Journal of Population Economics (2025) 38:60
https://doi.org/10.1007/s00148-025-01109-z

ORIGINAL PAPER

Robotization, internal migration and rural decline

Karim Bekhtiar[1]

Received: 2 August 2024 / Accepted: 30 May 2025

Abstract

This paper is the first to analyze the effects of robotization on internal migration flows and rural decline, which is an important driving force of societal and political polarization in many developed economies. Using detailed migration flow data from Austria, I show that robotization has caused significant declines in manufacturing employment, to which populations reacted by increasingly migrating out of affected regions. Since rural regions rely much more than cities on manufacturing employment, these migratory responses largely consist of rural-to-urban flows. Overall, increases in robotization explain roughly one-fourth of rural-to-urban net migration between 2003 and 2016, which is primarily driven by young and medium/low-skilled individuals. Technology-driven labor demand shocks, thus, make an important contribution to rural decline, deepening the cleavage between advantaged and disadvantaged regions.

Keywords Employment · Internal migration · Robots · Rural decline

JEL Classification J21 · J23 · J61 · O14 · P25 · R23

1 Introduction

Over the last decades, population declines in remote rural areas have become a persistent feature of demographic change in both Europe and the USA. As young and highly educated individuals increasingly migrate towards the cities, declining rural regions are left with lasting declines in human capital (Bjerke and Mellander 2017) and economic performance (Dax and Fischer 2018), the disappearance of many private and public services (Rickardsson 2021) and drastic shifts in the age structure (Johnson et al. 2015). At the same time, rural areas in most developed economies have larger

Responsible editor: Milena Nikolova

✉ Karim Bekhtiar
bekhtiar@ihs.ac.at

1 Institute for Advanced Studies (IHS), Vienna, Austria

Published online: 09 July 2025

shares of manufacturing employment than urban areas.[1] Similarly, Autor (2019, 2020) documents that highly skilled occupations are much more prevalent in cities, while rural areas are more reliant on employment in low- and middle-skilled jobs (especially in recent decades). This leaves rural areas more exposed to shocks to these segments of the skill distribution, which are especially prevalent in the manufacturing sector. While the context-specific causes of rural decline in Europe and the USA are not well understood, recent work by Johnson and Lichter (2019) shows that rural-to-urban migration flows in the USA are tightly linked to declines in manufacturing.

This paper is the first to shed light on the connection between the rise of robotization, a major cause of the manufacturing decline, and rural-to-urban migration in an advanced economy. Following the seminal work of Blanchard and Katz (1992), it is well established in the economic literature that labor demand shocks prompt out-migration responses and population declines in affected regions. It is, however, much less understood where these internal migrants move and what the consequences for regional disparities are. This paper aims to close this gap by showing that internal migration flows caused by automation-based labor demand shocks are specifically directed from rural to urban areas, thereby contributing to the decline of remote rural regions. To this end, I use detailed data on internal migration flows in Austria during the period 2003–2016. While most studies concerned with internal migration typically rely on rather crude approximations of migration flows via observed changes in population counts, this data has the unique feature that it allows tracking migration flows by origin and destination region. This information is crucial for examining the direction of internal migration flows, and thus for linking them to rural decline. Since existing studies on internal migration typically do not have information on the destination regions, rural-to-urban migration is generally not examined in this literature, even though it is one of the prime consequences of internal migration.

To relate internal migration trends to robotization, I follow Acemoglu and Restrepo (2020) and Dauth et al. (2021) and predict changes in robotization as a shift-share variable, using regional industry structures and industry-level data on changes in robotization from the International Federation of Robotics (IFR). To isolate the causal effect of robotization on internal migration and rural depopulation, I rely on variation in industry-level robotization trends in other high-income countries. As is shown in Borusyak et al. (2022), leveraging plausibly exogenous variation in robotization shocks in other high-income countries isolates the component of robot adoption that is driven by exogenous advances in technological possibilities. Applying this identification strategy to the Austrian data confirms a robust negative effect of robotization on manufacturing employment and a positive effect on out-migration flows, indicating that robotization has had displacement effects in highly exposed local labor markets, which in turn led to migratory responses of affected workers.

Decomposing these migration flows by the type of origin and destination region (urban or rural) reveals that robotization led to out-migration in affected rural areas, with the majority of this out-migration taking the form of rural-to-urban migration

[1] See Table 1 (panel G) for Austria and Table A1 in the Supplementary Material for other European countries and the USA.

flows, thereby contributing to rural depopulation. Overall, the estimations suggest that increases in robotization explain roughly one-fourth of all rural-to-urban net migration flows during the observational period. This effect on rural-to-urban migration flows is primarily driven by the demographic sub-groups whose employment prospects are most heavily affected by the robotization shock, namely by young and medium- to low-skilled individuals. Their increase in net out-migration exclusively operates through increases in out-migration rates, indicating that robotization-induced population declines in remote rural areas are driven by these affected groups leaving highly exposed rural regions for the cities.

This paper relates to the extensive literature on the effects of industrial robots on labor market outcomes, as well as the literature on migratory responses to local labor demand shocks. It contributes to this literature by (i) showing that robotization shocks prompt out-migration responses in a similar fashion as other large-scale labor demand shocks and (ii) connecting these migratory responses to a highly relevant demographic trend in recent decades—rural decline.[2] This paper further relates to an extensive literature on left-behind regions, which has shown that economic decline of disadvantaged regions has fostered discontent and political polarization.[3] It contributes to this literature by showing how technological progress deepens the cleavage between advantaged and disadvantaged regions, specifically through its impact on rural population loss. To the best of my knowledge, this paper is the first to present causal evidence on a connection between automation-based shifts in labor demand and rural decline.

2 Descriptive evidence

To illustrate the close connection between out-migration and general population trends in rural regions, Fig. 1 compares the change in overall population counts (panel A) and the migration balance (panel B) of all Austrian regions between 2001 and 2016. Urban and rural areas are classified according to the urban-rural-classification from the Austrian statistical agency Statistics Austria. This classification consists of three broad categories: urban centers, regional centers, and rural areas, each consisting of several subcategories. It is graphically depicted in Figure A1 in the Supplementary Material. For this paper, I consider regions classified as "urban centers" (large, medium, or small) as urban, while all remaining regions (including regional centers) are classified as rural.[4] While urban centers (which are indicated by name in Fig. 1) generally showed

[2] On migration responses to labor demand shocks, see, for example, Blanchard and Katz (1992), Bound and Holzer (2000), Boman (2011), Cadena and Kovak (2016), Huttunen et al. (2018), Foote et al. (2019), Greenland et al. (2019), Jauer et al. (2019), Dix-Carneiro and Kovak (2019), Notowidigdo (2020), Faber et al. (2021), Peri and Zaiour (2023), or Konietzny (2024). Apart from migration responses, recent work by Costanzo (2025) has further shown that robotization may affect fertility decisions and thus has effects on demographic structures that go beyond migration effects.

[3] See for example Wuthnow (2018), Autor et al. (2020), MacKinnon et al. (2022), Rodríguez-Pose et al. (2023), Alamá-Sabater et al. (2024), Connor et al. (2024) or Pike et al. (2024) among many others.

[4] Robustness checks where regional centers are instead classified as urban are discussed in Section 5. In sum, all results presented in this paper are robust to this choice.

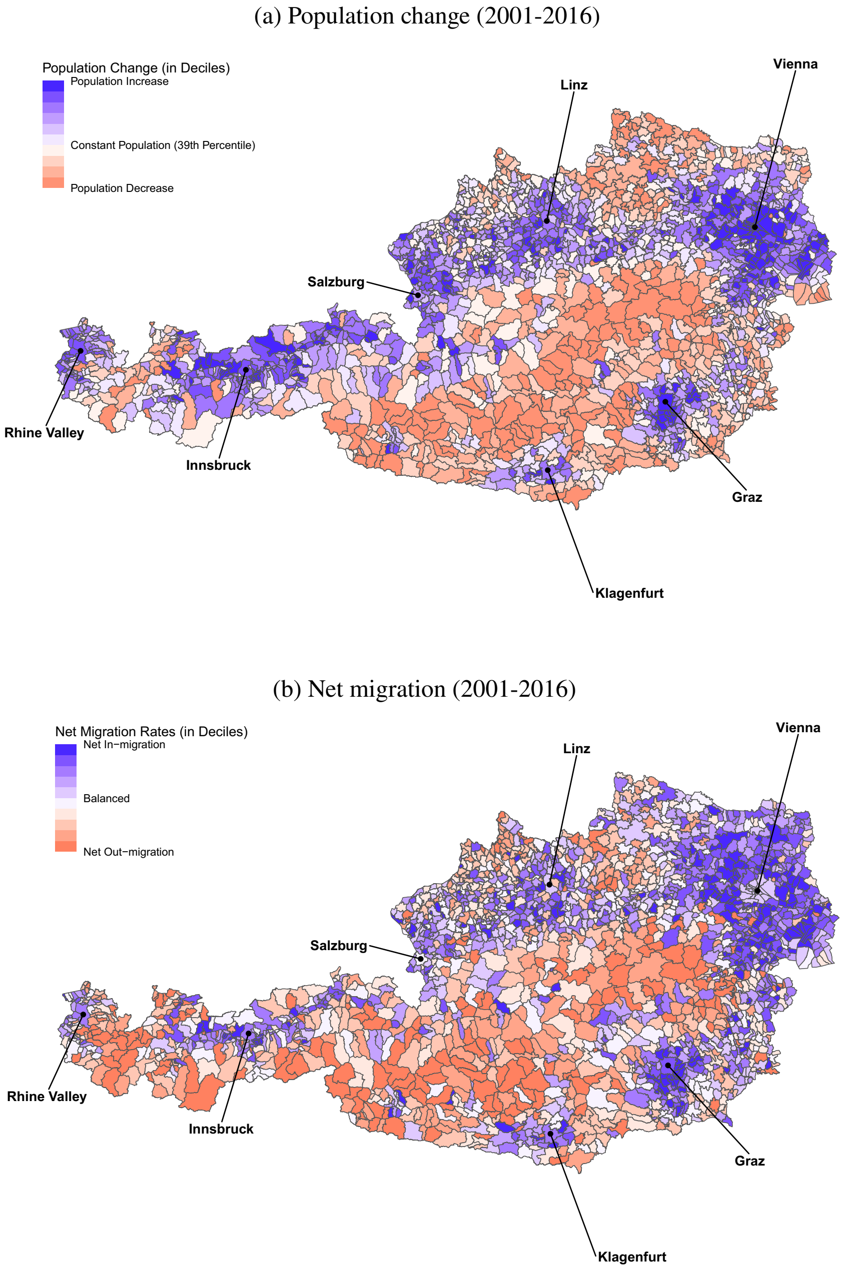

Fig. 1 Population change and migration balance (2001–2016). Note: Regions are classified according to the urban-rural classification from the Austrian Statistical Agency (Statistics Austria; see Figure A1 in the Supplementary Material). Large urban centers (according to the urban-rural classification) are indicated by name. Population data is from the decennial census (2001) and the register-based labor market statistics (2016). Data on migration flows is taken from the Austrian migration statistics. All data sources are available from Statistics Austria and are described in more detail in Section 3

Table 1 Descriptive statistics (2001–2016)

	Urban	Rural		
		All	Growing	Declining
	(1)	(2)	(3)	(4)
Panel A: Share of population				
2001	50.03%	49.97%	30.94%	19.03%
2016	52.60%	47.40%	31.08%	16.32%
Change	+2.57%	−2.57%	+0.14%	−2.70%
Panel B: Share of municipalities				
with population declines	14.29%	42.17%		
with negative migration balance	16.45%	45.78%		
Panel C: Population change 2001–2016 (in % of 2001 population)				
Population change	+14.70%	+3.51%	+9.60%	−6.40%
Migration balance	+13.01%	+3.42%	+7.70%	−3.53%
Internal	+1.72%	−1.72%	+1.80%	−7.44%
External	+11.29%	+5.14%	+5.90%	+3.91%
Birth balance	+1.69%	+0.08%	+1.90%	−2.87%
Panel D: Internal migration balance by destination type				
Total	+1.72%	−1.72%	+1.80%	−7.44%
Urban destination	–	−1.72%	+0.36%	−5.09%
Rural destination	+1.72%	–	+1.44%	−2.35%
Panel E: Internal migration balance by age				
Total	+1.72%	−1.72%	+1.80%	−7.44%
Age 0 to 34	+2.88%	−2.88%	−0.51%	−6.73%
Age 35 to 64	−0.95%	+0.95%	+1.83%	−0.48%
Age 65 and above	−0.21%	+0.21%	+0.48%	−0.23%
Panel F: Share of individuals aged 65 and older				
2001	15.78%	15.14%	14.14%	16.76%
2016	17.98%	19.17%	17.99%	21.41%
Increase	+2.21%	+4.03%	+3.85%	+4.65%
Panel G: Share of manufacturing industries in total employment				
2001	19.85%	26.62%	26.15%	27.38%
2016	15.66%	23.24%	22.69%	24.30%
Decrease	−4.19%	−3.37%	−3.46%	−3.08%

Note: Regions are classified according to the urban-rural classification from the Austrian Statistical Agency (Statistics Austria; see Figure A1 in the Supplementary Material). Population data is from the decennial census (2001) and the register-based labor market statistics (2016). Migration flow data is from the Austrian migration statistics. Since the register-based census, the register-based labor market statistics and the migration statistics are collected from the same administrative register and refer to the same reference date (October 31st of any year), they are consistent and directly comparable. Therefore, the birth balance can be calculated as the part of the population change that is not explained by the migration balance. Data on manufacturing employment is taken from the Austrian Social Security Database (ASSD). All data sources are described in more detail in Section 3. All statistics are calculated as population-weighted averages increases in population counts and net in-migration, a large fraction of rural regions experienced population losses through out-migration. These declining rural regions tend to be in more remote areas of Austria, as rural regions in closer proximity to urban centers also experienced population growth through positive population spillovers from nearby cities (Veneri and Ruiz 2016). While the Austrian population is divided in roughly equal parts between urban and rural regions (Table 1, panel A), around 42% of all rural areas are characterized by declining population counts (panel B), which are strongly driven by out-migration (panel C). The majority of these out-migration flows in declining rural areas is directed towards the cities (panel D) and is accounted for by younger individuals (panel E). As a consequence, rural-to-urban migration leads to older rural societies (panel F) and declines in the birth balance (panel C). This highlights that rural out-migration not only directly decreases population counts in declining rural areas, but also has an indirect negative effect through the acceleration of natural decline (Johnson et al. 2015).

Importantly, panel G of Table 1 shows that rural areas are on average more reliant on employment in the manufacturing industries, as these industries account for a larger fraction of total employment (27% in 2001) as opposed to urban areas (20%). This strong reliance on manufacturing employment leaves rural areas particularly exposed to changes in labor demand in these industries, which are tightly linked to industrial robotization. If these labor demand disruptions cause internal migration responses (as is suggested by a vast literature following the seminal work of Blanchard and Katz 1992), it is very likely that these internal migration flows from rural regions are directed towards the cities and thereby contribute to rural decline. To investigate this hypothesis, this paper focuses on three main questions: (i) did robotization reduce employment specifically in the manufacturing industries, (ii) have these disruptions in labor demand prompted out-migration responses, and (iii) to what degree these migration responses contribute to rural decline.

3 Data

This section presents an overview of all primary data sources used in the analysis. While these data are in principle available for all Austrian municipalities, the analysis is carried out at the aggregated level of 158 commuting zones. This approach is chosen to account for the fact that a local shock to a plant in municipality i does not only influence employment (and reactions related to employment losses) in the same municipality. Rather it is to be expected that employment in neighboring municipalities will react as well, simply because some workers who worked in the same plant, and thus are directly affected by the shock, commuted there from neighboring areas. The construction of these commuting zones uses municipality-to-municipality commuting data from the Austrian register-based census and strictly follows the methodology used for US commuting zones described in Tolbert and Sizer (1996) and Dorn (2009).[5]

[5] Supplementary Material Appendix D presents a more detailed description of these commuting zones, as well as robustness checks regarding their construction.

To investigate the migratory responses to robotization, I use register-based data on migration flows from the Austrian migration statistics. This data contains detailed information on changes of the municipality of residence within Austria. It is compiled by Statistics Austria from the central residence register, which contains mandatory reports of all Austrian residents on their primary (and if applicable secondary) place of residence. In Austria, reporting ones place of residence to the local authorities is required by law, and therefore, the central residence register contains information on all individuals legally residing in Austria. The migration statistics covers all changes of the primary residence of all individuals that have been registered in Austria for at least 90 days. Therefore, this data allows to reliably track the number of individuals that moved their primary residence between municipality i and municipality j (or moved between municipality i and countries outside of Austria) in any year starting in 2002.[6] As this data covers the entirety of the population legally residing in Austria, it allows a much more precise measurement of migration flows than other administrative data sources, which often only refer to the employed population (like the employer-employee data from the Austrian Social Security Database discussed below). Hence, the Austrian migration statistics also allows to track the migration behavior of young individuals and labor market entrants who may also react to a regional decline in employment prospects.

Data on robotization comes from the International Federation of Robotics (IFR). The IFR offers rich industry-level data on robot stocks and deliveries for many high-income countries. This data is collected by the IFR through an annual survey of industrial robot suppliers worldwide and covers about 90% of the global market for industrial robots.[7] For Austria, country-level robotization trends are available starting in 1993, while a detailed industry-level breakdown is available from 2003 onward. Most manufacturing industries (according to the NACE-Rev. 2 classifications) are available on the 2-digit or 3-digit industry level, while several other industries are available at the 1-digit level (see Table E1 in the Supplementary Material).[8] Figure A2 in the Supplementary Material shows the change in robotization in Austria over the period 1993 to 2016. During this time period, industrial robot density has increased substantially from 0.597 to 2.532 robots per 1000 workers. By 2003, robot density had reached approximately 1.047 robots per 1000 workers. Thus, the majority of the increase in robotization falls in the period 2003–2016, for which the IFR data includes a detailed industry-level breakdown of robot stocks for Austria.

[6] Due to data privacy reasons Statistics Austria only provides municipality-level migration flows with additional information on the type of destination region (according to the urban-rural classification in Supplementary Material Figure A1), but not on the exact destination region. This data was provided as a special delivery from Statistics Austria.

[7] The IFR data has been introduced into the economic literature in the seminal contribution of Graetz and Michaels (2018). A detailed survey of the database and other applications can be found in Klump et al. (2022), or Bekhtiar et al. (2024).

[8] The industry-level IFR data also contains unclassified robot stocks, which are not accounted for by the reported industries. For Austria, about 30% of all robots are unclassified, which is very similar to the proportion of unclassified robots for the USA reported in Acemoglu and Restrepo (2020). I follow Acemoglu and Restrepo (2020) and allocate these unclassified robots to the available industries according to the proportions of classified robots in the data.

To measure the structure of regional employment as well as changes in manufacturing employment, I use data from the Austrian Social Security Database (ASSD, Zweimüller et al. 2009). The ASSD is a register-based database, which covers all private sector employees in Austria, starting in 1975. This data contains a variety of information about the individual workers, as well as detailed information about the firms these workers are employed in. Crucially, it contains information on the geographic location of firms and their industry affiliation (at the NACE-Rev. 2 four-digit level).

4 Research design

Estimation

Measuring any commuting zones robot exposure would ideally require detailed firm-level data on robot adoption. Since such data is not available for Austrian firms, I follow Acemoglu and Restrepo (2020) and Dauth et al. (2021) and construct a measure for regional robot exposure in commuting zone r from the industry-level robotization data as a shift-share variable. The idea of a shift-share research design is that industry-specific shocks affect regions differently, depending on the structure of their local economy.[9] Therefore, the shift-share measure for regional robot exposure is constructed by interacting the local industry structure with the industry-specific change in robot density:

$$\Delta Robots_{r,t} = \sum_i \frac{Emp_{i,r,t}}{Emp_{r,t}} \times \frac{\Delta Robots_{i,t}}{Emp_{i,t}} \tag{1}$$

In Eq. 1, the industry-level change in robotization $\Delta Robots_{i,t}$ in industry i over period t (normalized by overall employment in this industry) is interacted with the share of industry i in commuting zone r's overall employment (measured at the beginning of period t). This projects the industry-level robotization change in industry i onto the commuting zone-level, while considering the relative importance of industry i for commuting zone r's overall employment. I then compute local exposure to robotization as the weighted sum of industry-level robotization changes, whereby the region-specific employment shares (which are known in the theoretical literature on shift-share inference as exposure shares) serve as weights. Calculating $\Delta Robots_{r,t}$ as outlined in Eq. 1 requires (i) data on the industry-specific robotization shock and (ii) detailed regional data on the employment shares. While the industry-level robotization data is available from the IFR, exposure shares are calculated from the ASSD (see Section 3).

Throughout the analysis, this measure of regional robot exposure serves as the main explanatory variable of interest. To estimate the effect of changes in robot exposure

[9] See also Borusyak et al. (2025) for a detailed overview of the recent literature on shift-share inference.

on manufacturing employment and internal migration flows, I estimate equations of the form:

$$\Delta Y_{r,t} = \gamma \Delta Robots_{r,t} + X'_{r,t}\beta + \rho_r + \tau_t + \epsilon_{r,t} \quad (2)$$

whereby $\Delta Y_{r,t}$ denotes the outcome of interest (changes in manufacturing employment or net out-migration rates), $\Delta Robots_{r,t}$ is the measure for robot exposure from Eq. 1 and $X_{r,t}$ is a vector of control variables. The model is estimated as a stacked difference model, using changes over two time periods 2003–2009 and 2009–2016, which allows for the inclusion of period fixed effects τ_t and commuting zone fixed effects ρ_r.[10] All estimations are weighted by the start-of-period working-age population.

The vector of control variables $X_{r,t}$ includes several sets of distinct variable types. The first set of covariates controls for the demographic characteristics of the local workforce. For this, I include the detailed age-sex-education-nationality distribution of the local working-age population, measured in the initial year of each panel period (i.e., 2003 or 2009) to avoid endogenous contamination.[11] The inclusion of the composition of the local working-age population is motivated by concerns that commuting zones with different demographic structures are very likely to be on different trends regarding population changes and migration flows. Furthermore, it has been shown in recent work by Acemoglu and Restrepo (2022) and Zhang et al. (2022) that the structure of the workforce (particularly the age composition) has a direct impact on robotization trends. Therefore, this very detailed set of demographic variables is included to control for this simultaneous impact of the demographic structure on robotization and migration trends.

Secondly, controls that aim at capturing regional heterogeneity are included. These controls include the start-of-period logarithm of the gross regional product (total and per-capita) and the start-of-period regional unemployment rate (to control for differences in economic performance) and the start-of-period share of the population living in urban areas (to control for different population trends depending on the degree of urbanization).

The next set of covariates controls for other types of labor demand shocks. For this, I include shift-share variables for changes in import- and export-exposure from

[10] Robot adoption is strongly concentrated within the manufacturing sector. Therefore, most industries outside of manufacturing experienced zero robotization. In Eq. 1 this means that the regional sum of all exposure shares of industries with non-zero robot adoption is generally smaller than 1, such that $\sum_i \frac{Emp_{i,r}}{Emp_r} < 1$. As is explained in detail in Borusyak et al. (2022), conventional period fixed effects do not properly isolate within period variation in shift-share applications with incomplete exposure shares. To correct this, they recommend to interact the period fixed effects with the regional sum of the incomplete exposure shares, as only in this case, the fixed effects fully absorb between period variation. Therefore, the period fixed effects τ_t in Eq. 2 refer to the interaction of conventional period dummies with the regional sum of the incomplete exposure shares. In OLS estimations the incomplete shares for the measure for regional robot exposure in Eq. 1 are used, while in 2SLS regressions, the lagged exposure shares for the computation of the instrument (from Eq. 3) are used.

[11] The composition of the local working-age population is included in 64 age-sex-education-nationality cells, where each cell indicates the size of the respective group in 1000 individuals. The 64 demographic cells are defined by 4 age groups (ages 15–34, 35–49, 50–64, and 65 and above), 2 gender groups (male, female), 4 educational groups (highest level of education completed is either compulsory schooling, apprenticeship, high school or university) and 2 nationalities (Austrian or foreign citizen). These control variables are constructed from publicly available data from the Austrian census and the Austrian register-based labor market statistics.

China and the former Eastern Bloc, as well as ICT-capital intensity.[12] Adao et al. (2019) have shown that other types of labor demand shocks that can be expressed as shift-share variables have a mechanical correlation with $\Delta Robots_{r,t}$, since they can be constructed from similar exposure shares. Therefore, these control variables have to be included to control for other large-scale labor demand shocks originating in international trade or other forms of automation technologies. Data on import- and export-exposure comes from the UN-Comtrade database, while data on ICT-intensity is taken from the EU-KLEMS database.[13]

By a similar logic, I also control for shocks to labor supply originating in migration from foreign citizens. Following Card (2001), the migrant share in a region is a strong predictor for migration inflows. To the extent that this migrant share correlates with the industry exposure shares used in Eq. 1 to construct the regional measure for robot exposure, migration-based labor supply shocks are also mechanically correlated with the robotization shock (see Adao et al. 2019). To account for this, I include changes in the migrant population, differentiated by four educational groups.

Lastly, I control for the regional start-of-period industry structure, to check for the possibility that commuting zones with different industry structures are on different trends, both in robotization as well as in changes in employment or migration flows. This is done in two different ways. Firstly, the share of manufacturing employment is included as additional control. Secondly, instead of the manufacturing share, a more detailed set of industry structure controls are included. These include the initial period employment shares of sub-industries of manufacturing (production of food products, consumer goods, industrial goods, and capital goods), as well as industries outside of manufacturing (construction, personal services, and business services).

All variables used during the analysis are described in detail in Table A2 in the Supplementary Material.

Identification strategy

One major reason for endogeneity concerns in Eq. 2 is that the adoption of robots might be correlated with unobserved industry-specific demand shocks, which simultaneously influence employment trends or internal migration decisions. For example, negative shocks to the domestic demand for goods produced by industry i might reduce that industry's demand for industrial robots. Such demand shocks could be related to changes in employment or migration flows in areas where industry i is a relevant part of the local economy. In such a scenario, the estimate for γ in Eq. 2 would no longer isolate the effect of industrial robotization but would additionally reflect effects arising from the unobserved demand shock.

[12] Since the Austrian economy traditionally has very strong ties to the countries of the former Eastern Bloc, I follow Dauth et al. (2014) in considering trade exposure with both China and the East. Therefore, the shift-share variables for import- and export-exposure reflect changes in trade exposure from China, Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, and the succession states of the former USSR - Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan and Uzbekistan.

[13] The Comtrade data, which is only available at the commodity level, has been crosswalked to the ISIC-Rev. 4/NACE-Rev. 2 classification using the `concordance`-package in R (Liao et al. 2020). The EU-KLEMS data comes from the September 2017 release.

Another source for endogeneity concerns relates to the construction of the predicted robotization measure in Eq. 1. Here, the industry-level change in robotization is assigned to any commuting zone r purely via the regional structure of employment. This implicitly assumes that all firms in a given industry i are equally likely to adopt robots. Any violation of this assumption leads to a measurement error in the explanatory variable, which, to the degree that it is systematically related to unobserved regional characteristics, would lead to a bias in the estimate for γ. Consider, for example, the presence of regional agglomeration effects that incentivize high-performing firms to settle in a certain commuting zone. If high-performing firms are also more likely to adopt industrial robots (as recent findings in Bonfiglioli et al. 2024 and Koch et al. 2021 suggest), then the predicted robotization measure in Eq. 1 would have a measurement error that is systematically related to this unobserved agglomeration effect.

To address these concerns I follow Acemoglu and Restrepo (2020) and Dauth et al. (2021) and construct an instrumental variable that leverages exogenous variation in robot adoption from other high-income countries. Since industry-level robotization trends in other high-income countries are unrelated to unobserved regional characteristics in any Austrian region (like regional demand shocks or agglomeration economies), this approach isolates changes in the supply of robots, which are driven by advances in the technological frontier. Similarly to the measure for robot exposure in Eq. 1, this instrumental variable is constructed as a shift-share variable, where industry-level robotization changes in other high-income countries are interacted with regional exposure shares.

$$\Delta Robots_{r,t}^{IV} = \sum_{i} \frac{Emp_{i,r,t-15}}{Emp_{r,t-15}} \times \frac{\Delta Robots_{i,t}^{OtherCountries}}{Emp_{i,t-15}} \tag{3}$$

To further remove the instrumental variable in Eq. 3 from the robot exposure measure in Eq. 1 the exposure shares used to construct the instrument are lagged by 15 years.

As has been shown in recent work by Adao et al. (2019) and Borusyak et al. (2022), the validity of this instrumental variable hinges on the exogeneity of the industry-level robotization shocks occurring in other high-income countries. The underlying identifying assumption, thus, is that industry-level robotization trends in other high-income countries $\Delta Robots_{i,t}^{OtherCountries}$ are quasi-randomly assigned with respect to unobserved regional characteristics in Austria. In the examples described above, this means that the robotization trends in other high-income countries must not have a direct impact on region-specific demand shocks in Austria or the location decisions of robotizing Austrian firms. As is shown in Borusyak et al. (2022), this exogeneity of the robotization shocks is both necessary and sufficient for the instrumental variable to be valid. Hence, the regional exposure shares (i.e., the lagged industry structure) are allowed to be endogenous.[14] To construct these robotization shocks occurring in other

[14] In a related paper Goldsmith-Pinkham et al. (2020) argue that the exogeneity of the exposure shares is also a sufficient condition for the validity of the instrumental variable. Borusyak et al. (2022), however,

high-income countries, I use industry-level robotization changes in Canada, Denmark, Finland, France, Italy, Mexico, Norway, Spain, Sweden, the UK, and the USA.[15]

While the exogeneity of the robotization shocks, which essentially mirrors a standard exclusion restriction, cannot be tested directly, Borusyak et al. (2022) propose several plausibility tests. These tests aim to assess the plausibility of quasi-random shock assignment by assessing whether the robotization shocks themselves and the constructed instrument are balanced (i.e., not systematically related to pre-determined characteristics in Austria). In sum, these tests indicate that both the shocks and the instrumental variable are reasonably balanced. A more detailed discussion of these tests is provided in Supplementary Material Appendix B. To further probe the sensitivity of the analysis with regard to the construction of the shift-share instrument in Eq. 3, I conduct a range of robustness checks relating to the definition of exposure shares, the definition of the panel periods, and the pool of donor countries. These robustness checks are presented in Section 6.

Standard errors

Throughout the analysis, I report two types of standard errors. Firstly, all estimations report conventional robust standard errors, clustered by region (at the level of the nine Austrian federal states) and time period. To correct these standard errors for the small number of clusters, they are inflated using the Bias-Corrected-Cluster-Robust-Variance-Matrix-correction for few clusters described in Cameron and Miller (2015). Secondly, shift-share-exposure robust standard errors from Adao et al. (2019) are reported. As is outlined in detail in Adao et al. (2019), conventional clustered standard errors might be unreliable in shift-share settings, as the regression residuals are likely to be correlated across (potentially distant) commuting zones with similar exposure shares. These standard errors are, thus, a shift-share analog to conventional cluster-robust standard errors, as they essentially cluster commuting zones with similar industry structures.

5 Results

Employment & migration flows

Panel A of Table 2 shows the estimation results for the change in the manufacturing employment-to-population ratio. Overall, the estimations show a robust negative effect of industrial robotization on manufacturing employment in all specifications. Including only the baseline set of controls in column 1 of Table 2 results in precisely estimated negative coefficients of −0.265 in the OLS regression and −0.575 in the

show that the orthogonality of the shocks is both sufficient and necessary and that in the Goldsmith-Pinkham et al. (2020) setting of exogenous regional exposure shares, shock exogeneity is implicitly fulfilled due to the exogenous (i.e., quasi random) assignment of the regional exposure shares. See also Borusyak et al. (2025) for a detailed comparison of these two approaches.

[15] Canada, Mexico, and the USA are not available as separate countries in the IFR data, but are rather aggregated to a single region (North America).

Table 2 Robotization, manufacturing employment, and migration flows (2003–2016)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent variable: Δ Manufacturing-employment-to-population ratio ×100						
OLS						
Δ Robots	−0.265	−0.207	−0.202	−0.218	−0.173	−0.107
	(0.035)***	(0.042)***	(0.041)***	(0.029)***	(0.024)***	(0.041)**
	[0.037]***	[0.039]***	[0.039]***	[0.042]***	[0.038]***	[0.040]***
2SLS						
Δ Robots	−0.575	−0.401	−0.388	−0.429	−0.459	−0.476
	(0.134)***	(0.156)**	(0.141)***	(0.135)***	(0.091)***	(0.114)***
	[0.095]***	[0.072]***	[0.070]***	[0.077]***	[0.065]***	[0.066]***
Panel B: Dependent variable: Net out-migration rate ×100						
OLS						
Δ Robots	0.146	0.087	0.061	0.069	0.047	−0.011
	(0.051)***	(0.053)	(0.116)	(0.075)	(0.071)	(0.127)
	[0.042]***	[0.048]*	[0.054]	[0.091]	[0.093]	[0.069]
2SLS						
Δ Robots	0.594	0.879	0.877	0.874	0.886	1.101
	(0.289)**	(0.277)***	(0.176)***	(0.243)***	(0.281)***	(0.382)***
	[0.157]***	[0.152]***	[0.145]***	[0.166]***	[0.165]***	[0.169]***
First stage results	0.011	0.012	0.012	0.011	0.011	0.011
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
	[0.0008]***	[0.0007]***	[0.0007]***	[0.0007]***	[0.0007]***	[0.0007]***
First stage F	43.62	41.67	38.65	32.56	32.24	30.66
Period FE	x	x	x	x	x	x
Region FE	x	x	x	x	x	x
Demographics	x	x	x	x	x	x
Regional char.		x	x	x	x	x
Labor supply			x	x	x	x
Labor demand				x	x	x
Manuf. share					x	
Industry structure						x

2SLS regression. Contrasting those two estimates suggests that the OLS estimate is slightly upward biased. Such an upward bias is consistent with an unobserved positive demand shock that simultaneously increases robot adoption and employment. This pattern could also be caused by the presence of agglomeration economies that (i) incentivize robotizing firms to settle in certain commuting zones, (ii) increase those firms' productivity via agglomeration effects, and thereby (iii) have a positive impact on employment. In both cases, the OLS estimate would absorb the positive impact

Table 2 continued

	(1)	(2)	(3)	(4)	(5)	(6)
Commuting zones	158	158	158	158	158	158
Periods	2	2	2	2	2	2
Observations	316	316	316	316	316	316

Notes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. Conventional cluster-robust standard errors are shown in parentheses, and shift-share clustered standard errors from Adao et al. (2019) are shown in brackets. Units of observation are 158 clustered commuting zones (for details see Supplementary Material Appendix D). All specifications include a set of commuting zone and period fixed effects, whereby the period fixed effects are interacted with the sum of exposure shares used to construct the explanatory variable (OLS) or the instrument (2SLS). Demographic controls include the start-of-period structure of the local workforce in 64 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product (total and per-capita) and the unemployment rate, as well as the start-of-period degree of urbanization. Shift-share controls are included as the changes in import- and export-exposure and ICT-intensity (labor demand shifts) and changes in the migrant population differentiated by 4 educational groups (labor supply shifts). The detailed industry structure controls include start-of-period employment shares of several sub-industries of manufacturing (production of food products, consumer goods, industrial goods, and capital goods), as well as industries outside of manufacturing (construction, personal services, and business services). All regressions are weighted by the start-of-period working-age population

of the unobserved demand shock/agglomeration effect, resulting in an upward bias of the estimate. The fact that 2SLS shows a stronger negative estimate in all specifications suggests that the instrumentation strategy is able to address these endogeneity concerns. Including further control variables in columns 2 to 6 of Table 2 has only a moderate impact on the size of the 2SLS estimate, which stays relatively stable over all following specifications. In the full specification, including all available control variables in column 6 of Table 2, the 2SLS estimation suggests a negative effect of −0.476. In Table A3 in the Supplementary Material this effect is decomposed by age groups, which reveals that the majority of the shock incidence (52% of the effect on manufacturing employment) falls on younger workers below the age of 35. The robotization shock, thus, particularly hampers the employment prospect of young workers, a group that is known in the literature to be more geographically mobile in response to labor demand shocks (Bound and Holzer 2000).[16]

A vast literature, following the seminal work of Blanchard and Katz (1992), has shown that after local labor demand shocks, migration responses play an important role in the local labor markets' return to equilibrium (see, for example, Jauer et al. 2019). To examine whether the labor market disruptions caused by industrial robots documented in panel A of Table 2 have led to increased out-migration, panel B of Table 2 presents estimations of the effect of robotization on net out-migration rates. For any period t that spans the years $j = 1, ..., J$ this measure is constructed as:

$$\frac{\sum_{j=1}^{J} Net\ Outflow_j}{Population_{j=1}} = \frac{\sum_{j=1}^{J}(Outflow_j - Inflow_j)}{Population_{j=1}} \tag{4}$$

[16] Further results on the employment effects of robotization are provided in Supplementary Material Appendix C.

Hence, net out-migration rates are calculated by subtracting migration inflows from migration outflows and summing up over all years that make up the panel period. The measure is then normalized by the initial year working-age population to arrive at a relative measure of net out-migration flows.

The estimation results for the migratory response in panel B of Table 2 show that robotization has led to an increase in net out-migration rates during 2003–2016. Here, the full specification in column 6 suggests that one more industrial robot per 1000 workers leads to net out-migration flows of around 1.101% of the start-of-period working-age population. This effect is robust over all specifications and statistically significant in both standard error definitions.

Comparing the results for the OLS and 2SLS estimations shows that the 2SLS point estimates are drastically larger than the OLS estimates. This picture is again consistent with the presence of unobserved positive demand shocks or agglomeration effects that reduce migration responses, as in both cases the OLS estimate would absorb their reducing effect, leading to a downward bias in the OLS estimate. Additionally, recent work by Borusyak et al. (2022) has shown that there is another factor in migration regressions, like the one estimated in panel B of Table 2, that can lead to an, at times severe, attenuation of estimated effects on migration behavior. This problem arises whenever the local labor demand shocks between origin and destination regions are correlated. In this case, the estimated migration effects are biased toward zero (even if the labor demand shock is plausibly exogenous). While the size of the estimated migration response in panel B of Table 2 suggests that severe attenuation of the estimated effect is unlikely, it cannot be fully ruled out. Therefore, it is possible that the estimated effect on net out-migration rates represents a lower bound of the true effect.[17]

Looking at the results of the first stage estimation shows that the instrument is strong and highly relevant. Here, the point estimate of 0.011 indicates that for one additional robots installed in the countries used to construct the instrument, 0.011 additional robots are installed in Austria. This point estimate in the first-stage regression partly reflects the size difference between Austria and the aggregate of all countries used to construct the instrument. Here, Austria increased its robot stock (in raw units) by around 3.2% of the total volume installed in the countries used to construct the instrument.[18] Since the instrument is constructed in per-*Austrian*-worker terms (see Eq. 3), this difference carries over to the size of the first stage coefficient. If robot adoption in Austria were entirely explained by the adoption pace in the IV countries this, thus, would imply a first-stage coefficient of 0.032. Hence, the point estimate of 0.011 implies that around one-third of overall robot adoption in Austria is explained by common trends between Austria and the countries used to construct the instrument, while the remaining two-thirds are explained by (possibly endogenous) regional determinants in Austria.

[17] Borusyak et al. (2022) propose a way of correcting this attenuation, by including migration-weighted averages of the shocks to other regions as an additional control variable. The construction of this control variable requires data on migration flows in periods preceding the observational period. Since the Austrian migration flow data is only available from 2002 onward, this correction cannot be implemented in this setting.

[18] In total, there were 6,719 units installed in Austria, while there were 207,255 units installed in the IV countries.

Table A4 in the Supplementary Material presents estimations using an alternative migration measure. Here, the log-change in working-age population counts is used to approximate migratory responses. In the literature on migratory responses to local labor demand shocks, the log-change in working-age population counts is frequently used as the primary measure for migration responses (especially when more detailed data on migration in- and outflows is not available). Table A4 shows that using the log-change in working-age population counts to approximate migration responses yields similar results as when using net out-migration rates. Consistent with previous results, these estimations suggest that robotization leads to significant decreases in the size of the working-age population, both overall (Table A4, panel A) and when focusing only on rural areas (panel B). Comparing the effect size to similar results in Faber et al. (2021) suggests that the overall population decline induced by robotization (−0.320; panel A) is slightly smaller than in the USA, where they find an estimated effect of −0.560 (see Faber et al. 2021, Table 2).

Rural depopulation

While the results in Table 2 confirm that robotization shocks led to out-migration in a similar fashion as is firmly established for other types of labor demand shocks, these results do not tell much about the direction of these migration flows. To lay a specific focus on the question whether robotization causes migration flows directed from rural to urban areas, and thereby contributes to rural depopulation, I use the fact that the data on net out-migration rates used in Table 2 contains detailed information on the region of origin, as well as the destination. As any commuting zone may consist of both urban and rural areas (see Supplementary Material Appendix D), the net outflow from any commuting zone can be decomposed into the respective contributions of rural and urban areas:

$$\frac{\sum_{j=1}^{J} Net\ Outflow_j}{Population_{j=1}} = \frac{\sum_{j=1}^{J} Net\ Outflow_j^{Rural}}{Population_{j=1}} + \frac{\sum_{j=1}^{J} Net\ Outflow_j^{Urban}}{Population_{j=1}} \tag{5}$$

Using the available information on the destination type (urban, rural, or abroad), the net outflows from rural areas can be further decomposed by destination:

$$\frac{\sum_{j=1}^{J} Net\ Outflow_j^{Rural}}{Population_{j=1}} = \left.\begin{aligned} &\frac{\sum_{j=1}^{J} Net\ Outflow_j^{Rural\to Urban}}{Population_{j=1}} + \\ &\frac{\sum_{j=1}^{J} Net\ Outflow_j^{Rural\to Rural}}{Population_{j=1}} + \end{aligned}\right\} \text{Internal} \\ \left.\frac{\sum_{j=1}^{J} Net\ Outflow_j^{Rural\to Abroad}}{Population_{j=1}}\right\} \text{External} \tag{6}$$

Hence, the net out-migration rate from all rural regions in any commuting zone is decomposed into flows directed towards urban or rural areas (internal migration) and flows with other countries (external migration).[19]

Table 3 applies this decomposition to the net out-migration rates from rural areas. Here, column 1 shows the effect of industrial robots on all rural net outflows. This effect (1.060) is on a very similar magnitude as when net outflows from both rural and urban areas are considered (1.101; Table 2, panel B, column 6). Decomposing this effect into the part explained by external migration (column 2) and internal migration (column 3) makes clear that increases in net out-migration flows are exclusively driven by increases in internal net out-migration. Further decomposing these internal migration flows into rural-to-urban and rural-to-rural flows in columns 4 and 5 of Table 3 reveals that a large part of this effect stems from rural-to-urban migration. While one more additional robot per 1000 workers increases internal out-migration rates from rural areas by around 1.136%, approximately 0.612% of this increase is accounted for by outflows that are directed towards urban areas. This effect for rural-to-urban net out-migration rates is precisely estimated and significant at the 1%-level in both standard error definitions. This coefficient in column 4 of Table 3 provides direct evidence that robotization contributes to population declines in rural areas by specifically increasing rural-to-urban internal migration flows.[20]

Column 5 of Table 3 shows that robotization also has an increasing effect on rural-to-rural migration flows. Here, the estimation suggests a positive effect of 0.524. Since the demographic trends in rural regions are very heterogeneous between declining remote regions and growing regions in close proximity to the large cities (see Fig. 1), it is interesting to see whether these rural-to-rural migration flows are directed towards more centrally located rural areas. This is investigated in columns 6 and 7 of Table 3, where the overall rural-to-rural effect is further decomposed into flows directed to central and remote rural regions. Here, it becomes apparent that a large part of the rural-to-rural migration response is directed towards rural regions that lie in close proximity to large urban centers. This type of rural-to-(central) rural migration accounts for an additional 16.1% of all internal migration movements, which are caused by the robotization shock. In sum, the estimation results in Table 3 show that robotization has prompted strong internal migration responses in rural areas, which are predominately directed towards urban areas (around 54% of the total effect) and rural regions in close proximity to these urban centers (another 16%).

Since the dependent variables used in the estimations shown in Table 3 are computed by subtracting in-migration flows from out-migration flows (to arrive at the desired net out-migration measure in Eq. 4) it is interesting whether the increase in rural-to-urban

[19] While the migration flow data contains detailed information on the region of origin, it does not contain information on the exact destination region. Rather, the type of destination is provided (as defined in the urban-rural-classification from Statistics Austria in Supplementary Material Figure A1). While this does not allow a detailed reconstruction of the destination region, it allows for a distinction between rural and urban destinations.

[20] In Table 3 the intermediate regional class "regional centers" (see Supplementary Material Figure A1) is classified as rural area. To check whether this choice affects the results, Table A5 in the Supplementary Material presents estimates, where "regional centers" are included in urban areas. The estimates in Table A5 show that the results are unaffected by this choice.

Table 3 Robotization and net out-migration in rural areas (2003–2016)

	Total	External	Internal			Rural-to-rural flows	
			All	Rural-to-urban	Rural-to-rural	Central rural	Remote rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2SLS							
Δ Robots	1.060	−0.075	1.136	0.612	0.524	0.183	0.341
	(0.362)***	(0.067)	(0.428)***	(0.201)***	(0.232)**	(0.037)***	(0.207)
	[0.145]***	[0.024]***	[0.166]***	[0.074]***	[0.101]***	[0.035]***	[0.076]***
First Stage F	30.66	30.66	30.66	30.66	30.66	30.66	30.66
% of Internal migration response			100%	53.9%	46.1%	16.1%	30.0%
Period FE	x	x	x	x	x	x	x
Region FE	x	x	x	x	x	x	x
Demographics	x	x	x	x	x	x	x
Regional char.	x	x	x	x	x	x	x
Labor supply	x	x	x	x	x	x	x
Labor demand	x	x	x	x	x	x	x
Industry structure	x	x	x	x	x	x	x
Commuting zones	158	158	158	158	158	158	158
Periods	2	2	2	2	2	2	2
Observations	316	316	316	316	316	316	316

Notes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. Conventional cluster-robust standard errors are shown in parentheses, and shift-share clustered standard errors from Adao et al. (2019) are shown in brackets. Units of observation are 158 clustered commuting zones (for details see Supplementary Material Appendix D). All specifications include a set of commuting zone and period fixed effects, whereby the period fixed effects are interacted with the sum of exposure shares used to construct the instrument. Demographic controls include the start-of-period structure of the local workforce in 64 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product (total and per-capita) and the unemployment rate, as well as the start-of-period degree of urbanization. Shift-share controls are included as the changes in import- and export-exposure and ICT-intensity (labor demand shifts) and changes in the migrant population differentiated by 4 educational groups (labor supply shifts). The detailed industry structure controls include start-of-period employment shares of several sub-industries of manufacturing (production of food products, consumer goods, industrial goods, and capital goods), as well as industries outside of manufacturing (construction, personal services, and business services). All regressions are weighted by the start-of-period working-age population net out-migration stems from an increase in out-migration flows or rather a decrease in in-migration flows. To answer this question, panel A of Table 4 presents separate estimations for those two components of net out-migration rates. Panel B presents similar estimations for net out-migration rates from rural areas towards other centrally

Table 4 Contribution of in- and out-flows to rural depopulation (2003–2016)

	Net out-migration (1)	Out-migration (2)	In-migration (3)
Panel A: Rural-to-urban migration			
2SLS			
Δ Robots	0.612	0.793	0.181
	(0.201)***	(0.092)***	(0.135)
	[0.074]***	[0.078]***	[0.049]***
First Stage F	30.66	30.66	30.66
Panel B: Rural-to-central rural migration			
2SLS			
Δ Robots	0.183	0.277	0.094
	(0.037)***	(0.038)***	(0.055)*
	[0.035]***	[0.046]***	[0.036]***
First Stage F	30.66	30.66	30.66
Period FE	x	x	x
Region FE	x	x	x
Demographics	x	x	x
Regional char.	x	x	x
Labor supply	x	x	x
Labor demand	x	x	x
Industry structure	x	x	x
Commuting zones	158	158	158
Periods	2	2	2
Observations	316	316	316

Notes: *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$ Conventional cluster-robust standard errors are shown in parentheses, and shift-share clustered standard errors from Adao et al. (2019) are shown in brackets. Units of observation are 158 clustered commuting zones (for details see Supplementary Material Appendix D). All specifications include a set of commuting zone and period fixed effects, whereby the period fixed effects are interacted with the sum of exposure shares used to construct the instrument. Demographic controls include the start-of-period structure of the local workforce in 64 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product (total and per-capita) and the unemployment rate, as well as the start-of-period degree of urbanization. Shift-share controls are included as the changes in import- and export-exposure and ICT-intensity (labor demand shifts) and changes in the migrant population differentiated by 4 educational groups (labor supply shifts). The detailed industry structure controls include start-of-period employment shares of several sub-industries of manufacturing (production of food products, consumer goods, industrial goods, and capital goods), as well as industries outside of manufacturing (construction, personal services, and business services). All regressions are weighted by the start-of-period working-age population located rural areas. Comparing columns 2 and 3 of Table 4 shows that the increase in net out-migration rates is exclusively driven by an increase in out-migration (column 2), while the estimates for the effect of robotization on in-migration are small. Hence, population declines in remote rural areas, which are induced by the robotization shock, specifically operate through individuals leaving exposed areas towards the cities and more centrally located rural areas.

Taken together the results in Tables 3 and 4 clearly show that robotization has increased migration flows from rural areas towards large urban centers. The majority of these flows are directed at cities. However, a non-negligible part is also explained by increased migration into rural areas that lie in close proximity to the large cities. As these specific types of internal migration flows greatly contribute to population declines in many remote rural areas, these results show that robotization-based labor demand disruptions have contributed to the decline of remote rural regions in Austria between 2003 and 2016.

To benchmark the magnitude of this effect Fig. 2 presents a counterfactual calculation, where robotization is held constant at its 2003 level. This Figure shows that between 2003 and 2016 rural areas in Austria lost around 3.62% of their 2003 working-age population through rural-to-urban net outflows. In the absence of robotization, this number drops to around 2.67%. Increases in robotization, thus, explain around one-fourth of all rural-to-urban migration flows during the period 2003 to 2016.

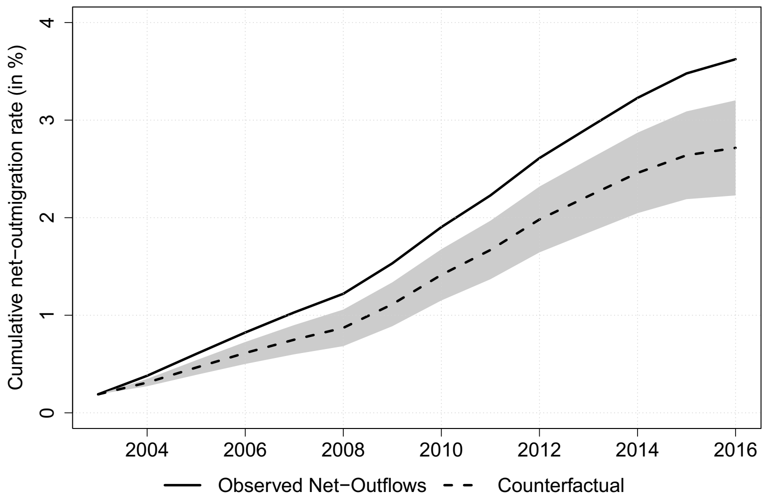

Fig. 2 Benchmarking effect size: cumulative rural-to-urban net out-migration (2003–2016). *Notes:* The counterfactual evolution of the cumulative net out-migration rate is calculated by multiplying the observed change in robots per 1000 workers (1.485; Figure A2 in the Supplementary Material) by the estimated effect of one additional robot per 1000 workers on the rural-to-urban net out-migration rates of the working-age population (0.612; Table 3, column 4). The resulting contribution of industrial robots to the change in the net out-migration rate is then spread out evenly over the entire observational period and subtracted from the observed trends to construct the counterfactual. The grey area corresponds to 90% confidence interval (computed from the conventional cluster-robust standard errors)

Heterogeneous effects by population subgroups

While the results in Tables 2 to 4 show that industrial robotization has led to reductions in labor demand in the manufacturing industries and increased out-migration, specifically out of rural areas, this section explores heterogeneous effects by age, gender, and skill level. For this Table 5 presents estimates for rural-to-urban net out-migration decomposed by age and gender groups. Here, the estimate in the first row of column 1 corresponds to the total effect of industrial robots on rural-to-urban migration. To better assess the total effect of automation-induced out-migration on the age structure of rural areas, Table 5 considers migratory responses of the entire population (instead

Table 5 Rural-to-urban migration by age and gender (2SLS estimates)

	Dependent variable: Net outflow from rural areas by age group				
	All	Age 0 to 14	Age 15 to 34	Age 35 to 49	Age 50 and above
	(1)	(2)	(3)	(4)	(5)
Panel A: All					
Δ Robots	0.483	0.096	0.295	0.087	0.006
	(0.149)***	(0.028)***	(0.089)***	(0.034)**	(0.025)
	[0.058]***	[0.013]***	[0.035]***	[0.018]***	[0.007]
First Stage F	30.87	30.87	30.87	30.87	30.87
Panel B: Male					
Δ Robots	0.317	0.031	0.203	0.054	0.029
	(0.124)**	(0.012)**	(0.084)**	(0.027)**	(0.014)**
	[0.044]***	[0.006]***	[0.031]***	[0.012]***	[0.004]***
First Stage F	30.87	30.87	30.87	30.87	30.87
Panel C: Female					
Δ Robots	0.168	0.066	0.092	0.032	−0.022
	(0.034)***	(0.018)***	(0.005)***	(0.009)***	(0.011)**
	[0.019]***	[0.008]***	[0.008]***	[0.008]***	[0.005]***
First Stage F	30.87	30.87	30.87	30.87	30.87
Panel D: Relative contribution to net out-migration by age					
All		19.9%	61.1%	18.0%	1.2%
Male	65.6%	6.4%	42.0%	11.2%	6.0%
Female	34.7%	13.7%	19.1%	6.6%	−4.6%
Period FE	x	x	x	x	x
Region FE	x	x	x	x	x
Demographics	x	x	x	x	x
Regional char.	x	x	x	x	x
Labor supply	x	x	x	x	x
Labor demand	x	x	x	x	x
Industry structure	x	x	x	x	x

Table 5 continued

	Dependent variable: Net outflow from rural areas by age group				
	All (1)	Age 0 to 14 (2)	Age 15 to 34 (3)	Age 35 to 49 (4)	Age 50 and above (5)
Commuting zones	158	158	158	158	158
Periods	2	2	2	2	2
Observations	316	316	316	316	316

Notes: *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. Conventional cluster-robust standard errors are shown in parentheses, and shift-share clustered standard errors from Adao et al. (2019) are shown in brackets. Units of observation are 158 clustered commuting zones (for details see Supplementary Material Appendix D). All specifications include a set of commuting zone and period fixed effects, whereby the period fixed effects are interacted with the sum of exposure shares used to construct the instrument. Demographic controls include the start-of-period structure of the local workforce in 64 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product (total and per-capita) and the unemployment rate, as well as the start-of-period degree of urbanization. Shift-share controls are included as the changes in import- and export-exposure and ICT-intensity (labor demand shifts) and changes in the migrant population differentiated by 4 educational groups (labor supply shifts). The detailed industry structure controls include start-of-period employment shares of several sub-industries of manufacturing (production of food products, consumer goods, industrial goods, and capital goods), as well as industries outside of manufacturing (construction, personal services, and business services). Since these estimates reflect effects on the entire population (instead of just regarding the working-age population), all regressions are weighted by the start-of-period size of the overall population

of just regarding the working-age population as in Tables 2 to 4). This allows to also examine migratory responses of the age groups "0 to 14" and "65 and older."[21] While the age group "0 to 14" clearly does not migrate on their own, but rather moves along with their migrating parents, a decline in this age group still has important implications for the age structure (both present and future) of rural areas. Especially if automation-induced labor demand shocks hit young families and parents, which then respond by migrating to the cities, the age group "0 to 14" might also experience a downward trend in population counts in rural areas, which further accelerates societal aging of the population (Johnson et al. 2015). Since Table 5 looks at the rural-to-urban component of net out-migration rates of the entire population the total effect (0.483; panel A, column 1) is somewhat smaller when compared to the results for the working-age population (0.612; Table 3, column 4). This already suggests that the age groups "0 to 14" and "65 and older" are less mobile than the working-age population. This is further confirmed by the estimates in columns 2 to 5, which present the decomposition of the total effect by age groups. Here, around 61% of the total effect (panel D, column 3) is explained by the out-migration of individuals between the age of 15 and 34, while another 20% (panel D, column 2) of the total effect stems from children under the age of 15 who out-migrate with their parents. Hence, around 81% of the total migratory response are accounted for by the out-migration of individuals below the age of 35, showing that automation-based labor demand shocks lead to out-migration of predominantly young individuals out of affected rural areas. While the age group "35 to 49"

[21] For better readability, the age groups "50 to 64" and "65 and older" are aggregated to a single category in Table 5.

also shows relevant, although much smaller, migratory responses, individuals above the age of 50 do not respond to disruptions in labor demand by moving to the cities.

Panels B and C of Table 5 further decompose the total effect by gender. Since males account for a larger fraction of manufacturing employment, and thus bear a stronger shock incidence, they also account for a higher fraction of the migratory response, with around two-thirds of the total effect being explained by male migration.

Since technological change is known to have very heterogeneous effects on different skill groups, it is likely that it also affects the migration behavior differently, depending on the skill levels of affected individuals (see also Beerli et al. 2023). This

Table 6 Percentage change of working-age population in rural areas by skill groups (2SLS estimates)

		By skill-group		
	All	High-skill	Medium-skill	Low-skill
	(1)	(2)	(3)	(4)
Δ Robots	−0.440	−0.073	−0.091	−0.275
	(0.047)***	(0.034)**	(0.084)	(0.033)***
	[0.045]***	[0.012]***	[0.049]*	[0.029]***
First Stage F	30.66	30.66	30.66	30.66
Contribution to total effect		16.6%	20.7%	62.5%
Period FE	x	x	x	x
Region FE	x	x	x	x
Demographics	x	x	x	x
Regional char.	x	x	x	x
Labor supply	x	x	x	x
Labor demand	x	x	x	x
Industry structure	x	x	x	x
Commuting zones	158	158	158	158
Periods	2	2	2	2
Observations	316	316	316	316

Notes: *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. Conventional cluster-robust standard errors are shown in parentheses, and shift-share clustered standard errors from Adao et al. (2019) are shown in brackets. Units of observation are 158 clustered commuting zones (for details see Supplementary Material Appendix D). All specifications include a set of commuting zone and period fixed effects, whereby the period fixed effects are interacted with the sum of exposure shares used to construct the instrument. Demographic controls include the start-of-period structure of the local population in 64 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product (total and per-capita) and the unemployment rate, as well as the start-of-period degree of urbanization. Shift-share controls are included as the changes in import- and export-exposure and ICT-intensity (labor demand shifts) and changes in the migrant population differentiated by 4 educational groups (labor supply shifts). The detailed industry structure controls include start-of-period employment shares of several sub-industries of manufacturing (production of food products, consumer goods, industrial goods, and capital goods), as well as industries outside of manufacturing (construction, personal services, and business services). High-skill workers are defined as university graduates. Medium-skill workers are individuals who finished high school or an apprenticeship, and low-skill workers have finished compulsory schooling or less. The dependent variables are constructed as percentage changes where the change in the population by skill group is divided by the initial year's working-age population. Hence, all skill group-based variables have a common denominator and thus sum up to the aggregated change. All regressions are weighted by the start-of-period working-age population is investigated in Table 6. Since the migration flow data does not contain information on educational attainment, migratory responses of different skill groups are approximated by percentage changes in population counts of each respective skill group. Therefore, the results in Table 6 cannot distinguish between the type of destination region (urban or rural), but rather approximate all migratory responses in rural areas. Using percentage changes in the working-age population instead of the logarithm has the advantage that the overall effect on the entire working-age population (in column 1 of Table 6) can be additively decomposed into the respective contributions of different skill groups. The estimation results for high-, medium- and low-skilled workers in columns 2 to 4 of Table 6 show that the majority of the migration response to the robotization shock is caused by movements of individuals in the middle and at the bottom of the skill distribution. Together these two groups account for around 83% of all migratory responses to the robotization shock.

Taken together Tables 5 and 6 show that the rural-to-urban migration flows caused by robotization are predominantly driven by those individuals that bear the strongest shock incidence. These groups are mainly young workers (below the age of 35; see Table A3) and workers of medium to low skill levels.

Heterogeneous effects by shock exposure

Table 7 shows heterogeneous effects by exposure to the robotization shock. Columns 2 and 3 decompose the overall effect of industrial robots on the manufacturing employment-to-population ratio by effects occurring in the top-5 most exposed

Table 7 Effect heterogeneity by shock exposure

		By industry exposure		By regional exposure	
	Total effect	Top-5	Other	< Median	≥ Median
	(1)	(2)	(3)	(4)	(5)
Panel A: Δ Manufacturing employment-population-ratio $\times$ 100					
Δ Robots	−0.476	−0.071	−0.405	−0.147	−0.329
	(0.114)***	(0.037)*	(0.125)***	(0.060)**	(0.070)***
	[0.066]***	[0.039]*	[0.085]***	[0.039]***	[0.066]***
First Stage F	30.66	30.66	30.66	30.66	30.66
Panel B: Net out-migration rate $\times$100 (Rural)					
Δ Robots	1.060			0.130	0.930
	(0.362)***			(0.077)*	(0.411)**
	[0.145]***			[0.033]***	[0.135]***
First Stage F	30.66			30.66	30.66

Table 7 continued

		By industry exposure		By regional exposure	
	Total effect	Top-5	Other	< Median	≥ Median
	(1)	(2)	(3)	(4)	(5)
Panel C: Net out-migration rate × 100 (Rural-to-urban)					
Δ Robots	0.612			−0.062	0.673
	(0.201)***			(0.079)	(0.245)***
	[0.074]***			[0.025]**	[0.072]***
First Stage F	30.66			30.66	30.66
Period FE	x	x	x	x	x
Region FE	x	x	x	x	x
Demographics	x	x	x	x	x
Regional char.	x	x	x	x	x
Labor supply	x	x	x	x	x
Labor demand	x	x	x	x	x
Industry structure	x	x	x	x	x
Commuting zones	158	158	158	158	158
Periods	2	2	2	2	2
Observations	316	316	316	316	316

Notes: *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. Conventional cluster-robust standard errors are shown in parentheses, and shift-share clustered standard errors from Adao et al. (2019) are shown in brackets. Units of observation are 158 clustered commuting zones (for details see Supplementary Material Appendix D). All specifications include a set of commuting zone and period fixed effects, whereby the period fixed effects are interacted with the sum of exposure shares used to construct the instrument. Demographic controls include the start-of-period structure of the local population in 64 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product (total and per-capita) and the unemployment rate, as well as the start-of-period degree of urbanization. Shift-share controls are included as the changes in import- and export-exposure and ICT-intensity (labor demand shifts) and changes in the migrant population differentiated by 4 educational groups (labor supply shifts). The detailed industry structure controls include start-of-period employment shares of several sub-industries of manufacturing (production of food products, consumer goods, industrial goods, and capital goods), as well as industries outside of manufacturing (construction, personal services, and business services). Columns 2 and 3 decompose the overall employment effect by industry exposure. The top-5 industries with the strongest change in robot exposure are the manufacture of motor vehicles, electronic components and devices, rubber and plastic products, metal products, as well as household and domestic appliances. The "other" category in column 3 summarizes all remaining manufacturing industries. Regions in columns 4 and 5 are split along the median of regional robot exposure (calculated using the average robot exposure of both panel periods). All regressions are weighted by the start-of-period working-age population

industries and the remaining manufacturing industries.[22] Here, it stands out that, while the top-5 most robotized industries account for a relevant part of the total negative effect on manufacturing employment, the remaining industries are responsible for the majority of the employment effect. Hence, the negative effect robotization has had on manufacturing employment in Austria is not only driven by those heavily robotized

[22] The top-5 industries with the strongest change in robot exposure are the manufacture of motor vehicles, electronic components, and devices, rubber and plastic products, metal products, as well as household and domestic appliances.

industries, but instead is a much broader phenomenon affecting the entirety of the manufacturing sector.

Columns 4 and 5 of Table 7 decompose the overall employment and migration effects into the contributions of highly and less exposed regions. For this, the dependent variables are interacted with dummies that take the value of one if a region is above or below the median of the average change in robot exposure during 2003–2016. This approach ensures that the coefficients in columns 4 and 5 sum up to the total effects in column 1. Regarding this decomposition of the employment effect in panel A shows that the majority of the negative effect of robotization is explained by those regions that lie above the median of average robot exposure. Nevertheless, regions below the median still show relevant negative reactions. This picture translates to the effect on net out-migration rates from rural areas (panel B) where again the majority of the migration response is driven by regions with the highest exposure to the robot shock, while less exposed regions also show significant migration responses, albeit at a much smaller magnitude. Interestingly, this pattern does not persist when specifically regarding rural-to-urban migration flows in panel C of Table 7. Here, the entirety of the effect on rural-to-urban migration is explained by those regions that are especially affected by changes in robotization. While less-exposed regions thus show some minor effects on manufacturing employment and overall migration behavior, the effect on rural-to-urban migration is exclusively driven by regions that are particularly exposed to the robotization shock.

6 Robustness checks

Fixed exposure shares

To increase the strength of the first stage the instrumental variable used during the main part of this paper relies on exposure shares that are lagged by 15 years for each of the two-panel periods, instead of exposure shares that are uniformly fixed at the same base year (see Eq. 3). To assess the impact of updating the exposure shares, column 2 of Table A6 in the Supplementary Material presents estimation results where the exposure shares for both panel periods are fixed at the common base year 1988 (i.e., 15 years before the start of the first-panel period). Fixing the exposure shares markedly reduces the first-stage F-statistic, which drops to values below 10. With regard to the estimated effects, all previous conclusions remain intact.

Long-difference specification

Column 3 of Table A6 in the Supplementary Material shows the results of a long-difference specification over the entire observational period 2003–2016. Comparing these long-difference results to the baseline specification using stacked differences (column 1) shows that the primary results remain intact. Notably, the long-difference specification results in a much larger estimated effect of robotization on migration flows, indicating that unobserved heterogeneity along the spatial and time dimensions appears to bias the estimate in a long-difference specification. Controlling for this unobserved heterogeneity via the inclusion of period and commuting zone fixed effects in the stacked-difference specification thus leads to a smaller size of the estimated migration response in the baseline specification. This, however, does not seem to be the case for the employment estimations. Lastly, the long-difference specification also results in a much weaker first stage.

Pool of donor countries for the instrument

A potential concern for the validity of the instrumental variable stems from possible correlations between industry-level robot adoption between subgroups of countries that are caused by (potentially endogenous) factors other than the increased supply of robots due to technological progress. Since some of the countries used to construct the instrument share a common currency, and thus a common monetary policy with Austria, the simultaneous effects of common macroeconomic shocks on investment in robots and outcome variables (i.e., changes in manufacturing employment or migration behavior), therefore, are a source of concern. If factors such as the Euro Crisis, or changes in monetary policy, which rather prominently took place during the sample period, influence investment decisions in industrial robots specifically in certain industries, this might lead to correlations between robotization shocks in Austria and other member states of the European Union that is not driven by changes in the supply of robots, and thus does not represent increased availability of industrial robots due to technological progress. To the degree that such common macro shocks influence the outcome variables, this might violate the exogenous shocks assumption. In principle, the period fixed effects are able to deal with such a problem, if such effects are homogeneous across commuting zones. If such shocks, however, affect some industries more strongly than others, this might introduce regional heterogeneity in this effect, which might not be captured by period fixed effects. To assess whether the results are influenced by such contamination of the instrumental variable column 4 of Table A6 in the Supplementary Material presents results for an alternative computation of the instrument for which only robotization changes from countries outside the European Monetary Union are used, while column 5 presents estimates where only countries outside of Europe are used. Comparing the results for the baseline instrument in column 1 of Table A6 to the results for the alternative instruments in columns 4 and 5 of Table A6 shows that all results are robust to the exclusion of these countries in the computation of the instrument.

Regional selection into robot usage

A further source of concern regarding the empirical strategy stems from strong heterogeneity between rural areas and cities. For example, the regional pattern of robot usage might be driven by larger firms (which are more common in urban areas). Similarly, robotization might be concentrated in areas with a more suitable age or skill composition of the local workforce. If this is the case, then the instrument might be contaminated by these selection processes. To control for this possibility column 6 of Table A6 includes the average firm size in a commuting zone (differentiated by rural and urban regions) as additional control variables, while column 7 includes age and skill shares of the local workforce (differentiated by rural and urban regions). Again, all results are robust to these additional checks.

7 Conclusion

It has been long established in the economic literature that internal migration plays a crucial role in the recovery of local labor markets after large-scale shocks to labor demand. While this mechanism is well understood, the question of where internal migrants move after a shock has remained largely unstudied. This question is, however, of particular relevance as internal migration flows are a major contributing factor to population declines in many rural areas in both Europe and the USA. This phenomenon, which is known as rural depopulation, poses a great challenge for many rural areas, and also for society as a whole, as it is closely connected to increases in geographical inequality and social and political polarization.

In this paper, I explore the connection between changes in labor demand, which are caused by the rise of industrial robotization, internal migration, and rural depopulation in Austria during the period 2003–2016. The results of the analysis show that industrial robotization has had a substantial negative impact on manufacturing employment, and increased out-migration in local labor markets most exposed to the robotization shock. Laying a specific focus on rural areas reveals that a large part of their internal out-migration flows are directed towards urban areas, thereby contributing to the decline of many rural regions. In sum, the estimations suggest that rural-to-urban migration flows, which are specifically caused by industrial robotization, explain roughly one-fourth of all rural-to-urban movements between 2003 and 2016. This increase in net out-migration exclusively operates through increases in out-migration rates, indicating that robotization-induced population declines in remote rural areas are driven by individuals leaving highly exposed rural regions toward the cities. Exploring heterogeneous effects by population subgroups further shows that these rural-to-urban migration flows are primarily driven by those individuals that bear the strongest incidence of the robotization shock, namely young and medium- and low-skilled individuals.

One important consequence of rural decline is a deepening of the cleavage between advantaged and disadvantaged regions. With recent increases in societal and political polarization, future work should explore how rural decline and its causes contribute to this development.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s00148-025-01109-z.

Acknowledgements I want to thank Editor Milena Nikolova, as well as three anonymous referees for very productive comments that greatly improved the quality of the paper. Furthermore, I want to thank Rudolf Winter-Ebmer, Benjamin Bittschi, Ethan Lewis, Michael Pfaffermayer, Richard Sellner, and various seminar participants at the Central European University in Vienna, the RWI workshop for causal inference with spatial data in Essen, the University of Innsbruck, the Johannes Kepler University Linz, the Institute for Advanced Studies (IHS), the Austrian Institute for Economic Research (WIFO), the EALE-conference 2022, the NOeG-conference 2022, the GGDC-Conference 2024 and the VfS-Conference 2024 for useful comments. I further want to thank Statistics Austria for providing the migration flow data.

Funding Open access funding provided by Institute for Advanced Studies Vienna. The research presented in this paper was funded by the anniversary fund of the Austrian National Bank (OeNB; grant number 18462) and has received additional financial support from the Austrian Economic Association (NOeG) via the NOeG-Dissertation Fellowship 2021.

Data availability This paper uses proprietary data from the International Federation of Robotics (IFR) and the Austrian Statistical Office (Statistik Austria). The author does not have permission to share these data. The IFR data can be purchased under https://ifr.org/worldrobotics/, and the migration flow data can be obtained as a special delivery from Statistik Austria (https://www.statistik.at). The author offers to assist in the data application process and will provide replication codes and remaining materials upon reasonable request.

Declarations

Competing interests The author declares no competing interests.

References

Acemoglu D, Pascual R (2020) Robots and jobs: evidence from US labor markets. J Polit Econ 128(6):2188–2244

Acemoglu D, Pascual R (2022) Demographics and automation. Rev Econ Stud 89(1):1–44

Adao R, Kolesár M, Morales E (2019) Shift-share designs: theory and inference. Q J Econ 134(4):1949–2010

Alamá-Sabater L, Márquez MÁ, Tortosa-Ausina E, Cravo J (2024) Urban–rural links in relaunching left-behind places: the case of Portuguese municipalities. J Econ Geog lbae037

Autor D (2020) The faltering escalator of urban opportunity. MIT Work of the Future Report 108–36

Autor DH (2019) Work of the past, work of the future. AEA Papers and Proceedings 109:1–32

Autor D, Dorn D, Hanson G, Majlesi K (2020) Importing political polarization? The electoral consequences of rising trade exposure. Am Econ Rev 110(10):3139–3183

Beerli A, Indergand R, Kunz JS (2023) The supply of foreign talent: how skill-biased technology drives the location choice and skills of new immigrants. J Popul Econ 36(2):681–718

Bekhtiar K, Bittschi B, Sellner R (2024) Robots at work? Pitfalls of industry-level data. J Appl Economet 39(6):1180–1189

Bjerke L, Mellander C (2017) Moving home again? Never! The locational choices of graduates in Sweden. Ann Reg Sci 59(3):707–729

Blanchard OJ, Katz LF (1992) Regional evolutions. Brook Pap Econ Act 23(1):1–76

Boman A (2011) Does migration pay? Earnings effects of geographic mobility following job displacement. J Popul Econ 24:1369–1384

Bonfiglioli A, Crinò R, Fadinger H, Gancia G (2024) Robot imports and firm-level outcomes. Econ J 134(664):3428–3444

Borusyak K, Hull P, Jaravel X (2022) Quasi-experimental shift-share research designs. Rev Econ Stud 89(1):181–213

Borusyak K, Hull P, Jaravel X (2025) A practical guide to shift-share instruments. J Econ Perspect 39(1):181–204

Borusyak K, Dix-Carneiro R, Kovak BK (2022) Understanding migration responses to local shocks

Bound J, Holzer HJ (2000) demand shifts, population adjustments, and labor market outcomes during the 1980s. J Law Econ 18(1):20–54

Cadena BC, Kovak BK (2016) Immigrants equilibrate local labor markets: evidence from the great recession. Am Econ J Appl Econ 8(1):257–290

Cameron AC, Miller DL (2015) A practitioner's guide to cluster-robust inference. J Hum Resour 50(2):317–372

Card D (2001) Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. J Law Econ 19(1):22–64

Connor DS, Berg AK, Kemeny T, Kedron PJ (2024) Who gets left behind by left behind places? Camb J Reg Econ Soc 17(1):37–58

Costanzo C (2025) Robots, jobs, and optimal fertility timing. J Popul Econ (forthcoming)

Dauth W, Findeisen S, Suedekum J (2014) The rise of the east and the far east: German labor markets and trade integration. J Eur Econ Assoc 12(6):1643–1675

Dauth W, Findeisen S, Suedekum J, Woessner N (2021) The adjustment of labor markets to robots. J Eur Econ Assoc 19(6):3104–3153

Dax T, Fischer M (2018) An alternative policy approach to rural development in regions facing population decline. Eur Plan Stud 26(2):297–315

Dix-Carneiro R, Kovak BK (2019) Margins of labor market adjustment to trade. J Int Econ 117:125–142

Dorn D (2009) Essays on inequality, spatial interaction, and the demand for skills. Ph.D. thesis

Faber M, Sarto A, Tabellini M (2021) Local shocks and internal migration: the disparate effects of robots and Chinese imports in the US

Foote A, Grosz M, Stevens A (2019) Locate your nearest exit: mass layoffs and local labor market response. ILR Rev 72(1):101–126

Goldsmith-Pinkham P, Sorkin I, Swift H (2020) Bartik instruments: what, when, why, and how. Am Econ Rev 110(8):2586–2624

Graetz G, Michaels G (2018) Robots at work. Rev Econ Stat 100(5):753–768

Greenland A, Lopresti J, McHenry P (2019) Import competition and internal migration. Rev Econ Stat 101(1):44–59

Huttunen K, Møen J, Salvanes KG (2018) Job loss and regional mobility. J Law Econ 36(2):479–509

Jauer J, Liebig T, Martin JP, Puhani PA (2019) Migration as an adjustment mechanism in the crisis? A comparison of Europe and the United States 2006–2016. J Popul Econ 32:1–22

Johnson KM, Lichter DT (2019) Rural depopulation: growth and decline processes over the past century. Rural Sociol 84(1):3–27

Johnson KM, Field LM, Poston Jr DL (2015) More deaths than births: subnational natural decrease in Europe and the United States. Popul Dev Rev 41(4):651–680

Klump R, Jurkat A, Schneider F (2022) Tracking the rise of robots: a survey of the IFR database and its applications. J Econ Stat 242(5–6):669–689

Koch M, Manuylov I, Smolka M (2021) Robots and firms. Econ J 131(638):2553–2584

Konietzny R (2024) Workers responses to increasing import exposure and the implications of these for their well being

Liao S, Kim IS, Miyano S, Zhu F (2020) concordance: product concordance. https://CRAN.R-project.org/package=concordance. R package version 2.0.0

MacKinnon D, Kempton L, O'Brien P, Ormerod E, Pike A, Tomaney J (2022) Reframing urban and regional developmend for left behind places. Camb J Reg Econ Soc 15(1):39–56

Notowidigdo MJ (2020) The incidence of local labor demand shocks. J Law Econ 38(3):687–725

Peri G, Zaiour R (2023) Changes in international immigration and internal native mobility after COVID-19 in the USA. J Popul Econ 36(4):2389–2428

Pike A, Béal V, Cauchi-Duval N, Franklin R, Kinossian N, Lang T, Leibert T, MacKinnon D, Rousseau M, Royer J, Servillo L, Tomaney J, Velthuis S (2024) Left behind places: a geographical etymology. Reg Stud 58(6):1167–1179

Rickardsson J (2021) The urban-rural divide in radical right populist support: the role of residents characteristics, urbanization trends and public service supply. Ann Reg Sci 67(1):211–242

Rodríguez-Pose A, Terrero-Dávila J, Lee N (2023) Left-behind versus unequal places: interpersonal inequality, economic decline and the rise of populism in the USA and Europe. J Econ Geog 23(5):951–977

Tolbert CM, Sizer M (1996) US commuting zones and labor market areas: a 1990 update. Econ Res Service Staff Paper 9614

Veneri P, Ruiz V (2016) Urban-to-rural population growth linkages: evidence from OECD Tl3 regions. J Reg Sci 56(1):3–24

Wuthnow R (2018) The left behind: decline and rage in rural America. Princeton University Press

Zhang X, Palivos T, Liu X (2022) Aging and automation in economies with search frictions. J Popul Econ 35(2):621–642

Zweimüller J, Winter-Ebmer R, Lalive R, Kuhn A, Wuellrich J-P, Ruf O, Büchi S (2009) Austrian social security database. Working Paper No. 0903, NRN: The Austrian Center for Labor Economics and the Analysis of the Welfare State