higher education entering the Polish labor market *"saturated with freshly baked managers, teachers, economists, lawyers, sociologists, and political scientists"* (Dziennik Gazeta Prawna, 2012a). The record-breaking unemployment rates of people with higher education (Dziennik Gazeta Prawna, 2012b), lack of job prospects in the profession after graduation, and the persistence of relatively low wages in Poland led to the *"exodus of youth"* (Financial Times, 2014).

Given Poland's long-standing high emigration rates, the massive and sudden inflow of Ukrainian workers could increase the Polish *'exodus'*, for example, by intensifying competition in the affected local labor markets. However, Polish emigration decreased in parallel with the inflow of temporary workers from Ukraine.[9] Furthermore, the share of highly educated emigrants in all Polish emigrants has decreased from a long-standing trend of above 40% to below 35% (Giesing and Schikora, 2023).[10] Could the unexpected

[9]See Figure A4 in the Appendix.

[10]This indicates a decrease in brain drain from Poland, as the overall share of tertiary education attainment in Poland remained stable after the inflow of temporary workers from Ukraine. In particular, the educational attainment of the 25-34 age group, which was most likely to emigrate (Giesing and Schikora, 2023), also remained stable (see Figure 3a).

inflow of temporary workers from Ukraine be contributing to the drop in Polish emigration, particularly of highly educated citizens?

Whereas Polish graduates often preferred to emigrate and take up manual work abroad to avoid low-paying positions below their qualifications in Poland (Onet, 2012b), Ukrainians were willing to accept even low-wage jobs in Poland. As temporary foreign workers spend a significant share of their income in the home country, their reservation wage is determined by the relative exchange rate between the currencies of their home and host country (Dustmann *et al.*, 2021). Figure 1a shows that the value of the Polish zloty increased from roughly 2 to around 7 hryvnia after Russian aggression. Thus, whereas Ukrainian employees were not necessarily low-skilled, they were likely to have a lower reservation wage. As a result, Ukrainian workers were willing to do even low-wage jobs that natives were not. Furthermore, Figure 3b shows that almost 90% of Ukrainian workers were employed in blue-collar jobs that generally do not require academic education. They were thus engaged in occupations complementary to the skills of the highly educated Polish emigrants.

3 Data

To estimate the impact of the inflow of Ukrainian workers on the local migration patterns in Poland, I exploit panel data at the county level.[11] I combine multiple administrative data and unique historical data based on military records.

Migration data. I use two sources of administrative data on migration. First, data on the internal and international migration patterns, my main outcome variables, is provided by the Central Statistical Office of Poland (Statistics Poland). This county-level data is based on administrative records from the Polish Universal Electronic Population Registration System, which centrally collects from local authorities all information on

[11] Counties are the second administrative level (NUTS-4) in Poland. My original sample includes all 380 counties. Due to administrative changes, I aggregate the data of Walbrzych county and the city with county rights Walbrzych, which was part of Walbrzych county until 2013. This results in a final sample size of 379. Table A1 in the Appendix reports the descriptive statistics.

mandatory (de-)registrations for a permanent stay.[12]

Second, to measure the spatial distribution of Ukrainian workers across Polish local labor markets, I use county-level administrative records of the Ministry of Family, Labor and Social Policy on firms' statements on the employment of a foreigner.[13] In particular, I use variation across Polish counties in the firms' statements on hiring Ukrainian citizens in 2019 as a proxy for the exposure intensity to the labor supply shock. This has twofold reasons. First, this data is not available at the county level before 2019. Second, to carry out the baseline analysis without the migration activity distortion due to the COVID-19 pandemic, I restrict the analysis to the years before 2020.

Historical data for the instrument. To generate the instrument, I take advantage of unique historical data. In particular, I construct a novel data set with distances from places to which Ukrainians were forcibly resettled in 1947 during the military operation Vistula described in section 2.2. First, I geolocate data based on archive military records collected by Misiło (2013). Second, to calculate the relative size of the historical network of Ukrainians in Poland, I combine the available information on the size of the military transports with data from Becker *et al.* (2020) on the population size of affected counties based on the first census in Poland after World War II from 1950.

Mechanisms and control variables. My primary source of administrative data on mechanisms and control variables at the county level is Statistics Poland, which processes and provides administrative data, including contemporary local labor market information, collected from local authorities. In addition, for historical controls such as the number of railway stations in 1964, the measure of World War II destruction, and industrial production per capita in 1954, I draw on data from Becker *et al.* (2020).

[12] Therefore, this data does not encompass the inflow of Ukrainians, as they were only granted a temporary stay in Poland and thus were not eligible for permanent residency registration.

[13] Until 29 January 2022, citizens of Ukraine, Armenia, Belarus, Georgia, Moldova, and Russia were allowed to work in Poland without a work permit during a period not exceeding 6 months in consecutive 12 months on the basis of a firm's statement of the intention to employ a foreigner.

4 Empirical Strategy

4.1 Econometric Equation

I examine the impact of the inflow of Ukrainian temporary workers on the migration behavior of Poles by estimating the following baseline equation in first differences:

$$\Delta y_c = \beta \Delta m_c + \tau + \Delta \varepsilon_c. \tag{1}$$

Following Edo (2020) and Bohnet *et al.* (2022), I measure the intensity of the labor supply shock as $\Delta m_c = M_{c,2019}/L_{c,2013}$ where $M_{c,2019}$ is a proxy for the number of Ukrainian workers in county c standardized by the pre-shock working-age local population $L_{c,2013}$. $\Delta y_c = (Y_{c,2019} - Y_{c,2013})/L_{c,2013}$ is the change in either internal or international migration patterns, i.e. in-migration or out-migration, between 2019 (post-shock period) and 2013 (pre-shock period) in county c, standardized by the pre-shock working-age local population $L_{c,2013}$. τ represents the common time trend and $\Delta \varepsilon_c$ is the error term.

The dependent variable and the explanatory variables of interest are standardized by the same denominator. This allows me to account for the differential sizes of the local labor markets and interpret the coefficient of interest β as the absolute change in the number of migrants associated with the inflow of 100 foreign workers (Han *et al.*, 2022).[14]

First differences eliminate time-invariant county-specific characteristics and τ controls for the common time trend of the dependent variable and shocks that affect all counties in the same manner. Furthermore, the first difference specification with two time periods that includes the constant τ also accounts for potential structural data misreporting that is constant within counties over time or that changes over time but is constant across all counties. Furthermore, I use heteroskedasticity-robust standard errors and cluster them at the NUTS-3 level (one level higher than the county level) to account for possible serial correlation in migration patterns at the regional level.

The estimation of the first differences model from equation 1 is equivalent to a difference-

[14] For visualization purposes, in contrast to Han *et al.* (2022), I multiply the outcome variables by 100.

in-differences model with variable treatment intensity (Edo, 2020). Thus, my identification strategy relies on the common trend assumption. To test the validity of this assumption and examine the dynamics of the effect, I obtain the event study coefficients by interacting the instrumented inflow of Ukrainians in 2019 with yearly indicators and defining Δm_c as the difference in internal or international migration patterns between the respective post- or pretreatment year and 2013.

4.2 Endogeneity of Immigrants' Location Choices

The identifying assumption of equation 1 is that county-specific time-varying differences included in $\Delta\varepsilon_c$ are not related to the spatial location of Ukrainian workers. Yet, although the inflow of Ukrainians was unexpected, the location of Ukrainian workers across local labor markets in Poland is not random. Migrants' location choice is partly determined by the prospects of local labor markets, which are also determinants of the migration behavior of natives (Peri, 2016). Thus, counties attracting more immigrant workers would potentially have experienced higher in-migration trends even in the absence of the inflow of Ukrainian workers.

Figure 4 presents the results of a balancing test. It shows that several county characteristics, which potentially have an impact on migration patterns, are highly correlated with the location of Ukrainian workers. In particular, Ukrainians are more likely to choose counties with initially higher wages and lower unemployment. Therefore, a simple OLS model will most likely capture a spurious correlation between the migration patterns of Poles and the presence of Ukrainians driven by the prospects of local labor markets.

To address the endogenous location of immigrants, I make use of the instrumental variable approach. However, conventional instruments used in migration literature, such as shift-share or distance to the immigrants' country of origin, are not an adequate source of exogenous variation in the context of this study. As a result of the forced resettlement of Ukrainians shortly after World War II, Ukrainian networks in Poland do not follow the pattern typical to bordering countries. Furthermore, due to the subsequent persecution of

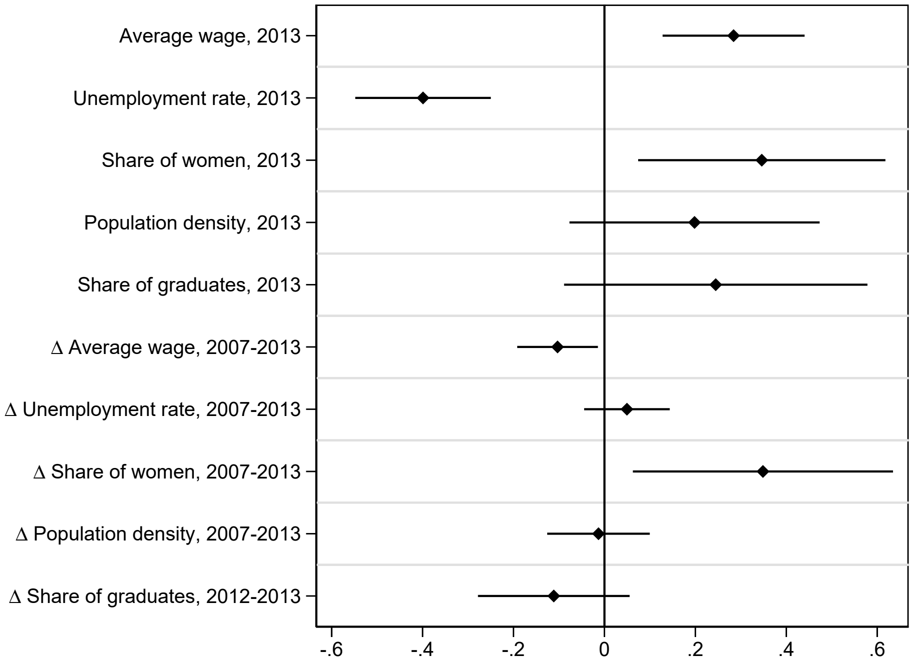


Figure 4: Correlates of the share of Ukrainians

Notes: This balancing test presents bivariate correlations with the share of Ukrainians (Standardized Beta Coefficients +95% CI). Due to data availability, I use the change in the share of graduates between 2012 and 2013 instead of the change between 2007 and 2013.

Ukrainian culture and language, in regions with a small resettled Ukrainian population, Ukrainians became assimilated. As a result, the historical share of Ukrainians is not predictive of the contemporary location choices of Ukrainian workers. Therefore, I propose a novel instrument to address concerns about the endogenous location of immigrants.

4.3 Distance to Historical Exposure Hotspots as Instrument

To capture exogenous variation in the location of Ukrainian workers across Polish counties, I use a novel instrument based on historical records on the forced resettlement of Ukrainians in Poland. In particular, I instrument the current distribution of Ukrainian workers with the distance from historical hotspots of Ukrainian networks that emerged due to Operation Vistula described in section 2.2.

The instrument combines the idea of exploiting historical settlements of immigrants as in a shift-share instrument with an alternatively used instrument based on the distance to the border of the immigrants' origin country. It is inspired by, for example, Dustmann *et al.* (2017) and Aksu *et al.* (2022), which use the distance to the border of the immigrants' origin country as an instrument for the increase in labor supply due to immigrant inflow. Dustmann *et al.* (2017) examine the impact of Czech commuters in German border regions who were daily commuters by law. Aksu *et al.* (2022) study the impact of Syrian refugees in Turkey, where initial registration camps were located close to the Syrian border. While both studies provide credible arguments for using distance to the immigrants' origin country border, they do not apply in the setting of this study. Ukrainian workers were not restricted to commute daily but were allowed to work in Poland for up to 6 months per year and had no other institutional incentives to stay closer to the Ukrainian border.

Therefore, instead of using distance from the Ukrainian border as an instrument, I use distance from the nearest historical forced settlement of Ukrainians. To account for the easier (forced) assimilation of small groups of displaced persons, I focus on larger communities of resettled Ukrainians. First, I geolocate places that were designated as final destinations for forcibly resettled Ukrainians in Operation Vistula. Second, I calculate the relative share of the resettled population by dividing the absolute size of resettlement by the size of the local population in 1950. Third, I define historical hotspots of Ukrainian networks as places where the share of forcibly resettled Ukrainians exceeded 10% of the local population. Then, I calculate the distance in kilometers from the centroid of each county to each of the hotspot points. Finally, I define the instrument as the minimum distance to any of the exposure hotspot points. Figure 5 visualizes the generated instrument.

I test the relevance condition by regressing the share of Ukrainian workers in 2019 against the generated distance instrument. The negative and statistically significant coefficient, presented in Figure 6a, indicates that the distance to the nearest exposure hotspot is a relevant predictor of the contemporary location of Ukrainian workers.[15]

The identifying assumption is the untestable exclusion restriction. In the underlying setting, I assume that the distance from the historical Ukrainian hotspots does not affect changes in local migration patterns beyond the contemporary inflow of temporary workers from Ukraine. As a first check of the plausibility of this assumption, I conduct a balancing test. Similarly to Figure 4, I regress several county characteristics, which potentially have

[15]Figure A5 in the Appendix shows a plot of this correlation.

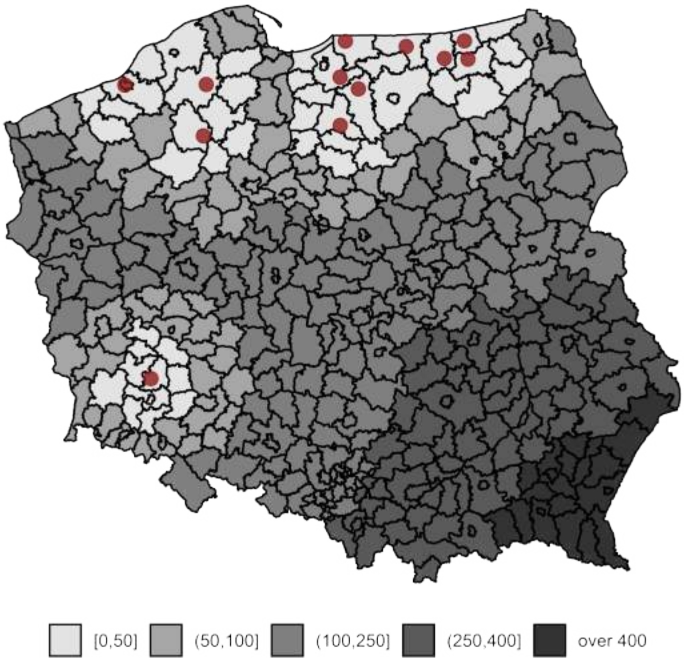


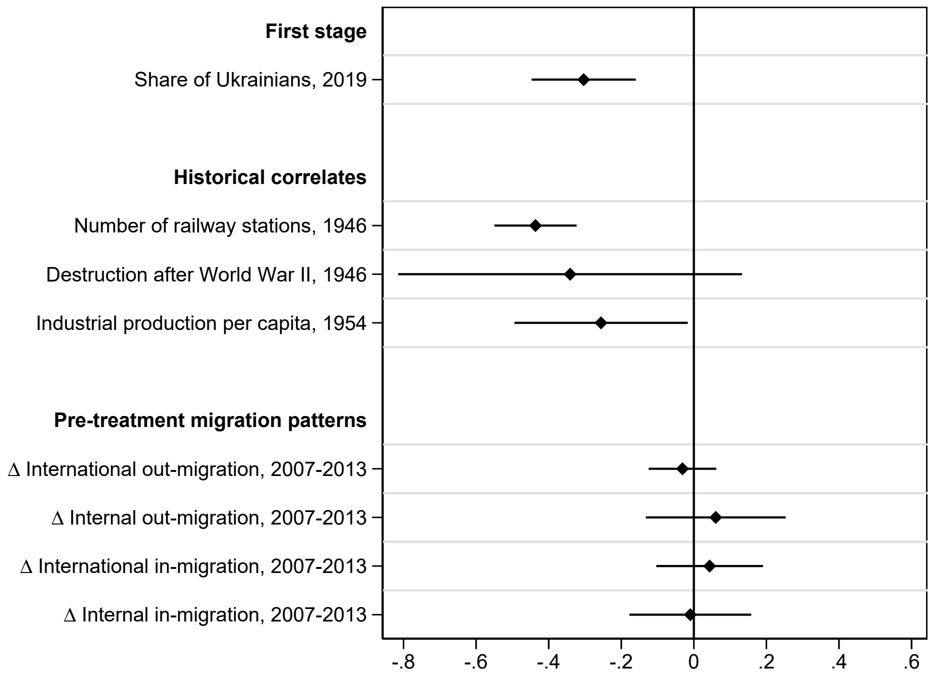
Figure 5: Distance instrument

Notes: This figure presents the variation in distance (in km) to the nearest exposure hotspot point. Exposure hotspot points are depicted in the map as red points and are defined as localities in which the share of forcibly resettled Ukrainians exceeded 10% of the local population. For visualization purposes, the continuous distance variable is presented with a discrete scale.

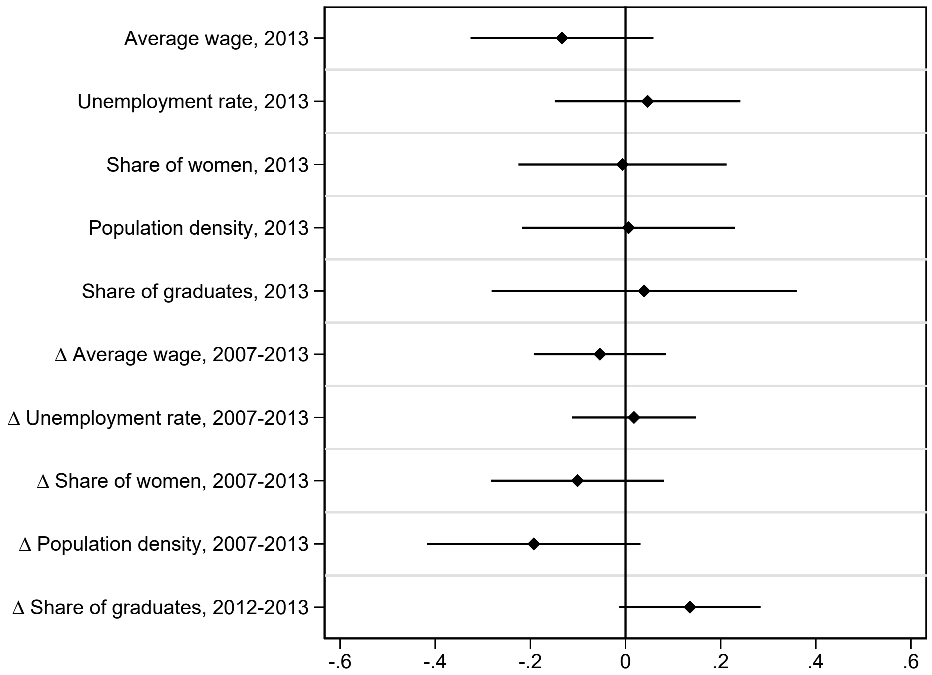
an impact on migration patterns, against the generated instrument. Figure 6b shows that none of the estimated coefficients is statistically different from zero. In particular, the instrument is not correlated with pre-treatment changes in local labor market conditions or their initial pre-treatment values.

Furthermore, I regress the instrument on possible historical factors linked to the location of the hotspot points and the changes in migration patterns in the pre-treatment period. The results in Figure 6a reveal that the instrument is not predictive of changes in migration patterns in the pre-treatment period, as the estimated coefficients are never significantly different from zero. The instrument is negatively correlated with factors related to the resettlement of Ukrainians, such as the number of railway stations in 1946, post-World War II destruction, and historical industrial production per capita, that could potentially impact modern-day outcomes.[16] The results are robust to controlling for those factors, thus, taken together these findings support the validity of my instrument.

[16]The extent of destruction after World War II is quantified by measuring the volume (in cubic meters) of urban buildings that were destroyed.



(a) First stage and correlates



(b) Balancing test

Figure 6: Correlates of the instrument

Notes: Both panels present bivariate correlations with the instrument (Standardized Beta Coefficients +95% CI). Panel (a): Due to data availability, I use the change in the share of graduates between 2012 and 2013 instead of the change between 2007 and 2013.

5 Results and Discussion

5.1 Main Results

OLS Estimates. I start by providing the results of a linear regression model using Equation 1 in Panel A of Table 1. First, I show results without the inclusion of control variables in Specification 1. Column 1 indicates that there is no evidence of a statistically significant correlation between exposure to the inflow of temporary workers from Ukraine and international out-migration from local labor markets. Next, I include a Bartik (1991) variable, that combines local industry shares at baseline with industry-specific growth rates at the national level to control for labor demand shocks related to industry structure in Specification 2.[17] Then, I include a set of controls for initial conditions such as initial population density, the share of graduates, the share of females, wages, and unemployment in Specification 3.[18] For international out-migration, the coefficient remains statistically not different from zero.

This null result could be a consequence of two factors that drive the coefficient in opposite directions. On the one hand, Ukrainians tend to settle in places with better labor market prospects, which are also likely to be negatively correlated with local out-migration. On the other hand, the complementarity between Ukrainians and Polish emigrants might lead to a positive correlation between the location of Ukrainians and high local international out-migration.

Column 2 shows a consistently negative correlation between exposure to Ukrainian workers and internal out-migration. This suggests that the complementarity effect does not play an important role in internal migration. As expected, due to local amenities, such as better labor market prospects, there is less internal out-migration from places that attract more immigrant workers.

[17]Thus, in the setting of this study Bartik variable is defined as $\Delta Bartik_c = \sum_k (s_{k,c}^{2013} \cdot (\Delta N_k / N_k^{2013}))$, where k stands for four different sector activities, namely manufacturing and construction, agriculture and trade, financial sector, and other services.

[18]Controlling for initial conditions in a first-differences setting allows for post-treatment changes in the relationship between the outcome variable and those county-specific characteristics.

Table 1: Inflow of Ukrainians and Local Migration Patterns

	Panel A: OLS				**Panel B: 2SLS**			
	Out-migration		In-migration		Out-migration		In-migration	
Specification	International	Internal	International	Internal	International	Internal	International	Internal
1. Basic regression (no controls)								
Share of Ukrainians	0.034	-0.512**	0.137***	1.162***	-0.498**	-1.886***	-0.040	-0.719
	(0.066)	(0.194)	(0.033)	(0.296)	(0.237)	(0.556)	(0.125)	(1.710)
First-stage F-stat					17.77			
2. Add Bartik variable								
Share of Ukrainians	0.046	-0.508**	0.148***	1.217***	-0.429*	-1.877***	0.023	-0.421
	(0.066)	(0.197)	(0.033)	(0.345)	(0.228)	(0.557)	(0.103)	(1.526)
First-stage F-stat					18.60			
3. Add controls for initial conditions								
Share of Ukrainians	0.144	-0.364*	0.085*	0.813*	-0.529**	-1.916***	-0.073	-0.879
	(0.096)	(0.190)	(0.043)	(0.430)	(0.264)	(0.583)	(0.096)	(1.193)
First-stage F-stat					25.96			
Clusters	72				72			
Observations	379				379			

Notes: The explanatory variable is the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013. All dependent variables are standardized by the same denominator as the explanatory variable. I instrument the current distribution of Ukrainian workers using distance from historical hotspots of Ukrainian networks. The controls for initial conditions include population density, the share of females, the share of graduates, the unemployment rate, and average wages in 2013. All regressions are weighted by the pre-treatment working-age population. Standard errors clustered at the NUTS3 level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Columns 3 and 4 report that counties with stronger exposure to the inflow of temporary workers from Ukraine experience higher internal and international in-migration for a permanent stay. Without the inclusion of control variables, this correlation is highly statistically significant, however, including controls for initial conditions reduces this correlation (see Specification 3). This confirms that the correlation between the inflow of Ukrainian workers and in-migration for permanent stay is driven by the characteristics of the affected counties.

Overall, the findings confirm, that resulting from the endogeneity of immigrant workers' location decisions, the simple OLS regression captures a spurious correlation between the migration patterns of Poles and the presence of Ukrainian workers driven by the (partly unobservable) characteristics of the affected counties. Thus, to interpret the results causally, I resort to the instrumental variables approach.

2SLS Estimates. I start again by providing the results without controls in Specification 1 in Panel B of Table 1. Columns 1 and 2 show that, on average, the inflow of Ukrainian workers to local labor markets significantly decreases the international and internal out-migration of the local population. This result is robust to controlling for potential confounders.[19]

The standardization of the outcome and the measure of treatment by the same denominator allows me to interpret the coefficient as the absolute change in the number of emigrants due to the inflow of 100 Ukrainian workers. On average, an inflow of 1000 workers into a county decreases the international out-migration of the local population by around 5 and the internal out-migration by around 19 inhabitants. The estimated effect size indicates that the labor supply shock contributed to the overall decrease in permanent emigration from Poland between 2013 and 2019 by around 30%.[20]

[19]Table A2 and Table A3 in the Appendix show that the results remain robust even with the inclusion of several time-varying controls and historical correlates, such as the number of railway stations in 1946, which is highly correlated with the instrument.

[20]The total decrease in emigration from Poland between 2013 and 2019 was 21 thousand. The inflow of Ukrainians can be attributed to the overall observedecrease in the emigration of around seven thousand inhabitants (calculated as the change in the Ukrainian workers divided by 1000 and multiplied with the point estimate of around 5). Seven thousand divided by 21 thousand equals around 30%.

Columns 3 and 4 show no statistically significant evidence of a decrease in international or internal in-migration to counties with higher exposure to Ukrainian workers. However, while not statistically significant, the size of the negative point estimate for internal in-migration may suggest that the inflow of Ukrainians crowds out in-migration from other Polish counties.

Pre-trends and dynamic effect. Figure 7 shows dynamic difference-in-differences coefficients in an event study graph.[21] Although some pretreatment coefficients are statistically significantly different from zero, overall there is no evidence of clear pretreatment trends. This suggests that the parallel trend assumption holds.

The observed effects are in line with the findings discussed earlier with one exception. The dynamic representation reveals statistically significant crowding-out of in-migration from other Polish counties as an initial response to the shock in counties with higher exposure to temporary workers from Ukraine. [22] This effect decreases in magnitude and becomes statistically insignificant for international in-migration after two and for internal in-migration after four years, indicating a reduction of this effect in the long run. However, the crowding-out effect seems to reappear during the COVID-19 pandemic.

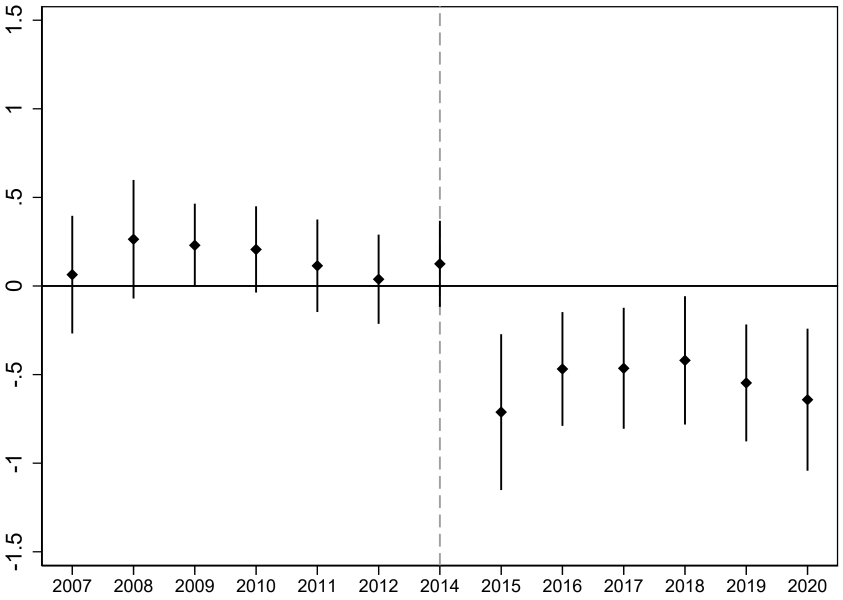
While the overall effect on local migration seems to balance out in the short run, in the long run, the magnitude of the decrease in out-migration appears to surpass the effect on in-migration. Furthermore, taking into account the size of the inflow of temporary workers from Ukraine, the results clearly indicate an enlargement of local labor markets.

5.2 Validity of the Empirical Results and Robustness Checks

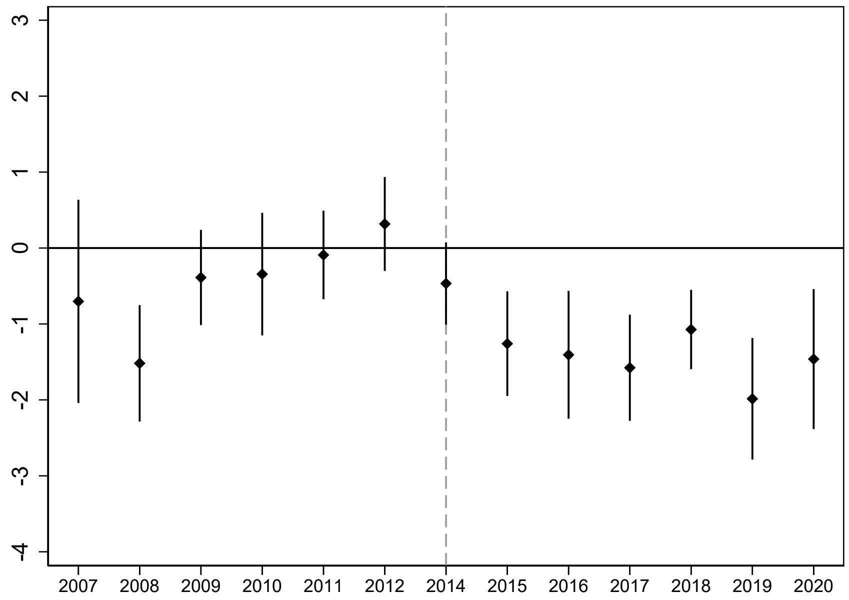
The main identification assumption is that the distance from historical Ukrainian settlements, which were established due to forced resettlement shortly after World War II, has no effect on migration patterns beyond the inflow of temporary workers from Ukraine.

[21] I control for the number of railway stations in 1946, which is highly correlated with the instrument.

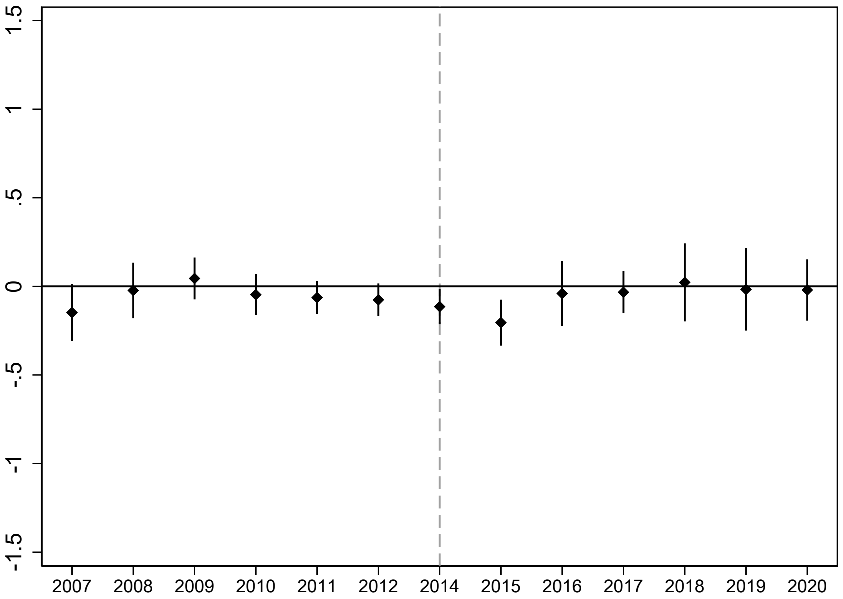
[22] This finding is in line with recent studies such as Dustmann *et al.* (2017), Amior and Manning (2018), and Monras (2020).



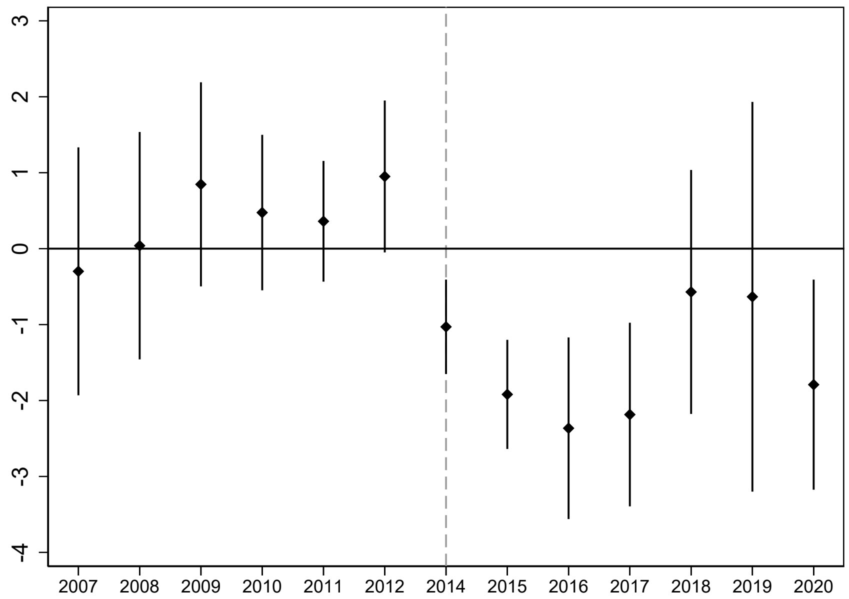
(a) International Out-migration



(b) Internal Out-migration



(c) International In-migration



(d) Internal In-migration

Figure 7: Inflow of Ukrainians and Local Migration Patterns - Event Study

Notes: The coefficients to the left of the vertical gray line show the trends before treatment. The coefficients are obtained by interacting the instrumented inflow of Ukrainians with annual indicators. I control for the number of railway stations in 1946. The reported standard errors were obtained using a bootstrap procedure.

If this assumption holds, I identify the local average treatment effect (LATE) for the subgroup of compliers to the instrument. In the context of this study, compliers are Ukrainian workers whose location decision was affected by the geographic proximity to the location of their historical ethnic networks. Given that the inflow of Ukrainian workers was unexpected, it is likely that Ukrainian ethnic networks in Poland played a crucial role in the location decision of Ukrainian workers and the group of compliers is sizable. This expectation is reinforced by the strong first stage.[23] The dynamic analysis reveals no indications of pre-treatment trends in migration outcomes between counties with different exposure to the inflow of Ukrainians, which suggests that the parallel trend assumption holds. Furthermore, to test the internal validity of the results, I run several robustness checks.

The Measure of the labor supply shock. I examine whether the results are sensitive to using alternative measures of the labor supply shock. First, in the baseline results, I do not consider seasonal workers as part of the labor supply shock due to the different legal and economic nature of such migration. Panel A in Table A4 in the Appendix shows that the results are robust to the inclusion of seasonal workers in the measure of the labor supply shock. Second, due to the migratory activity distortion during the pandemic, in the baseline results, I do not consider the measure of the labor supply shock from 2020 but from 2019 only. Panel B in Table A4 in the Appendix shows that the results are robust to using the declarations on the employment of a foreigner from 2020.

Furthermore, as both my treatment and outcome variables are standardized by the same denominator, there is a potential risk of spurious correlation. Table A5 in the Appendix shows that the results are robust to the implementation of the Kronmal (1993) specification correction, as suggested by Clemens and Hunt (2019) to address this concern.

Alternative definition of the instrument. I test if the results are robust to several alternative definitions of the instrument. Table A6 in the Appendix shows the results using the alternative thresholds of 12%, 8%, as well as 6% of forcibly resettled Ukrainians in the

[23] The first-stage F-test statistics are larger than the conventional lower bounds in all specifications, showing that the instrument is relevant and does not suffer from the weak instrument problem.

local population. The results using several other thresholds than 10% when generating the distance instrument are similar to those reported in the main analysis. Moreover, the results are robust to using a more continuous measure of the instrument. Table A7 in the Appendix shows results using as an alternative instrument the interaction of the historical share of Ukrainians with the distance to the hotspots.

Spatial spillovers and sensitivity to sample restrictions. To assess the robustness of the results to accounting for potential spatial spillovers, I present in Table A8 in the Appendix the results with standard errors following Conley (1999, 2008). The findings remain robust when allowing for spatial correlation within various cutoff distances. Furthermore, a possible source of concern is that the results may be driven by an outlier, such as a large city or a few counties in the commuting zone of a large city. Thus, I conduct a so-called leave-one-out approach. Table A9 and Table A10 in the Appendix provide results where I exclude for estimation in each row one of the six largest functional urban areas (FUA) in Poland.[24] Table A10 provides also two further robustness checks: in Panel C I exclude all counties from the six largest FUAs and in Panel D all 58 urban cores of all FUAs in Poland.

Furthermore, I examine if the results are not driven by counties with high initial levels of migration. In particular, Table A11 in the Appendix shows results where I exclude in each case 5% of counties with the highest initial international out-migration, the highest initial internal out-migration, the highest initial international in-migration, and the highest initial internal in-migration.[25]

McKenzie and Rapoport (2010) find that the self-selection of immigrants may vary with the strength of the migration network. Thus, as my instrument is based on the network of Ukrainians in Poland, the results may be potentially driven by either positively or negatively self-selected migrants. Therefore, as an additional robustness check, in

[24]Each of the FUAs consists of counties in a common commuting zone. Figure A6 in the Appendix provides a map with a visualization of the six largest FUAs in Poland.

[25]The results are more pronounced when excluding counties with the highest initial internal in-migration. This suggests that counties initially less attractive for internal migration experience a greater decrease in out-migration compared to those that were particularly attractive for internal in-migration prior to the inflow of Ukrainian workers.

Table A12 in the Appendix, I exclude 5% of counties closest to the historical hotspots of Ukrainian networks in Panel A and 5% of counties with the greatest distance to those exposure hotspots in Panel B.

Taken together, the results show that the magnitude and significance of coefficients of interest do not depend on the exclusion of several potential outliers and are not sensitive to the changes in the treatment measure and instrument definition. Moreover, I find no evidence of pre-treatment trends in migration outcomes between counties with different exposure to the inflow of Ukrainians, which suggests that the parallel trend assumption holds.

5.3 Mechanisms

The massive and unexpected supply shock of workers with low reservation wage could potentially further increase the out-migration rates, for example, by intensifying competition and putting downward pressure on wages in the affected local labor markets (Borjas, 2003). However, I find that the inflow of Ukrainians leads to a decrease in out-migration. In this section, I analyze the underlying mechanisms.

I first examine the impact of stronger exposure to the inflow of Ukrainian workers on average local wages. Figure 8 shows that there is no evidence of a decrease in wages, on the contrary, although not statistically significant, the point estimate is positive.[26] There are two possible explanations. First, a binding minimum wage could protect native workers who may be in competition with immigrants (Edo and Rapoport, 2019).[27] Second, the inflow of workers from Ukraine does not necessarily lead to increased competition in local labor markets, particularly if immigrants and natives are complements rather than substitutes.[28] Section 2.3 provides descriptive evidence on the complementarity between Ukrainians with low reservation wages and Poles, who often emigrate due to a lack of job

[26]Table A13 in the Appendix provides the complete regression results.

[27]Poland has a long tradition of minimum wages, which were first introduced as early as 1956. Figure A7 in the appendix shows the ratio of the minimum wage to average wages by county, indicating in which regions the minimum wage might play a particular role in protecting low-income workers.

[28]See for example Peri and Sparber (2009), Foged and Peri (2016), Mitaritonna *et al.* (2017), Akgündüz and Torun (2020), and Storm (2022).

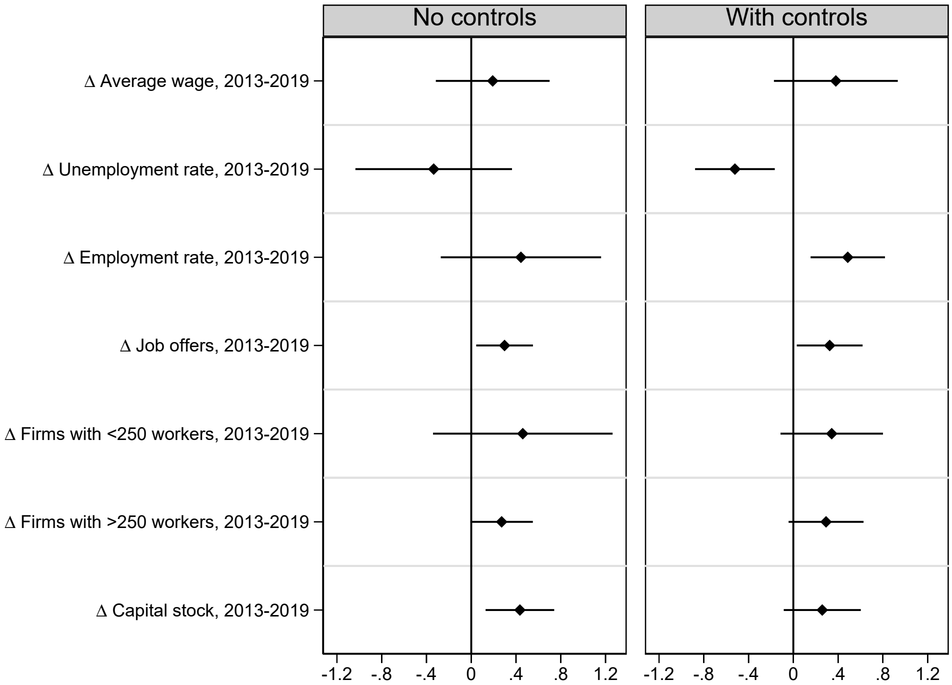


Figure 8: Scaling-up of local labor markets

Notes: This figure presents Standardized Beta Coefficients (+95% CI) using 2SLS. The explanatory variable is the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013. All dependent variables are standardized by the same denominator as the explanatory variable. I instrument the current distribution of Ukrainian workers using distance to historical hotspots of Ukrainian networks. Controls include population density, the share of females, the share of graduates, the unemployment rate as well as average wages in 2013.

prospects in the Polish labor market saturated with highly educated workers.

The remaining results presented in Figure 8 show evidence of upscaling, that is, an enlargement of local labor markets. In particular, I find evidence of an increase in job offers and employment as well as a decrease in unemployment in counties that are more exposed to the inflow of Ukrainian workers. I also find suggestive evidence of an increase in the number of firms with more than 250 workers. The point estimate on the change in the number of smaller firms is positive as well but estimated very imprecisely. In line with the increase in the number of firms, I find suggestive evidence of higher capital investments in counties more exposed to the inflow of Ukrainians.

Taken together, the results suggest an upscaling, that is, an enlargement of local labor markets, as a potential driver of the decrease in out-migration. On one hand, the sudden inflow of temporary workers from Ukraine with low reservation wages appears to foster the emergence of firms in counties with stronger exposure to this shock, leading to an increase in job offers and overall employment, as well as a decrease in unemployment. On the other hand, descriptive evidence underscores the abundance of highly educated natives at the time of the shock, highlighting the complementarity between Ukrainian workers and Polish emigrants. Consequently, highly educated natives, who could potentially emigrate, may now fill newly created non-manual positions, such as managers, accountants, or supervisors, which complement the jobs performed by Ukrainian workers. Furthermore, firms increase their investment in capital that is complementary to the high-skilled natives, medium-skilled natives, and immigrant workers (Lewis, 2011). This, in turn, contributes to the further enhancement of the local labor markets. Overall, the results indicate that the inflow of Ukrainian workers with low reservation wages facilitated the absorption of abundant natives into the local labor markets, preventing them from emigrating.

6 Conclusion

This paper investigates the effect of the unexpected and massive inflow of temporary workers that resulted from Russia's aggression against Ukraine in 2014 on the migration patterns in Poland. The empirical strategy relies on variation across local labor markets in the exposure intensity to Ukrainian workers in a first-difference framework. To address the endogenous location of immigrant workers, I propose a novel instrument based on unique historical data on the forced resettlement of Ukrainians in Poland after World War II.

I find that the inflow of Ukrainians into local labor markets reduces out-migration. On average, the inflow of 1000 Ukrainian workers into a county decreases local internal outmigration by around 19 and international out-migration by approximately 5 inhabitants. Furthermore, I find evidence of a decrease in in-migration as an initial response to the shock; however, this crowding-out effect diminishes after the first few years. The evidence on mechanisms suggests that local labor markets with larger exposure to Ukrainian workers scale up. In particular, I find evidence of an increase in job offers and employment in counties more exposed to Ukrainian workers. Given the suggestive evidence of complementarity between immigrant workers and native emigrants, this may indicate that potential native emigrants are absorbed by the enlarged local labor markets.

The findings have important policy implications, especially in light of the escalation of Russian aggression against Ukraine in 2022 and the subsequent decision to invoke the Temporary Protection Directive in the European Union. The latter has resulted in a significant increase in labor supply not only in Poland but also in other post-communist countries in Eastern and Central Europe, such as Lithuania or Latvia. These countries have also witnessed a notable rise in the number of highly educated citizens since the fall of the Iron Curtain and until recently were also characterized by high emigration rather than immigration. The results show that, in transition countries with an abundance of highly educated citizens, an immigration shock can mitigate the emigration from hosting communities. Thus, this paper points out the potential benefits of open borders and enabling access to the labor market, even for countries in transition without established immigration structures.

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Appendix

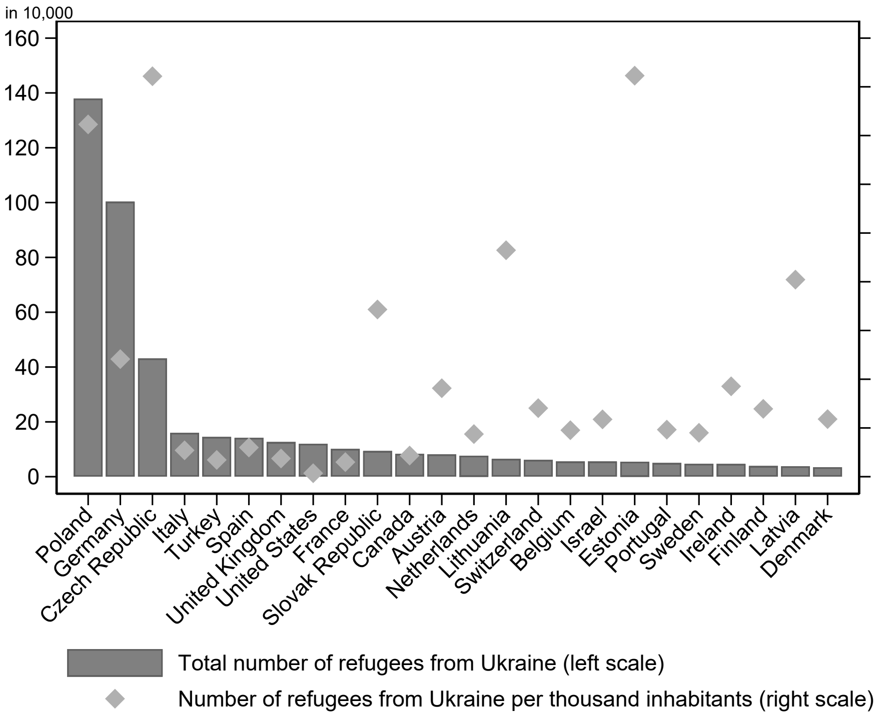

Figure A1: Refugees from Ukraine in OECD countries

Notes: This figure shows the recorded number of refugees from Ukraine in OECD countries as of mid-September 2022. Data source: OECD (2022a).

(a) Orthodox Church in Gorowo Ilawieckie

(b) Greek Catholic Church in Godkowo

Figure A2: Ukrainian churches in Poland

Notes: Examples of churches founded by the descendants of Ukrainians resettled as part of Operation Vistula. Panel (a): Orthodox church of the Dormition of the Holy Mother of God in Gorowo Ilaweckie (Cerkiew prawoslawna pod wezwaniem Zasniecia Najswietszej Bogurodzicy w Gorowie Ilaweckim). Panel (b): Greek Catholic church of the Protection of the Holy Mother of God in Godkowo (Cerkiew Greckokatolicka pod wezwaniem Opieki Przenajswietszej Bogurodzicy w Godkowie). Source: photographs taken by the author.

(a) School Complex in Gorowo Ilaweckie

(b) Primary School in Bartoszyce

Figure A3: Schools with Ukrainian as the language of teaching in Poland
Notes: Examples of schools in northern Poland with Ukrainian as the language of teaching. Panel (a): School Complex with Ukrainian as the Language of Teaching in Gorowo Ilaweckie (Zespol Szkol z Ukrainskim Jezykiem Nauczania w Gorowie Ilaweckim) includes high school and elementary school. Panel (b): Lesya Ukrainka Primary School No. 8 with Ukrainian as the Language of Teaching (Szkola Podstawowa nr 8 im. Lesi Ukrainki z Ukrainskim Jezykiem Nauczania). Source: photographs taken by the author.

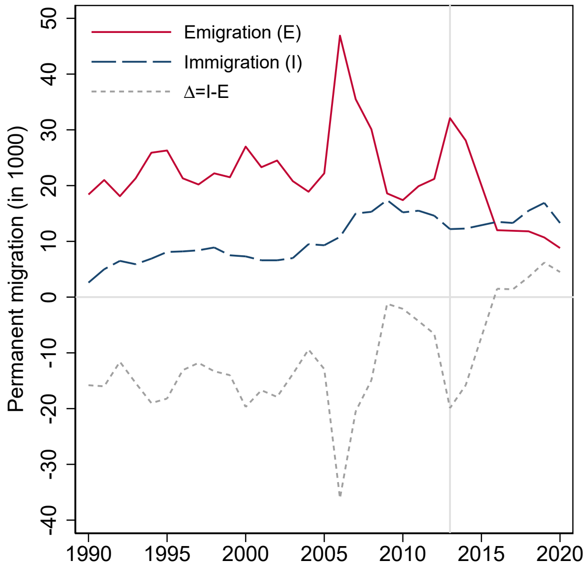

Figure A4: Migration patterns of Poles over time
Notes: Permanent emigration, permanent immigration, and net migration in Poland over time. The vertical gray lines indicate the period before and after the Russian aggression against Ukraine. Data source: Statistics Poland (2022).

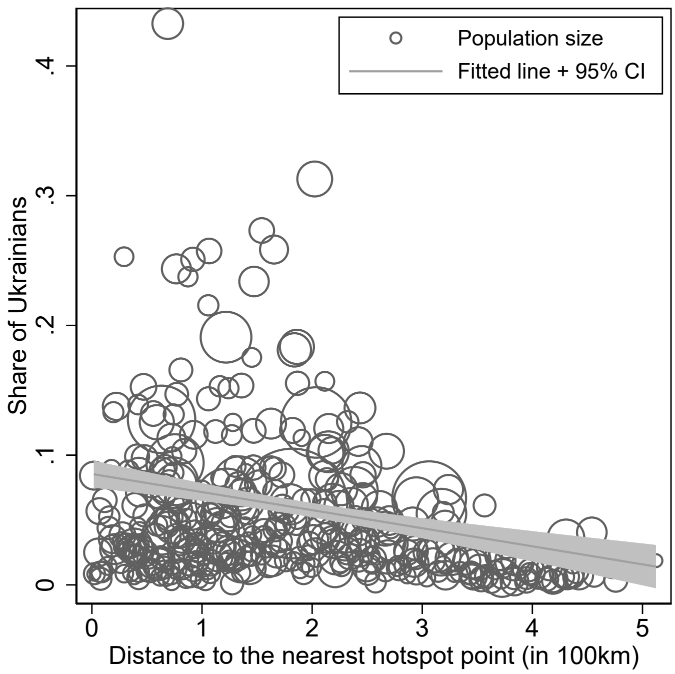

Figure A5: Share of Ukrainians and the Distance Instrument
Notes: This figure plots the share of Ukrainian workers against the distance of the centroid of each county to the nearest historical exposure hotspot point. The size of each circle reflects the size of the working-age population in each county in 2013.

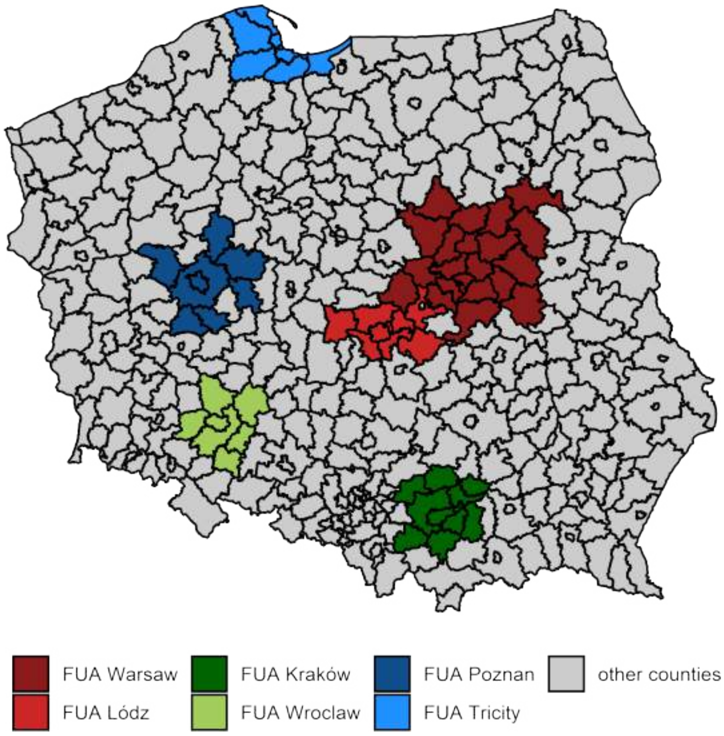

Figure A6: Functional Urban Areas in Poland

Notes: This figure presents the six largest Functional Urban Areas (FUAs) in Poland. Each of the FUAs consists of counties in a common commuting zone.

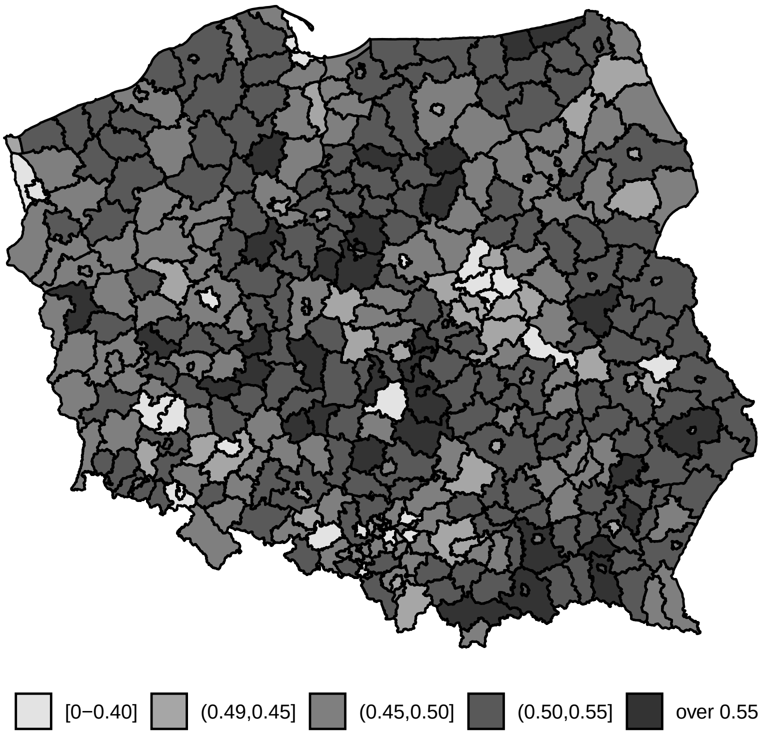

Figure A7: Ratio of minimum wage to average wage

Notes: This figure presents the spatial variation in the ratio of minimum wage to average wages. The larger the indicator, the greater the potential role that minimum wages play in the respective counties.

Table A1: Descriptive Statistics

	2013		2019		Δ 2013-2019	
	Mean	StD	Mean	StD	Mean	StD
International out-migration[a]	0.064	(0.084)	0.022	(0.034)	-0.042	(0.065)
Internal out-migration[a]	0.579	(0.672)	0.637	(0.714)	0.058	(0.058)
International in-migration[a]	0.017	(0.034)	0.020	(0.069)	0.003	(0.040)
Internal in-migration[a]	0.579	(1.163)	0.637	(1.399)	0.058	(0.325)
Average wages[a]	3.307	(0.506)	4.455	(0.636)	1.147	(0.206)
Unemployment rate	0.099	(0.034)	0.044	(0.022)	-0.055	(0.018)
Employment rate	0.293	(0.119)	0.347	(0.143)	0.053	(0.036)
Job offers[a]	1.175	(1.238)	1.982	(2.531)	0.807	(2.262)
Firms with $<$ 250 workers[a]	143.2	(44.48)	166.0	(51.58)	22.88	(9.556)
Firms with $>$ 250 workers[a]	0.122	(0.099)	0.126	(0.102)	0.004	(0.026)
Capital stock[a]	30.02	(27.06)	42.36	(38.64)	12.33	(15.75)
Share of women	0.511	(0.009)	0.511	(0.009)	-0.005	(0.018)
Population density	0.381	(0.675)	0.369	(0.654)	-0.012	(0.085)
Share of graduates	0.007	(0.019)	0.005	(0.014)	-0.003	(0.007)
Share of Ukrainians			0.052	(0.055)		
Distance from hotspot point[b]			1.770	(1.198)		
Number of railway stations[c]			13.22	(11.58)		
Destruction after WWII[c]			1774.7	(7621.8)		
Industrial production per capita[d]			6.885	(0.528)		
Observations			379			

Notes: [a] in 1000, [b] in 100 km, [c] in 1946, [d] in 1954.

Table A2: Including time-varying controls, 2SLS

	Out-migration		In-migration	
	International	Internal	International	Internal
Specification	(1)	(2)	(3)	(4)
1. Basic 2SLS (no controls)				
Share of Ukrainians	-0.498**	-1.886***	-0.0404	-0.719
	(0.237)	(0.556)	(0.125)	(1.710)
First-stage F-stat	17.77			
2. Add time-varying controls				
Share of Ukrainians	-0.571*	-1.998***	-0.057	-1.466
	(0.307)	(0.525)	(0.103)	(1.243)
First-stage F-stat	26.93			
3. Add controls for initial conditions				
Share of Ukrainians	-0.529**	-1.916***	-0.073	-0.879
	(0.264)	(0.583)	(0.0962)	(1.193)
First-stage F-stat	25.19			
4. Add time-varying and initial conditions controls				
Share of Ukrainians	-0.571*	-1.998***	-0.057	-1.466
	(0.307)	(0.525)	(0.103)	(1.243)
First-stage F-stat	26.93			
Clusters	72			
Observations	379			

Notes: The explanatory variable is the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013. All dependent variables are standardized by the same denominator as the explanatory variable. I instrument the current distribution of Ukrainian workers using distance from historical hotspots of Ukrainian networks. The time-varying controls include changes between 2013 and 2019 in the population density, the share of females, the unemployment rate, average wages, and the share of graduates. The controls for initial conditions include population density, the share of females, the unemployment rate, average wages, and the share of graduates in 2013. All regressions are weighted by the pre-treatment working-age population. Standard errors clustered at the NUTS3 level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Controling for historical correlates, 2SLS

	Out-migration		In-migration	
	International	Internal	International	Internal
Specification	(1)	(2)	(3)	(4)
1. Basic regression (no controls)				
Share of Ukrainians	-0.498**	-1.886***	-0.0404	-0.719
	(0.237)	(0.556)	(0.125)	(1.710)
First-stage F-stat	17.77			
2. Control for number of railway stations in 1946				
Share of Ukrainians	-0.635**	-2.320***	-0.253	-1.883
	(0.281)	(0.571)	(0.196)	(2.207)
First-stage F-stat	17.20			
3. Control for destructions after World War II				
Share of Ukrainians	-0.429*	-1.803***	-0.088	-1.160
	(0.227)	(0.566)	(0.134)	(2.012)
First-stage F-stat	15.01			
4. Control for industrial production per capita in 1954				
Share of Ukrainians	-0.429*	-2.140***	0.006	-1.286
	(0.246)	(0.578)	(0.171)	(2.276)
First-stage F-stat	15.39			
Clusters	72			
Observations	379			

Notes: The explanatory variable is the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013. All dependent variables are standardized by the same denominator as the explanatory variable. I instrument the current distribution of Ukrainian workers using distance from historical hotspots of Ukrainian networks. All regressions are weighted by the pre-treatment working-age population. Standard errors clustered at the NUTS3 level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Alternative Definition of Treatment, 2SLS

	Out-migration		In-migration	
	International	Internal	International	Internal
	(1)	(2)	(3)	(4)
Panel A: Include seasonal workers				
Share of Ukrainians	-0.516**	-1.955***	-0.042	-0.745
	(0.258)	(0.586)	(0.130)	(1.768)
First-stage F-stat	15.15			
Panel B: Statements on the employment of a Ukrainian from 2020				
Share of Ukrainians	-0.503**	-1.905***	-0.041	-0.726
	(0.238)	(0.561)	(0.126)	(1.715)
First-stage F-stat	20.23			
Clusters	72			
Observations	379			

Notes: The explanatory variable is the number of statements on the employment of a Ukrainian, in Panel A also including seasonal workers (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013. All dependent variables are standardized by the same denominator as the explanatory variable. I instrument the current distribution of Ukrainian workers using distance from historical hotspots of Ukrainian networks. All regressions are weighted by the pre-treatment working-age population. Standard errors clustered at the NUTS3 level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Kronmal's correction, 2SLS

	Out-migration		In-migration	
	International	Internal	International	Internal
	(1)	(2)	(3)	(4)
Share of Ukrainians	-0.490***	-1.724***	0.033	-0.067
	(0.164)	(0.577)	(0.096)	(1.369)
First-stage F-stat	16.17			
Clusters	72			
Observations	379			

Notes: The explanatory variable is the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers). I instrument the current distribution of Ukrainian workers using distance from historical hotspots of Ukrainian networks. Following Kronmal (1993), I control for the reciprocal of the pre-shock working-age local population in 2013. All regressions are weighted by the pre-treatment working-age population. Standard errors clustered at the NUTS3 level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Alternative definition of instruments, 2SLS

	Out-migration		In-migration	
	International	Internal	International	Internal
	(1)	(2)	(3)	(4)
Panel A: 10% threshold (baseline)				
Share of Ukrainians	-0.498**	-1.886***	-0.040	-0.719
	(0.237)	(0.556)	(0.125)	(1.710)
First-stage F-stat	17.77			
Panel B: 12% threshold				
Share of Ukrainians	-0.502**	-1.882***	-0.043	-0.694
	(0.233)	(0.544)	(0.123)	(1.66)
First-stage F-stat	18.65			
Panel C: 6% threshold				
Share of Ukrainians	-0.504**	-1.869***	-0.065	-0.713
	(0.249)	(0.519)	(0.117)	(1.468)
First-stage F-stat	21.53			
Panel D: 8% threshold				
Share of Ukrainians	-0.409*	-1.826***	-0.033	-0.683
	(0.245)	(0.544)	(0.123)	(1.669)
First-stage F-stat	19.11			
Clusters	72			
Observations	379			

Notes: The explanatory variable is the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013. All dependent variables are standardized by the same denominator as the explanatory variable. I instrument the current distribution of Ukrainian workers using distance from various definitions of historical hotspots of Ukrainian networks using different thresholds, i.e. relative size of the resettled Ukrainian population during Operation Vistula in the local population. The regressions include no controls. All regressions are weighted by the pre-treatment working-age population. Standard errors clustered at the NUTS3 level are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: ALTERNATIVE DEFINITION OF INSTRUMENT (CONT'D), 2SLS

	Out-migration		In-migration	
	International	Internal	International	Internal
	(1)	(2)	(3)	(4)
Panel A: 10% threshold, instrument interacted with historical share				
Share of Ukrainians	-0.498**	-1.887***	-0.041	-0.721
	(0.237)	(0.557)	(0.125)	(1.711)
First-stage F-stat	17.72			
Panel B: 12% threshold, instrument interacted with historical share				
Share of Ukrainians	-0.503**	-1.884***	-0.043	-0.695
	(0.233)	(0.544)	(0.123)	(1.661)
First-stage F-stat	18.60			
Panel C: 6% threshold, instrument interacted with historical share				
Share of Ukrainians	-0.505**	-1.871***	-0.065	-0.715
	(0.250)	(0.520)	(0.118)	(1.469)
First-stage F-stat	21.46			
Panel D: 8% threshold, instrument interacted with historical share				
Share of Ukrainians	-0.410*	-1.827***	-0.033	-0.685
	(0.246)	(0.544)	(0.123)	(1.670)
First-stage F-stat	19.05			
Clusters	72			
Observations	379			

Notes: The explanatory variable is the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013. All dependent variables are standardized by the same denominator as the explanatory variable. I instrument the current distribution of Ukrainian workers using distance from various definitions of historical hotspots of Ukrainian networks interacted with their historical share using different thresholds, i.e. relative size of the resettled Ukrainian population during Operation Vistula in the local population. The regressions include no controls. All regressions are weighted by the pre-treatment working-age population. Standard errors clustered at the NUTS3 level are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Conley standard errors, 2SLS

	Out-migration		In-migration	
	International	Internal	International	Internal
	(1)	(2)	(3)	(4)
Panel A: 25 km				
Share of Ukrainians	-0.498**	-1.886***	-0.0404	-0.719
	(0.212)	(0.557)	(0.125)	(1.808)
Panel B: 50 km				
Share of Ukrainians	-0.498*	-1.886***	-0.040	-0.719
	(0.282)	(0.685)	(0.133)	(1.672)
Panel C: 100 km				
Share of Ukrainians	-0.498*	-1.886***	-0.040	-0.719
	(0.282)	(0.517)	(0.077)	(NA)
Panel D: 150 km				
Share of Ukrainians	-0.498**	-1.886***	-0.040	-0.719
	(0.244)	(0.405)	(0.126)	(1.203)
Clusters	72			
Observations	379			

Notes: The explanatory variable is the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013. All dependent variables are standardized by the same denominator as the explanatory variable. I instrument the current distribution of Ukrainian workers using distance from historical hotspots of Ukrainian networks. All regressions are weighted by the pre-treatment working-age population. Conley standard errors using various cutoff distances are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Leave-One-Out: Exclude the Largest FUAs, 2SLS

	Out-migration		In-migration	
	International	Internal	International	Internal
	(1)	(2)	(3)	(4)
Panel A: Exclude FUA Warsaw				
Share of Ukrainians	-0.512**	-1.879***	-0.043	-0.740
	(0.235)	(0.571)	(0.121)	(1.717)
First-stage F-stat		18.58		
Observations		358		
Panel B: Exclude FUA Lodz				
Share of Ukrainians	-0.481**	-1.881***	-0.039	-0.719
	(0.229)	(0.549)	(0.123)	(1.686)
First-stage F-stat		19.30		
Observations		371		
Panel C: Exclude FUA Krakow				
Share of Ukrainians	-0.462**	-1.715***	0.049	0.636
	(0.229)	(0.537)	(0.083)	(1.071)
First-stage F-stat		19.29		
Observations		369		
Panel D: Exclude FUA Wroclaw				
Share of Ukrainians	-0.597**	-2.458***	-0.089	-1.555
	(0.301)	(0.540)	(0.159)	(2.116)
First-stage F-stat		18.54		
Observations		372		

Notes: The explanatory variable is the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013. All dependent variables are standardized by the same denominator as the explanatory variable. I instrument the current distribution of Ukrainian workers using distance from historical hotspots of Ukrainian networks. All regressions are weighted by the pre-treatment working-age population. Standard errors clustered at the NUTS3 level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Leave-One-Out: Exclude the Largest FUAs (cont'd), 2SLS

	Out-migration		In-migration	
	International	Internal	International	Internal
	(1)	(2)	(3)	(4)
Panel A: Exclude FUA Poznan				
Share of Ukrainians	-0.534**	-1.873***	-0.056	-0.784
	(0.246)	(0.570)	(0.130)	(1.761)
First-stage F-stat	16.74			
Observations	371			
Panel B: Exclude FUA Tricity (Gdansk, Gdynia, Sopot)				
Share of Ukrainians	-0.469*	-1.832***	-0.030	-1.237
	(0.249)	(0.581)	(0.128)	(1.765)
First-stage F-stat	15.49			
Observations	371			
Panel C: Exclude the six largest FUAs				
Share of Ukrainians	-0.612*	-2.253***	-0.007	-0.834
	(0.318)	(0.601)	(0.105)	(1.296)
First-stage F-stat	24.33			
Observations	317			
Panel D: Exclude urban cores of all 58 FUAs in Poland				
Share of Ukrainians	-0.515*	-2.099***	0.065	0.835
	(0.269)	(0.621)	(0.062)	(0.679)
First-stage F-stat	13.68			
Observations	334			

Notes: The explanatory variable is the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013. All dependent variables are standardized by the same denominator as the explanatory variable. I instrument the current distribution of Ukrainian workers using distance from historical hotspots of Ukrainian networks. All regressions are weighted by the pre-treatment working-age population. Standard errors clustered at the NUTS3 level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Exclude counties with high initial migration, 2SLS

	Out-migration		In-migration	
	International	Internal	International	Internal
	(1)	(2)	(3)	(4)
Panel A: Exclude counties with high initial international out-migration				
Share of Ukrainians	-0.482**	-1.887***	-0.0380	-0.705
	(0.224)	(0.552)	(0.126)	(1.726)
First-stage F-stat	17.26			
Observations	361			
Panel B: Exclude counties with high initial internal out-migration				
Share of Ukrainians	-0.495**	-1.760***	-0.0425	-0.885
	(0.245)	(0.568)	(0.131)	(1.797)
First-stage F-stat	15.93			
Observations	361			
Panel C: Exclude counties with high initial international in-migration				
Share of Ukrainians	-0.469*	-2.109***	-0.102	-1.273
	(0.256)	(0.641)	(0.153)	(2.063)
First-stage F-stat	13.46			
Observations	361			
Panel D: Exclude counties with high initial internal in-migration				
Share of Ukrainians	-0.625**	-2.163***	-0.081	-1.211
	(0.262)	(0.574)	(0.141)	(1.972)
First-stage F-stat	21.13			
Observations	361			

Notes: The explanatory variable is the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013. All dependent variables are standardized by the same denominator as the explanatory variable. I instrument the current distribution of Ukrainian workers using distance from historical hotspots of Ukrainian networks. All regressions are weighted by the pre-treatment working-age population. Standard errors clustered at the NUTS3 level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Sensitivity to hotspot exposure, 2SLS

	Out-migration		In-migration	
	International	Internal	International	Internal
	(1)	(2)	(3)	(4)
Panel A: Exclude counties closest to the hostpots				
Share of Ukrainians	-0.385*	-1.786***	-0.004	-0.474
	(0.217)	(0.515)	(0.110)	(1.562)
First-stage F-stat	21.82			
Panel B: Exclude counties with the lowest exposure to hotspots				
Share of Ukrainians	-0.550*	-1.434**	-0.081	-0.341
	(0.311)	(0.618)	(0.183)	(2.183)
First-stage F-stat	10.87			
Clusters	72			
Observations	379			

Notes: The explanatory variable is the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013. All dependent variables are standardized by the same denominator as the explanatory variable. I instrument the current distribution of Ukrainian workers using distance from historical hotspots of Ukrainian networks. All regressions are weighted by the pre-treatment working-age population. Standard errors clustered at the NUTS3 level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Evidence of Scaling-up of Local Labor Markets, 2SLS

	Average wage (1)	Unemployment rate (2)	Employment rate (3)	Job offers (4)	Firms with <250 workers (5)	Firms with >250 workers (6)	Capital stock (7)
Panel A: Basic 2SLS (no controls)							
Share of Ukrainians	0.192	-0.335	0.444	0.298**	0.461	0.272*	0.435***
	(0.259)	(0.357)	(0.366)	(0.129)	(0.409)	(0.142)	(0.156)
First-stage F-stat				17.77			
Panel B: Add time-varying controls							
Share of Ukrainians	0.178	-0.357	0.604**	0.291**	0.599**	0.305**	0.500***
	(0.279)	(0.329)	(0.243)	(0.139)	(0.298)	(0.152)	(0.178)
First-stage F-stat				20.34			
Panel C: Add controls for initial conditions							
Share of Ukrainians	0.369	-0.495***	0.406**	0.326**	0.229	0.281*	0.241
	(0.269)	(0.167)	(0.172)	(0.147)	(0.263)	(0.169)	(0.172)
First-stage F-stat				25.19			
Panel D: Add time-varying and initial conditions controls							
Share of Ukrainians	0.380	-0.522***	0.487***	0.325**	0.343	0.293*	0.259
	(0.282)	(0.182)	(0.170)	(0.150)	(0.234)	(0.171)	(0.176)
First-stage F-stat				26.82			
Clusters				72			
Observations				379			

Notes: This table presents Standardized Beta Coefficients using 2SLS. The explanatory variable is the number of statements on the employment of a Ukrainian in 2019 (proxy for the number of Ukrainian workers) standardized by the pre-shock working-age local population in 2013. All dependent variables are standardized by the same denominator as the explanatory variable. I instrument the current distribution of Ukrainian workers using distance from historical hotspots of Ukrainian networks. The time-varying controls include changes between 2013 and 2019 in the population density, the share of females, and the share of graduates. The controls for initial conditions include population density, the share of females, the share of graduates, the unemployment rate as well as average wages in 2013. All regressions are weighted by the pre-treatment working-age population. Standard errors clustered at the NUTS3 level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.