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Robotization, Internal Migration and Rural Depopulation in Austria

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Abstract

Internal migration flows from rural to urban areas have greatly contributed to population declines in many rural areas across both Europe and the US. At the same time there is mounting evidence for a tight connection between internal migration and shifts in labor demand, with the latter being heavily affected by the rise of automation technologies. Therefore this paper analyzes the effects industrial robotization has had on manufacturing employment and internal migration in Austria during the period 2003-2016, specifically focusing on rural-to-urban migration flows. The results show that robotization has caused significant declines in manufacturing employment to which populations reacted by increased out-migration. This migratory response takes the form of rural-to-urban migration, thereby contributing to population declines in many rural areas in Austria. These rural-to-urban movements are primarily driven by young and medium/low skilled individuals, i.e. those groups that bear the strongest shock incidence.

JEL classification: J21, J23, J61, R23

Keywords: Employment, internal migration, robots, rural depopulation

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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 US. 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, Field, and Poston Jr., 2015). As a consequence rural depopulation contributes to increased geographic inequality and fosters political polarization, as "the left behind" (Wuthnow, 2018) show increasingly strong support for populist political movements. Correspondingly, the support of declining rural regions contributed strongly to the victory of Donald Trump in the 2016 US elections (Scala and Johnson, 2017, Wuthnow, 2018), Brexit (Lee, Morris, and Kemeny, 2018) and the electoral success of far-right populist parties in several European countries (see for example Franz, Fratzscher, and Kritikos, 2018, Rickardsson, 2021 or Kenny and Luca, 2021).

Despite the detrimental impact of rural depopulation on economic, social and political cohesion in Europe and the US, most of the research concerned with the causes of rural-to-urban migration is focused on low and middle income countries.[1] A notable exception to this is the recent work of Johnson and Lichter (2019) who document large and persistent rural-to-urban migration flows for the US. With regards to the causes of rural-to-urban migration they argue for a close connection to declines in manufacturing employment in rural areas. This mirrors a well established notion in the economic literature that internal migration flows play a crucial role in the reaction to regional labor

[1] See for example Zhao (1999), Brueckner and Lall (2015), Lagakos, Mobarak, and Waugh (2018), Peri and Sasahara (2019) or Lagakos (2020).

demand shocks.[2] Since labor demand in the manufacturing industries has experienced growing pressure in recent decades through the rise of automation technologies[3], there thus appears to be scope for a connection between rural depopulation and automation.

Therefore this paper analyses the effects industrial robotization has had on internal migration and, more specifically, rural-to-urban migration in Austria during the period 2003–2016. For this I use detailed data on municipality-to-municipality migration flows. Following Acemoglu and Restrepo (2020) and Dauth et al. (2021) changes in robotization are predicted as a shift-share variable, using regional industry structures and industry-level data on robot densification from the International Federation of Robotics (IFR). To isolate the causal effect of robotization on internal migration and rural depopulation, predicted robot exposure is instrumented with a shift-share-type instrumental variable, which is constructed from industry level robotization trends in other high income countries. As is shown in Borusyak, Hull, and Jaravel (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 work-

[2] Prominent examples of this literature are Blanchard and Katz (1992), Bound and Holzer (2000), Cadena and Kovak (2016), Huttunen, Møen, and Salvanes (2018), Foote, Grosz, and Stevens (2019), Greenland, Lopresti, and McHenry (2019) or Notowidigdo (2020). For employment shocks caused by industrial robots, Faber, Sarto, and Tabellini (2021) have recently shown that robotization caused declines in the working age-population of particularly affected US local labor markets.

[3] See for example Autor, Levy, and Murnane (2003), Goos and Manning (2007), Autor, Katz, and Kearney (2008), Autor and Dorn (2013), Goos, Manning, and Salomons (2014), or Acemoglu and Restrepo (2020) among many others.

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

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 are mitigated by out-migration 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 depopulation. To the best of my knowledge, this paper is the first to present causal evidence on a connection between shifts in labor demand and rural depopulation.

The rest of this paper is structured as follows: Section 2 presents a descriptive overview over population trends in rural Austria. Section 3 presents the used data sources, while Section 4 discusses the empirical approach and the identification strategy. Section 5 presents the main results of the analysis and explores the robustness of these results. Lastly, Section 6 offers a brief discussion and concludes.

2 Rural Depopulation in Austria

To illustrate the close connection between out-migration and general population trends in rural regions, Figure 1 compares the change in overall population counts (panel A) and the migration balance (panel B) of all Austrian municipalities between

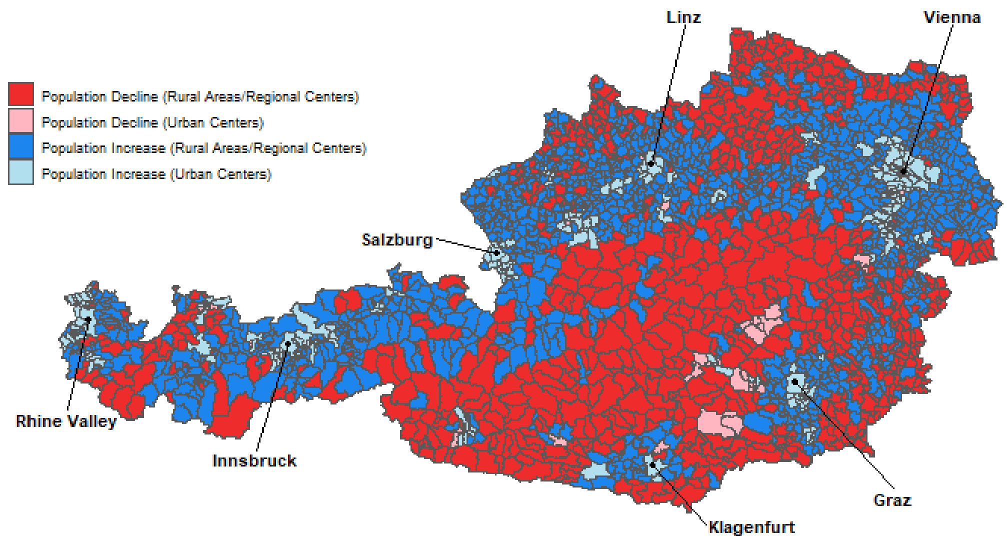
2001 and 2016.[4] While urban areas generally showed increases in population counts and net in-migration, a large fraction of rural municipalities experienced population losses through out-migration. These declining rural municipalities tend to be in more remote areas of Austria, as rural regions in closer proximity to urban centers also experienced population growth. While some rural regions thus appear to benefit from positive population spillovers from nearby urban centers (Veneri and Ruiz, 2016), around 46% of all rural municipalities show a negative migration balance for the period 2001 to 2016 (Table 1, panel A). By 2016 those declining rural municipalities on average lost about 6.4% of their 2001 population (panel B, column 4). These population losses in declining rural areas are largely driven by out-migration, which on average accounts for a population loss of around -3.53%. The remainder of the population loss is explained by the fact, that individuals who leave a municipality are typically younger, than those who stay behind, leading to older societies and declines in the birth balance. 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, Field, and Poston Jr., 2015).

Distinguishing between internal- and external-migration flows in panel B of Table 1 reveals that in the absence of migration from other countries (i.e. in the absence of external migration) the average net outflows in rural communities with declining populations would be much stronger with an average internal net outflow of around

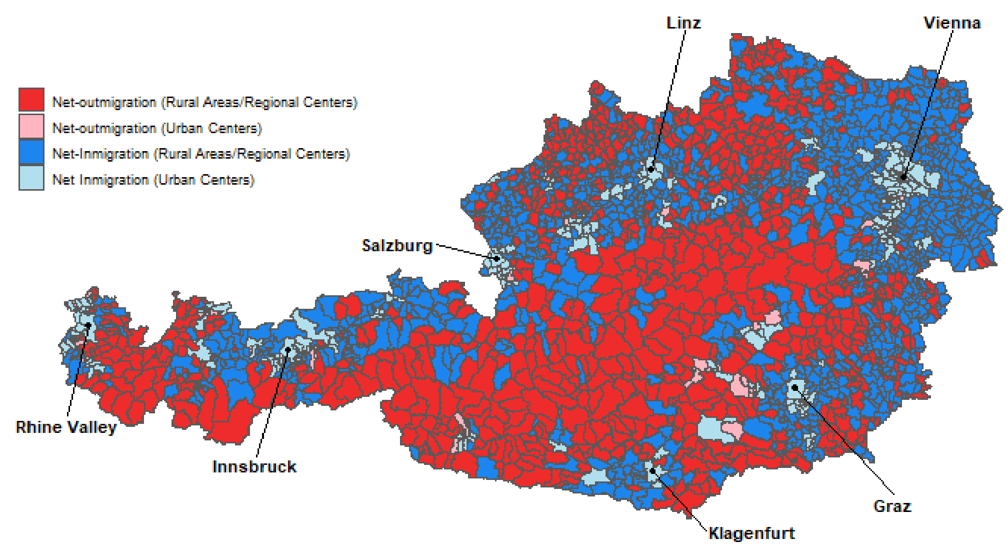
[4]Urban areas and rural areas are classified according to the urban-rural-classification from the Austrian statistical agency Statistics Austria. This classification consists of three broad categories of municipalities: urban centers, regional centers and rural areas, each consisting of several subcategories. It is graphically depicted in Figure A1 in the Appendix. For this paper, I consider municipalities classified as 'urban centers' (large, medium or small) as urban, while all remaining municipalities (including regional centers) are classified as rural. All results presented in this paper are robust to this choice.

Figure 1: Population trends (2001-2016) by municipality type

(a) Population Change (2001-2016)



(b) Net Migration (2001-2016)



Note: Municipalities are classified according to the urban-rural classification from the Austrian Statistical Agency (Statistics Austria - see Figure A1 in the Appendix). Large urban centers (according to the urban-rural classification) are indicated by name. All remaining urban centers (medium and small) are indicated by lighter colors. Rural areas and regional centers are depicted as a single category. Population data is from the decennial census (2001) and the registry based labor market statistics (2016). Data on net migration-flows is taken from the migration statistics. All data sources are available from Statistics Austria and are described in more detail in Section 3.

Table 1: Descriptives: (2001-2016)

	Urban	Rural		
		All	Growing	Declining
	(1)	(2)	(3)	(4)
Panel A: Fraction of municipaities				
with population declines:	14.29%	42.17%		
with negative migration balance:	16.45%	45.78%		
Panel B: Population change 2001-2016 (in % of 2001 population)				
Population Change:	+14.7%	+3.51%	+9.6%	–6.4%
Migration balance:	+13.01%	+3.42%	+7.7%	–3.53%
Internal:	+1.72%	–1.72%	+1.8%	–7.44%
External:	+11.29%	+5.14%	+5.9%	+3.91%
Birth balance:	+1.69%	+0.08%	+1.9%	–2.87%
Panel C: Internal migration balance by destination type:				
Total:	+1.72%	–1.72%	+1.8%	–7.44%
Urban destination:	+0%	–1.72%	+0.36%	–5.09%
Rural destination:	+1.72%	-0%	+1.44%	–2.35%
Panel D: Internal migration balance by age:				
Total:	+1.72%	–1.72%	+1.8%	–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 E: Share of individuals aged 65 and older:				
2001	15.78%	15.14%	14.14%	16.76%
2011	17.68%	17.84%	16.72%	19.87%
2016	17.98%	19.17%	17.99%	21.41%
Increase:	+2.21%	+4.03%	+3.85%	+4.65%
Panel F: Share of manufacturing industries in total employment:				
2001	14.47%	26.29%	25.8%	27.1%
2011	9.16%	23.42%	22.72%	24.68%
2016	10.97%	22.91%	22.44%	23.8%
Decrease:	–3.5%	–3.38%	–3.36%	–3.3%

Note: Municipalities are classified according to the urban-rural classification from the Austrian Statistical Agency (Statistics Austria - see Figure A1 in the Appendix). Population data is from the decennial census (2001), the register-based census (2011), and the register based labor market statistics (2016). Migration flow data is from the 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 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.

−7.44% (panel B, column 4), which is partly compensated by the inflow of migrants from other countries.

Decomposing the internal migration balance by destination type in panel C of Table 1 shows that the majority of net outflows from declining rural municipalities are directed towards urban areas (column 4). While there are also relevant net outflows to other rural areas, the outflows towards urban areas account for more than two thirds of the total net outflows from these municipalities. This trend is almost exclusively driven by out-migration of individuals under the age of 35 (panel D, column 4), which leads to faster aging of those declining rural areas. Here the average share of individuals aged 65 or older has increased much stronger in rural areas which experienced population declines than in other regions (panel E).

Lastly, panel F of Table 1 compares the employment structure in urban and rural areas. Here rural areas are on average more reliant on employment in the manufacturing industries, as these industries account for a larger fraction of total employment (26.29% in 2001) as opposed to urban areas (14.47%). 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.

3 Data:

Robotization:

Data on robotization comes from the International Federation of Robotics (IFR). The IFR offers a rich industry level data-set on robot stocks and deliveries for many high income countries. This data, which has become the most widely used data source when studying robotization, 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.[5] 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 classification) are available on the 2-digit or 3-digit industry level, while several other industries are available at the 1-digit level (see Table A11 in the Online Appendix).[6]

Figure A2 in the Appendix 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 has 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.

Migration-flows:

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, as well as changes of residence with other countries. 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

[5]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, Jurkat, and Schneider (2021).

[6]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 US 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.

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.[7]

Employment:

To measure the structure of regional employment as well as changes in manufacturing employment, I use data from the Austrian Social Security Database (ASSD, see 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, the ASSD contains information on the geographic location of firms, as well as the industry a firm belongs to. This allows for a detailed measurement of employment by industries on the municipality level.

Demographic structure of the workforce:

To control for the demographic structure of the local working age population, I use population data from the decennial Austrian census (2001 and 2011) and the register based labor market statistics (available annually from 2012 onward) from Statistics

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

Austria. As the labor market statistic is collected from the same administrative register as the register based census from 2011, these data sources are directly comparable. Since population data on the level of the Austrian municipalities is not available for years that lie between the census years 2001 and 2011, population counts for these years have been linearly interpolated.

4 Research Design:

Measuring regional 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 predict regional robot exposure from the industry level robotization data. For this I compute changes in robot density for any regional unit r 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.[8] Therefore the local industry structure is interacted with the industry specific shocks, to predict local robot exposure based on the structure of local employment:

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

In equation 1 the industry specific change in robotization $\Delta Robots_{i,t}$ in industry i over period t (normalized by overall employment in this industry) is interacted with

[8] Shift-share research designs are heavily used in the economic literature. Following the influential work of Bartik (1991) and Autor and Duggan (2003) they have been applied to a wide variety of questions. Some prominent applications relate to the effects of trade-shocks (e.g. Autor, Dorn, and Hanson, 2013 or Dauth, Findeisen, and Suedekum, 2014), offshoring (Hummels et al., 2014), routine biased technological change (Autor and Dorn, 2013) or credit market shocks (Greenstone, Mas, and Nguyen, 2020). A related literature, following the work of Card (2001), uses shift-share type variables to predict immigrant inflows.

the share of industry i in region r's overall employment (measured at the beginning of period t). This projects the industry level robotization change in industry i onto the regional level, while considering the relative importance of industry i for region r's overall employment. Local exposure to robotization then computes 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 equation 1 requires (i) data on the industry specific robotization shock and (ii) detailed regional data on the exposure shares. While the industry level robotization data is available from the IFR, local 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 on manufacturing employment and internal migration flows, I estimate equations of the form:

$$\Delta Y_{r,t} = \gamma \Delta Robots_{r,t} + X_{r,t}\beta + \rho_r + \tau_t + \epsilon_{r,t} \tag{2}$$

whereby $\Delta Y_{r,t}$ denotes the outcome of interest (log-changes in manufacturing employment or net out-migration-rates), $\Delta Robots_{r,t}$ is predicted robot exposure from equation 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 regional fixed effects ρ_r. All estimations are weighted by the start-of-period working age population.

Control Variables:

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 population. For this I include the detailed age-sex-education-nationality distribution of the local population (measured in the initial year of each panel period to avoid endogenous contamination).[9] The inclusion of the composition of the local population is motivated by concerns, that regions with different demographic structure 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) that the structure of the workforce (particularly the age composition) has a direct impact on robotization trends.[10] 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.

In the second step, controls that aim at capturing regional heterogeneity are included. These controls include the start-of-period logarithm of the gross regional product and the 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

[9] The composition of the local population is included in 68 age-sex-education-nationality cells, where each cell indicates the size of the respective group in the overall population in 1000 individuals. The 68 demographic cells are defined by 5 age groups (ages 0-14, 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).

[10] Acemoglu and Restrepo (2022) document the fact that jobs that are automatable by industrial robots are predominantly performed by middle aged workers, since these are the workers which mainly perform routine manual tasks. As aging reduces labor supply from middle aged workers (and thereby increases their wage rate) the relative price of robots vis-a-vis those workers drops. This makes robotization more profitable and thus leads to stronger robot adoption in sectors which rely more heavily on middle aged workers.

China and the former Eastern Block,[11] as well as ICT-capital intensity. As is laid out in detail by Adao, Kolesár, and Morales (2019) other types of labor demand shocks, that can be expressed as shift-share type variables have a mechanical correlation with $\Delta Robots_{r,t}$, since they are 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.[12]

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 equation 1 to predict regional robot exposure, migration based labor supply shocks are also mechanically correlated with predicted robot exposure (see Adao, Kolesár, and Morales, 2019). Therefore I include changes in the migrant population, differentiated by 4 educational groups. Labor supply related controls are however only included in employment regressions, because migration flows of non-Austrian citizens are themselves a component of population changes and migration

[11]This follows the approach of Dauth, Findeisen, and Suedekum (2014) who showed for Germany that trade with countries of the former Eastern Block is more relevant for the German case. Therefore the shift-share variables for import- and export-exposure are computed as changes in import- and export-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.

[12]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 `comtradr`-package in R. The EU-Klems data comes from the September 2017 release.

flows (i.e. the dependent variables in all regressions except employment regressions).

Lastly I control for the regional start-of-period industry structure, to check for the possibility that regions with different industry structure 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.[13]

Fixed Effects:

To control for unobserved shocks that influenced all regions equally, all estimations include a set of period fixed effects. As the observational period ranges from 2003 to 2016, these period fixed effects are of particular importance, as they aim to control for confounding effects of the Great Recession. Therefore the two panel periods are defined such that they correspond to a pre-crisis period (2003-2009) and a post-crisis/recovery period (2009-2016).[14] However, as is emphasized in Borusyak, Hull, and Jaravel (2022), these period fixed effects require some adjustments. Robot adoption is strongly concentrated within the manufacturing sectors. Therefore most industries outside of manufacturing experienced zero robotization. In equation 1 this means, that the regional sum of all exposure shares of sectors with non-zero robot adoption is gen-

[13]For the detailed industry composition controls I follow Dauth et al. (2021) and 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, business services and the public sector).

[14]As can be seen in Figure A2 in the Appendix robotization in Austria was rather unaffected by the Great Recession, as the increase in robotization continued rather smoothly. This somewhat mitigates concerns about a confounding influence of the Great Recession. However the period fixed effects are included to more thoroughly control for this.

erally smaller than 1, such that $\sum_i \frac{Emp_{i,r}}{Emp_r} < 1$. As is explained in detail in Borusyak, Hull, and Jaravel (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 equation 2 refer to the interaction of conventional period dummies with the regional sum of the incomplete exposure shares. In OLS estimations the incomplete shares used for the computation of predicted robot exposure in equation 1 are used, while in 2SLS regressions the lagged exposure shares used for the computation of the instrument (from equation 3 – see section 4.1) are used.

Additionally all estimations contain a set of region fixed effects ρ_r to control for unobserved regional heterogeneity.

Commuting Zones:

To control for the possibility of spatial spillovers of local robotization shocks, I use so-called commuting zones (instead of the municipalities themselves) as unit of observation. Clearly a local shock to a plant in municipality k, does not only influence employment (and outcomes related to employment) 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. Also a number of studies have shown, that local shocks influence employment in other plants in the same local labor market via agglomeration effects (see for example Gathmann, Helm, and Schönberg 2018 or Helm 2019). To control for these spillover effects more aggregated local labor markets are often used in the literature to examine the consequences of local shocks.

The underlying idea is, that aggregated regional units more closely correspond to local labor markets, and therefore spillovers caused by commuting patterns are less of an issue than when using the municipalities themselves. While some studies use existing geographical units, which are usually defined as administrative areas, districts or states, to approximate local labor markets, I use commuting zones as they are a data driven way to define local labor markets based on the strength of their commuting ties. Using commuting zones appears to be less arbitrary than using predefined administrative areas, and has a straightforward appeal as they are specifically designed to contain a larger fraction of commuters within their borders. The construction of these commuting zones strictly follows the methodology used for US commuting zones described in Tolbert and Sizer (1996) and Dorn (2009) (for details see Online Appendix C).[15]

Standard Errors:

Throughout the analysis I report two types of standard errors, namely conventional heteroskedasticity robust standard errors, as well as the exposure robust standard errors from Adao, Kolesár, and Morales (2019) (henceforth referred to as AKM-standard errors). As is outlined in detail in Adao, Kolesár, and Morales (2019) conventional standard errors might be unreliable in shift-share settings, as the regression residuals are likely to be correlated across (potentially distant) regions with similar exposure shares. To account for this possibility I report both sets of standard errors.[16]

[15] The US commuting zones estimated by Tolbert and Sizer (1996) are widely used in studies on labor market shocks in the US. See for example Autor, Dorn, and Hanson (2013, 2015, 2021), Autor and Dorn (2013), Acemoglu et al. (2016), or Acemoglu and Restrepo (2020) among others.

[16] Adao, Kolesár, and Morales (2019) show in their paper that the AKM-standard errors might be downward biased and thus overreject if the number of industries used to construct the shift-share variable is too small. Since the IFR-data only includes 26 different industries, which can be used for the computation of $\Delta Robots_{it}$, this is a potential concern in this setting. To address this concern, I

4.1 Identification Strategy:

One major reason for endogeneity concerns in equation 2 is that the adoption of robots might be correlated with unobserved regional 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 equation 2 would no longer isolate the effect of industrial robotization but would additionally reflect effects arising from the unobserved demand shock.

Another source for endogeneity concerns relates to the construction of the predicted robotization measure in equation 1. Here the industry level change in robotization is assigned to any region 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 incentivise high performing firms to settle in a certain region. If high performing firms are also more likely to adopt industrial robots (as recent findings in Bonfiglioli et al., 2020 and Koch, Manuylov, and Smolka, 2021 suggest) the predicted robotization measure in equation 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.

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apply a modification to the computation of these standard errors that results in more conservative estimates. The details and performance of this modification are discussed in Online Appendix D.

(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 is driven by advances in the technological frontier. Similarly to predicted robot exposure in equation 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 equation 3 from the predicted robot exposure measure in equation 1 the exposure shares used to construct the instrument are lagged by 15-years.

As has been shown in recent work by Adao, Kolesár, and Morales (2019) and Borusyak, Hull, and Jaravel (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, Hull, and Jaravel (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.[17] To construct these robotization shocks occuring in other high income countries I use industry level robotization changes in Canada, Denmark, Finland, France, Italy, Mexico, Norway, Spain, Sweden, the United Kingdom and the United States.[18]

While the exogeneity of the robotization shocks, which essentially mirrors a standard exclusion restriction, cannot be tested directly, Borusyak, Hull, and Jaravel (2022) propose several plausibility tests. These tests aim to asses 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. The following two subsections present these balance tests on the industry and on the regional level.

Industry Level Balance Tests

To asses the quasi-random assignment of the industry level shocks used to construct the instrument, Table 2 presents industry level balance tests. These tests are conducted by estimating the following industry level regression:

$$Y_{i,t}^{Austria} = \beta \Delta Robots_{i,t}^{OtherCountries} + \tau_t + \epsilon_{i,t} \tag{4}$$

[17] In a related paper Goldsmith-Pinkham, Paul, and Swift (2020) argue that the exogeneity of the exposure shares is also a sufficient condition for the validity of the instrumental variable. Borusyak, Hull, and Jaravel (2022) however show, that the orthogonality of the shocks is both sufficient and necessary and that in the Goldsmith-Pinkham, Paul, and Swift (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.

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

where start-of-period values of some observed industry level characteristic in Austria $Y_{i,t}^{Austria}$ are regressed on the industry level robotization changes in other countries $\Delta Robots_{i,t}^{OtherCountries}$ which are also used in equation 3 to construct the regional level instrumental variable. To isolate within-period variation of the robotization shocks, the estimations control for period fixed effects. The regression in equation 4 is estimated separately for each of the start-of-period characteristics of industries in Austria $Y_{i,t}^{Austria}$. These balance variables aim to test for the balance of the shocks with respect to the industry level composition of the workforce, as well as other industry characteristics related to productivity, capital intensity and the average wage rate. Data on industry level workforce characteristics has been calculated from the ASSD, while all remaining indicators have been calculated from EU-Klems data.[19]

The results of the industry level balance tests in Table 2 show that industry level changes in robot adoption in the countries used to construct the instrument are significantly correlated with the age composition of the workforce in Austria, while the estimates for all other balance variables are insignificant. The measure for the age composition used in this estimation is computed analogously to Acemoglu and Restrepo (2022) who use the ratio of old to middle aged workers to show that aging of the workforce (which would be equivalent to an increase in this ratio) leads to increases in robot adoption. The significant and negative estimate of -0.854 for this balance test indicates that greater robot adoption in the other high income countries predict a stronger reliance on middle aged workers in Austrian industries.[20]

[19] Because the ASSD does not contain any information on the skill level of workers, no industry level balance variables related to the skill composition of the workforce are available. Similarly EU-Klems only includes such information up to 2005. Therefore balance tests related to the skill composition cannot be performed at the industry level and are postponed to regional level tests.

[20] This correlation likely stems from (i) the age structure having an influence on robotization changes (as shown by Acemoglu and Restrepo, 2022) and (ii) industry level age structures being correlated

Table 2: Industry level balance tests for instrumental variable:

Balance variable	Coef. (1)	SE (2)
Start-of-period ratio of old workers to middle aged workers	-0.854	(0.422)**
Start-of-period share of blue collar workers	1.467	(1.659)
Start-of-period labor productivity:	0.108	(0.204)
Start-of-period capital/labor ratio:	-0.515	(1.034)
Start-of-period ICT-capital/capital stock	-0.032	(0.055)
Start-of-period log(avg. hourly real wage)	0.018	(0.019)
Industries:	26	
Time Periods:	2	
Industry-Period Shocks:	52	

Notes: * < 0.10, ** < 0.05, *** < 0.01. This Table shows industry level regressions of the respective balance variables on the industry level robotization shocks $\Delta Robots_{i,t}^{OtherCountries}$ used in equation 3 to construct the instrumental variable. The industry level robotization shocks are summed up over all countries and are then normalized to have zero-mean and unit variance. The ratio of old workers to middle aged workers is constructed by dividing industry level employment of workers aged 50 or older, by employment of workers age 35 to 49. Industry level data on employment by age and worker type (blue collar) is taken from the ASSD data, while all remaining industry level balance variables are taken from the EU-KLEMS September 2017 Release (July 2018 Update). All regressions control for period fixed effects and are weighted by industry size. Heteroskedasticity robust standard errors are reported in brackets.

In sum these industry level balance tests in Table 2 show that the shocks used to compute the instrument are reasonably balanced, with the exception of the age composition of the workforce. This suggests that it is crucial to control for workforce characteristics in the regional level estimations, as the exogeneity of the robotization shocks (and thus the exogeneity of the entire instrument) is likely only fulfilled when conditioning on demographic characteristics of the workforce.

Regional Level Balance Tests

Table 3 presents estimation results for regional level balance tests. For this I follow the recommendations in Borusyak, Hull, and Jaravel (2022) and Goldsmith-Pinkham,

across countries. Table A5 in the Appendix shows that this is indeed the case, as the industry level age structure of the workforce in Austria is significantly correlated with the age structures in countries used to construct the instrument.

Paul, and Swift (2020) and regress several observed regional covariates $Y_{r,t}^{Austria}$ directly on the instrument $\Delta Robots_{r,t}^{IV}$:

$$Y_{r,t}^{Austria} = \beta \Delta Robots_{r,t}^{IV} + \tau_t + \epsilon_{i,t} \tag{5}$$

While the industry level balance tests address the exogeneity of the robotization shocks themselves, these regional tests aim to assess the plausibility of the exogeneity of the actual instrumental variable with respect to several regional balance variables. These regional balance variables $Y_{r,t}^{Austria}$ are measured at the beginning of each panel period and are thus pre-determined with respect to the robotization shocks occurring during the following panel period. Because the population data from the Austrian census includes more detailed information on certain characteristics of the working age population than is available at the industry level, these regional level balance tests allow to include more detailed balance variables relating to the composition of the working age population. Therefore these regional balance tests can also examine balance of the instrument with respect to the skill-distribution of the working age population, as well as the migrant share. Additionally the same measure for the age-structure is included on the regional level, as was previously tested on the industry level (i.e. the ratio of old to middle aged workers from Acemoglu and Restrepo, 2022).

Following the recommendation in Borusyak, Hull, and Jaravel (2022) the estimates in column 1 control only for period fixed effects to asses the within period variation of the instrument. Here the different standard error definitions lead to different conclusions. While the shift-share robust AKM-standard errors suggest that the instrument is balanced (i.e. not significantly related to any of the pre-determined balance variables), the White-heteroskedasticity robust standard errors suggest that the instrument is unbalanced with respect to several of the balance variables. In particular the estimates

Table 3: Regional balance tests for instrumental variable:

Balance variable	Only period FE: Coef. (1)	SE (2)	Additional controls: Coef. (3)	SE (4)
Start-of-period share of manufacturing employment	0.0153	(0.0046)*** [0.0339]		
Start-of-period ratio of old workers to middle aged workers	-0.0334	(0.0253) [0.2668]	0.0052	(0.0022)** [0.0225]
Start-of-period % of high education population:	0.0018	(0.005) [0.0506]	0.0011	(0.001) [0.0069]
Start-of-period % of medium education population:	-0.0002	(0.0052) [0.0565]	0.0002	(0.0006) [0.0035]
Start-of-period % of low education population:	-0.0345	(0.0126)*** [0.1426]	-0.0013	(0.0016) [0.0104]
Start-of-period % of foreign born population	0.0008	(0.0047) [0.0777]	0.0012	(0.0011) [0.0108]
Start-of-period log(gross regional product)	-0.0211	(0.3073) [4.0293]	-0.0023	(0.0053) [0.0154]
Start-of-period log(unemployment rate)	0.1531	(0.0503)*** [0.3806]	0.0225	(0.0154) [0.0555]
Period Fixed Effects	x		x	
Region Fixed Effects			x	
Share of Manufacturing Employment			x	

Notes: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets, and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). Period fixed effects are interacted with the sum of exposure shares used to construct the instrument. All regressions are weighted by start-of-period working age population.

suggest that the instrument predicts a higher initial period manufacturing share and a lower share of low-skilled workers.

Since it is to be expected that the instrument is correlated with a higher share of manufacturing employment (as robotization is heavily concentrated within manufacturing), column 3 presents balance tests, where regional fixed effects and the share of manufacturing in total employment are included as additional controls. These estimations in column 3 suggest that the instrument is unbalanced with respect to the age-structure of the workforce (as in the industry level balance tests in Table 2). This unbalance however is only indicated by the White-robust standard errors, while the

AKM-standard errors again suggest that the instrument is well balanced. Apart from this possible imbalance with respect to the age-structure there is no significant relation between the instrument and any other balance variable beyond what is explained by the industry structure and regional fixed effects. Hence, while the shift-share robust AKM-standard errors suggest that the instrument is balanced, conventional robust standard errors suggest that the assumption of quasi-random assignment of the robotization shocks holds only conditional on the age-composition of the workforce and the industry structure.

5 Results:

Manufacturing Employment:

Table 4 shows the estimation results for the log-change in manufacturing employment. Since the balance tests in Section 4.1 indicate that the exogeneity of the instrument likely only holds conditional on the age-distribution of the workforce, all estimations include the detailed set of demographic controls as well as regional and period fixed effects.

Overall the estimations in Table 4 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 4 results in precisely estimated negative coefficients of -3.921 in the OLS regression and -5.984 in the 2SLS regression (column 1 of Table 4). Contrasting those two estimates suggest 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) incentivise robotizing firms to settle in certain regions, (ii) increases those firms productivity via

Table 4: Robotization and Manufacturing Employment (2003-2016)

	Dependent Variable: Δ log(Manufacturing Employment) $\times 100$					
	(1)	(2)	(3)	(4)	(5)	(6)
OLS:						
Δ Robots	-3.921	-3.711	-4.932	-4.137	-2.743	-0.885
	(1.106)***	(1.177)***	(1.226)***	(1.297)***	(1.254)**	(1.333)
	[0.337]***	[0.45]***	[0.452]***	[0.476]***	[0.413]***	[0.438]**
2SLS:						
Δ Robots	-5.984	-6.254	-6.458	-4.006	-3.599	-4.343
	(2.079)***	(2.266)***	(2.282)***	(2.311)*	(1.858)*	(1.683)**
	[0.713]***	[0.626]***	[0.604]***	[0.495]***	[0.394]***	[0.299]***
First Stage Results:	0.011	0.011	0.011	0.011	0.011	0.011
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
	[0.0004]***	[0.0003]***	[0.0004]***	[0.0004]***	[0.0004]***	[0.0003]***
First Stage F-Statistic:	43.59	41.71	39.83	33.68	33.24	32.78
Period Fixed Effects	x	x	x	x	x	x
Region Fixed Effects	x	x	x	x	x	x
Demographic Controls	x	x	x	x	x	x
Regional Characteristics		x	x	x	x	x
Labor Supply Shifts			x	x	x	x
Labor Demand Shifts				x	x	x
Manufacturing Share					x	
Detailed Industry Structure						x
Commuting Zones	158	158	158	158	158	158
Periods	2	2	2	2	2	2
Observations	316	316	316	316	316	316

Notes: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). All specifications include a set of region 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 (demographic controls relating to the age-group 0-14 are not included in employment regressions). Regional characteristics control for the start-of-period logarithm of the gross regional product 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) and the public sector. All regressions are weighted by start-of-period working age population.

agglomeration effects and thereby (iii) have a positive impact on employment. In both cases the OLS estimate would absorb the positive impact 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 suggest that the instrumentation strategy is able to address these endogeneity concerns.

Including further control variables in columns 2 to 6 of Table 4 has only a moderate impact on the size of the 2SLS estimate, which stays relatively stable over all following specifications. Still the inclusion of controls for other types of labor demand shocks (trade and ICT exposure) in column 4 somewhat reduces the size of the estimated effect. In the full specification including all available control variables in column 6 of Table 4 the 2SLS estimation suggests a negative effect of -4.34 suggesting that one more additional robot per thousand workers reduces manufacturing employment by about 4.3 percent. Between 2003 and 2016 robot density in Austria increased by around 1.49 additional robots per 1000 workers (see Appendix Figure A2). Hence the estimated effect implies that robotization has decreased manufacturing employment in Austria by about 6.47% during this timeframe. To get a sense of the magnitude of this effect Panel A of Figure A3 in the Appendix presents the counterfactual evolution of the manufacturing share when holding robotization constant. During 2003 to 2016 the manufacturing share in Austria declined from around 20.96% to 18.14%. Holding robotization constant at its 2003 level shows that in the absence of robotization the manufacturing share in 2016 would only have declined to 19.09% (i.e. by about 0.95 percentage points less). Robotization thus explains around one third of the decline in the manufacturing share.

This effect on manufacturing employment however need not be associated with reductions in overall employment. The literature on labor market effects of automation technologies suggests the possibility of positive employment spillovers of automation technologies to non-manufacturing industries which would mitigate or even offset employment losses in manufacturing. As is outlined in the theoretical model of Autor and Dorn (2013), automation technology driven productivity gains in manufacturing under certain conditions have the potential to raise aggregate demand (and thereby also employment) in the service sector. For the specific case of industrial robotization Dauth et al. (2021) have documented such spillover effects for Germany. While they do find negative employment effects of robotization in the manufacturing industries, these effects are fully offset by employment growth in the non-manufacturing industries. This possibility of spillover effects to non-manufacturing employment is investigated in Panel A of Table A1 in the Appendix. Here the estimation for non-manufacturing employment results in a small and insignificant estimate of -0.031 (column 2 of Table A1), suggesting that no employment spillovers to non-manufacturing took place. Similarly, distinguishing between blue-collar and white-collar occupations in columns 3 and 4 shows that the negative employment effect is exclusively concentrated on blue-collar employment.

To further investigate the mechanisms of employment adjustment to the robotization shock, panel B of Table A1 repeats the employment regressions from panel A using the percentage change in employment (instead of the log-change) as dependent variable. Panels C and D then decompose this effect on the percentage change into the respective contributions of separations and new hirings.[21] These estimates in column 1 of Table A1 show that the negative employment effect in the manufacturing industries is exclusively driven by a reduction in new contracts (panel D) while separations are significantly reduced (panel C). Robotization thus even increased job stability for

[21]This decomposition uses the fact, that the percentage change in employment can be written as $\frac{Emp_{t=2}-Emp_{t=1}}{Emp_{t=1}} = \frac{Hirings-Separations}{Emp_{t=1}}$. Unfortunately the ASSD data does not allow to further distinguish between voluntary separations and involuntary job loss.

incumbent manufacturing workers. The reduction in new hirings however strongly dominates the reduction in separations, leading to the overall negative effect on employment in the manufacturing sector. This result suggests that the burden of the robotization shock primarily falls on individuals seeking to enter new employment, rather than displacing incumbent workers. This result is very similar to results for the German case in Dauth et al. (2021) who also find that the majority of the disemployment effect in manufacturing falls on non-incumbent workers.

Table A2 in the Appendix presents estimation results for the effect on manufacturing employment decomposed by age-groups. Here the results show, that the majority of the shock incidence (41% of the effect on manufacturing employment and 46% of the effect on blue-collar employment) falls on younger workers bellow 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 (see for example Bound and Holzer, 2000).

Internal Migration & Rural Depopulation:

To examine whether these disruptions in labor demand caused by industrial robots have led to increased out-migration, Table 5 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:

$$\frac{\sum_{j=1}^{J} \mathit{Net\ Outflow}_j}{\mathit{Population}_{j=1}} = \frac{\sum_{j=1}^{J} (\mathit{Outflow}_j - \mathit{Inflow}_j)}{\mathit{Population}_{j=1}} \tag{6}$$

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.

Table 5: Robotization and Internal Migration (2003-2016)

	Dependent Variable: Net-outmigration-rate ×100				
	(1)	(2)	(4)	(5)	(6)
OLS:					
Δ Robots	0.22	0.203	0.261	0.229	0.155
	(0.116)*	(0.13)	(0.15)*	(0.15)	(0.165)
	[0.049]***	[0.046]***	[0.042]***	[0.042]***	[0.043]***
2SLS:					
Δ Robots	0.833	1.173	1.078	1.105	1.055
	(0.353)**	(0.459)**	(0.356)***	(0.362)***	(0.323)***
	[0.064]***	[0.073]***	[0.066]***	[0.067]***	[0.071]***
First Stage Results:	0.011	0.011	0.011	0.011	0.011
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
	[0.0003]***	[0.0003]***	[0.0003]***	[0.0003]***	[0.0002]***
First Stage F-Statistic:	37.09	34.58	27.94	27.58	29.77
Period Fixed Effects	x	x	x	x	x
Region Fixed Effects	x	x	x	x	x
Demographic Controls	x	x	x	x	x
Regional Characteristics		x	x	x	x
Labor Demand Shifts			x	x	x
Manufacturing Share				x	
Detailed Industry Structure					x
Commuting Zones	158	158	158	158	158
Periods	2	2	2	2	2
Observations	316	316	316	316	316

Notes: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). All specifications include a set of region 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 population in 68 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product and the unemployment rate, as well as the start-of-period degree of urbanization. Labor Demand Shifts include changes in import- and export-exposure and ICT-intensity. 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) and the public sector. All regressions are weighted by start-of-period working age population.

The estimation results for the migratory response in Table 5 show that robotization has lead to an increase in net out-migration rates during 2003-2016. Here the full specification in column 5 suggests, that one more industrial robot per 1000 workers leads to net out-migration flows of around 1.1% of the start-of-period working age population. This effect is robust over all specifications and statistically highly 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 consistent with recent findings in Borusyak, Dix-Carneiro, and Kovak (2022) who show that the OLS-estimates from migration regressions are (at times severely) biased towards zero when shocks between origin and destination regions are correlated. The sizable difference between the OLS and 2SLS estimates suggests that the instrumentation strategy is able to successfully address this issue, as the 2SLS estimation results in a rather large estimated effect.[22]

While the results in Table 5 confirm that robotization shocks lead to out-migration in a similar fashion as is firmly established for other types of labor demand shocks, these results remain silent about the direction of these internal 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 5 contains detailed information on the municipality of origin, as well as the destination. As any commuting zone may consist of both urban and rural areas (see Online Appendix C), the net outflow from

[22]Even if the instrumentation strategy would not be able to fully address this problem, the estimated effect in column 6 of Table 5 would be a lower bound of the true migration response, as Borusyak, Dix-Carneiro, and Kovak (2022) show that a correlation between shocks in origin and destination regions would always result in an attenuation of the estimate towards zero.

any commuting zone can be decomposed into the respective contributions of rural and urban areas:

$$\frac{\sum_{j=1}^{J} Net\ Outflow_j}{Population_{j=1}} = \frac{\sum_{j=1}^{J} Net\ Outflow_j^{Rural}}{Population_{j=1}} + \frac{\sum_{j=1}^{J} Net\ Outflow_j^{Urban}}{Population_{j=1}} \tag{7}$$

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

$$\frac{\sum_{j=1}^{J} Net\ Outflow_j^{Rural}}{Population_{j=1}} = \left.\begin{aligned} &\frac{\sum_{j=1}^{J} Net\ Outflow_j^{Rural \to Urban}}{Population_{j=1}} + \\ &\frac{\sum_{j=1}^{J} Net\ Outflow_j^{Rural \to Rural}}{Population_{j=1}} + \end{aligned}\right\} \text{Internal} \\ \left.\frac{\sum_{j=1}^{J} Net\ Outflow_j^{Rural \to Abroad}}{Population_{j=1}}\right\} \text{External} \tag{8}$$

Hence the net out-migration rate from all rural municipalities in any commuting zone is decomposed into flows directed towards urban or rural areas (internal migration) and flows with other countries (external migration).[23]

Table 6 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 (0.953) is on a very similar magnitude as when net outflows from both rural and urban

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

Table 6: Robotization and net out-migration in Rural Areas (2003-2016)

	Total	External	Internal		
			All	Rural to Urban	Rural to Rural
	(1)	(2)	(3)	(4)	(5)
OLS:					
Δ Robots	0.141	-0.001	0.142	0.057	0.085
	(0.164)	(0.024)	(0.181)	(0.09)	(0.103)
	[0.037]***	[0.005]	[0.041]***	[0.02]***	[0.025]***
2SLS:					
Δ Robots	0.953	-0.067	1.02	0.565	0.455
	(0.307)***	(0.048)	(0.342)***	(0.162)***	(0.202)**
	[0.061]***	[0.009]***	[0.069]***	[0.031]***	[0.042]***
First-Stage F:	29.77	29.77	29.77	29.77	29.77
Period Fixed Effects	x	x	x	x	x
Region Fixed Effects	x	x	x	x	x
Demographic Controls	x	x	x	x	x
Regional Characteristics	x	x	x	x	x
Labor Demand Shifts	x	x	x	x	x
Detailed 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: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets, and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). All specifications include a set of region 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 population in 68 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product and the unemployment rate, as well as the start-of-period degree of urbanization. Labor Demand Shifts include changes in import- and export-exposure and ICT-intensity. 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) and the public sector. All regressions are weighted by start-of-period working age population.

areas are considered (1.055 - Table 5, 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. Decomposing these internal migration flows into rural-to-urban and rural-to-rural flows in columns 4 and 5 of Table 6 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%, approximately 0.57% of this increase are accounted for by outflows that are directed towards urban areas. This effect for rural-to-urban net migration rates is precisely estimated and significant at the 1%-level in both standard error definitions. This coefficient in column 4 of Table 6 provides direct evidence that robotization contributes to population declines in rural areas by specifically increasing rural-to-urban internal migration flows.

Column 5 of Table 6 also provides evidence that robotization has an increasing effect on rural-ro-rural migration flows. Here the estimation suggests a positive effect of 0.455. This effect of robotization on rural-to-rural migration flows is somewhat smaller than the effect on rural-to-urban migration flows, highlighting that the increase in net out-migration rates from rural areas strongly operates through rural-to-urban migration.[24]

Since the dependent variables used in the estimations shown in Table 6 are computed by subtracting in-migration-flows from out-migration-flows (to arrive at the desired net out-migration measure in equation 6) it is interesting whether the increase in rural-to-urban net out-migration stems from an increase in out-migration flows, or rather a decrease in in-migration-flows. To answer this question Table 7 presents separate estimations on those two components of net out-migration rates. Comparing columns 2 and 3 of Table 7 shows that the increase in net out-migration rates is exclusively driven by an increase in out-migration (column 2), while the estimate for the effect of robotization on in-migration is small and statistically insignificant in both standard error definitions.

[24] The classification into rural and urban areas used in Table 6 is performed according to the urban-rural-classification from Statistik Austria (see Appendix Figure A1). This classification distinguishes between three broad categories (urban centers, regional centers and rural areas), each being comprised of several subcategories. In Table 6 the intermediate category 'regional centers' is classified as rural area. To check whether this choice affects the results, Table A4 in the Appendix presents estimates, where 'regional centers' are included in urban areas. The estimates in Table A4 show, that the results are unaffected by this choice.

Table 7: In-migration and out-migration in Rural Areas (2003-2016):

	Net Out-Migration	Out-migration	In-migration
	(1)	(2)	(3)
OLS:			
Δ Robots	0.057	0.03	-0.027
	(0.09)	(0.099)	(0.062)
	[0.02]***	[0.021]	[0.015]*
2SLS:			
Δ Robots	0.565	0.586	0.021
	(0.162)***	(0.169)***	(0.109)
	[0.031]***	[0.034]***	[0.021]
First-Stage F:	29.77	29.77	29.77
Period Fixed Effects	x	x	x
Region Fixed Effects	x	x	x
Demographic Controls	x	x	x
Regional Characteristics	x	x	x
Labor Demand Shifts	x	x	x
Detailed Industry Structure	x	x	x
Commuting Zones	158	158	158
Periods	2	2	2
Observations	316	316	316

Notes: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets, and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). All specifications include a set of region 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 population in 68 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product and the unemployment rate, as well as the start-of-period degree of urbanization. Labor Demand Shifts include changes in import- and export-exposure and ICT-intensity. 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) and the public sector. All regressions are weighted by start-of-period working age population.

Taken together the results in tables 6 and 7 clearly show that robotization has increased migration flows from rural to urban areas. As this specific type of internal migration flow greatly contributes to population declines in many rural areas, these results show that robotization based labor demand disruptions have contributed to rural depopulation in Austria between 2003 and 2016.

To benchmark the magnitude of this effect Panel B of Figure A3 in the Appendix 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 2.78%. Increases in robotization thus explain around one fourth of all rural-to-urban migration flows during the period 2003 to 2016.

5.1 Robustness Checks:

Pre-Trend Tests

To test whether the results in tables 4 to 7 are indeed driven by exogenous changes in the robotization shocks used to construct the instrument rather than by pre-trends in the outcome variables, Table 8 presents pre-trend tests. For these tests changes in the outcome variables between different pre-periods during 1991 and 2003 are regressed on the instrument for 2003 to 2016.

The pre-trend test for the log-change in manufacturing employment is presented in panel A of Table 8. Because the migration flow data used for the computation of net out-migration rates used in tables 5 to 7 are only available starting in 2002, these pre-trend tests can not be performed using migration-flow data. To asses the presence of pre-trends in internal migration, I therefore rely on an alternative measure for migration responses. For this I use the log-change in working age population counts (panel B) and the log-change in the rural working age population (panel C).[25] Because

[25] In the literature on migratory responses to local labor demand shocks the log-change in working age population counts is frequently used as primary measure for migration flows (especially when more detailed data on migration in- and outflows is not available). Table A3 in the Appendix 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 (as in Table 5). Consistent with previous results, these estimations suggest that robotization leads to significant decreases in the size of the working age population, both overall (Table A3, panel A) and when focusing only on rural areas (panel B).

these population counts are taken from the Austrian decennial census, pre-period data points are only available for the years 1991 and 2001. Therefore the pre-trend tests for log-changes in population related variables in columns 1 to 3 of Table 8 contain linearly interpolated population counts for the years 1997 and 2003. To be sure that the results are not driven by the linear interpolation of the population data, column 4 presents an additional pre-trend test which only relies on data from census years.

All pre-trend tests are conducted in two variations. Firstly I regress pre-period changes on the instrumental variable, controlling only for period fixed effects. Secondly I include all available control variables. Here it is important to note, that since the pre-period changes do not vary across the two panel periods, regional fixed effects can not be included in pre-trend tests including a full set of controls.

The estimation results for the pre-trend tests in Table 8 (panel B) suggest the presence of slightly negative pre-trends in the log-change of the working age population in the pre-periods 1991-1997 (column 1) and 1991-2001 (column 4). These pre-trends are however only significant using the conventional heteroskedasticity robust standard errors, while the shift-share-robust AKM-standard errors suggest that these pre-trends are statistically insignificant. Significant pre-trends in the log-change of the working age population are potentially concerning, as they indicate that regions with higher values for the instrument were on a negative population trend prior to the treatment. Conditioning on all available controls however reduces the estimates in size and renders these pre-trends statistically insignificant. All remaining pre-trend tests for log-changes in manufacturing employment (panel A) and log-changes in the rural working age population (panel C) result in insignificant estimates, indicating parallel pre-trends.

In sum the pre-trend tests in Table 8 are reassuring, as they indicate parallel pre-trends in all pre-periods. Only in the log-change of the working age population in panel B of Table 8 do these parallel pre-trends hold only conditionally on the available control

Table 8: Pre-trend tests

	1991-1997	1997-2003	1991-2003	1991-2001
	(1)	(2)	(3)	(4)
Panel A: Dependent Variable: Pre-Trend for Δ log(manufacturing employment)				
Control only for period FE	-0.0038	0.0031	-0.0007	
	(0.0074)	(0.0094)	(0.0132)	
	[0.1288]	[0.1247]	[0.2534]	
Full controls	0.0054	-0.0001	0.0053	
	(0.0092)	(0.0084)	(0.0103)	
	[0.0103]	[0.0085]	[0.0094]	
Panel B: Dependent Variable: Pre-Trend for Δ log(working-age population)				
Control only for period FE	-0.0027	-0.001	-0.0037	-0.0043
	(0.0012)**	(0.0014)	(0.0022)	(0.0019)**
	[0.004]	[0.0118]	[0.0156]	[0.0067]
Full controls	-0.0007	0	-0.0007	-0.001
	(0.0014)	(0.0014)	(0.0027)	(0.0023)
	[0.0011]	[0.001]	[0.002]	[0.0018]
Panel C: Dependent Variable: Pre-Trend for Δ log(rural working-age population)				
Control only for period FE	-0.0025	-0.0017	-0.0042	-0.004
	(0.002)	(0.0019)	(0.004)	(0.0033)
	[0.027]	[0.0296]	[0.0566]	[0.044]
Full controls	0.0006	0.0011	0.0018	0.0012
	(0.0013)	(0.0013)	(0.0026)	(0.0022)
	[0.001]	[0.001]	[0.0019]	[0.0017]
Commuting Zones	158	158	158	158
Periods	2	2	2	2
Observations	316	316	316	316

Notes: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets, and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). Period fixed effects are interacted with the sum of exposure shares used to construct the explanatory variable (OLS) or the instrument (2SLS). Since the pre-trend variables do not vary between time periods, regional fixed effects are omitted in regressions including a full set of controls. All regressions are weighted by start-of-period working age population.

variables, while pre-trends for the log-changes in manufacturing employment and rural working age population counts are also parallel in less rigorous specifications.

Alternative Instrumental Variable

Another 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 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, simultaneous effects of monetary policy on investment in robots and outcome variables (i.e. changes in manufacturing employment or migration behavior) therefore are a source of concern.[26] If 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 Monetary 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 changes in monetary policy influence the outcome variables this might violate the exclusion restriction. In principle the period fixed effects are able to deal with such a problem, if such monetary policy effects are homogeneous across regions. If changes in monetary policy 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 asses whether the results in Tables 4 to 6 are influenced by such contamination of the instrumental variable Table A6 in the Appendix presents results

[26]The instrument is constructed from industry level robotization changes in Canada, Denmark, Finland, France, Italy, Mexico, Norway, Spain, Sweden, the United Kingdom and the United States.

for an alternative computation of the instrument for which only robotization changes from countries outside the European Monetary Union are used. Comparing the results for the baseline instrument in column 2 of Table A6 to the results for the alternative instrument in column 3 of Table A6 shows that all results are robust to the exclusion of these countries in the computation of the instrument.

Commuting Zone Definitions

As mentioned in section 4 and explained in detail in Online Appendix C, I use clustered commuting zones as units of observation during the analysis. These commuting zones are estimated using a horizontal clustering algorithm which clusters units according to the strength of their commuting ties. As is explained in detail in Online Appendix C this algorithm requires a tuning parameter h, that governs when it stops clustering. To asses the influence of this tuning parameter h on the estimation results, Tables A8 and A9 in Online Appendix C present corresponding robustness checks. In sum all results are robust to different configurations of the clustering algorithm.

To check whether the commuting zones are adequate to control for spatial spillovers, Tables A8 and A9 also report the results of Moran's I test for spatial autocorrelation in the residuals. For the configuration of the clustering algorithm that is used during the primary analysis in this paper ($h = 0.985$) the Moran's I test is unable to reject the null of no spatial autocorrelation in all estimations. This suggests that the estimated commuting zones are able to capture spatial spillovers and thus the estimation results in Tables 4 to 7 are not affected by spatial autocorrelation. Importantly the estimation results for political districts (which are pre-defined administrative areas) and less restrictive configurations of the clustering algorithm (with $h < 0.985$) fail to consistently reject the null of no spatial autocorrelation.

5.2 Heterogeneous Effects by Population Subgroups

While the results in section 5 show that industrial robotization has lead 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 9 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 asses the total effect of automation induced out-migration on the age structure of rural areas, Table 9 considers migratory responses of the entire population (instead of just regarding the working age population as in tables 5 to 7). This allows to also examine migratory responses of the age groups '0 to 14' and '65 and older'.[27] 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 a rural area. 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. Since Table 9 looks at the rural-to-urban component of net out-migration rates of the entire population the total effect (0.471 - panel A, column 1) is somewhat smaller when compared to the results for the working age population (0.565 - Table 6, 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.

[27]For better readability the age groups '50 to 64' and '65 and older' are aggregated to a single category in Table 9.

Here around 59% of the total effect (panel D, column 3) is explained by out-migration of individuals between the age of 15 and 34, while another 23% (panel D, column 2) of the total effect stems from children under the age of 15 who out-migrate with their parents. Hence around 82% of the total migratory response are accounted for by the out-migration of individuals bellow 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' also show relevant, although much smaller, migratory responses, individuals above the age of 50 hardly respond to disruptions in labor demand by moving to the cities.

Panels B and C of Table 9 further decompose the total effect by gender. Since males account for a larger fraction of manufacturing employment (around 73% in 2001) and thus bare a stronger shock incidence, they also account for a higher fraction of the migratory response, with around 62% of the total effect being explained by male migration.

Different migratory responses by skill groups are shown in Table 10. Since the migration flow data does not contain information on educational attainment, migratory responses of different skill groups are approximated by percentage changes of the working age population. Therefore the results in Table 10 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 (as in Table A3 in the Appendix) has the advantage that the overall effect on the entire working age population (in column 1 of Table 10) 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 10 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.

Table 9: Rural-to-urban flows by age and gender (2SLS Estimates):

	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)
Panel A: All					
Δ Robots	0.471	0.109	0.277	0.08	0.006
	(0.131)***	(0.029)***	(0.079)***	(0.031)**	(0.019)
	[0.027]***	[0.008]***	[0.015]***	[0.008]***	[0.003]*
First-Stage F:	29.94	29.94	29.94	29.94	29.94
Panel B: Male					
Δ Robots	0.291	0.036	0.183	0.046	0.026
	(0.094)***	(0.015)**	(0.065)***	(0.022)**	(0.01)**
	[0.019]***	[0.004]***	[0.012]***	[0.005]***	[0.001]***
First-Stage F:	29.94	29.94	29.94	29.94	29.94
Panel C: Female					
Δ Robots	0.181	0.073	0.094	0.034	-0.021
	(0.048)***	(0.016)***	(0.025)***	(0.013)**	(0.012)*
	[0.01]***	[0.004]***	[0.004]***	[0.003]***	[0.002]***
First-Stage F:	29.94	29.94	29.94	29.94	29.94
Panel D: Relative Contribution to Net-Outmigration by Age					
All:		23.1%	58.86%	17.06%	1.25%
Male:	61.82%	7.59%	38.8%	9.82%	5.61%
Female:	38.44%	15.51%	20.07%	7.24%	-4.37%
Period Fixed Effects	x	x	x	x	x
Region Fixed Effects	x	x	x	x	x
Demographic Controls	x	x	x	x	x
Regional Characteristics	x	x	x	x	x
Labor Demand Shifts	x	x	x	x	x
Detailed 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: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets, and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). All specifications include a set of region 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 population in 68 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product and the unemployment rate, as well as the start-of-period degree of urbanization. Labor Demand Shifts include changes in import- and export-exposure and ICT-intensity. 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) and the public sector. All regressions are weighted by start-of-period total population.

Table 10: Percentage change of working age population in rural areas by skill groups:

		By Skill-Group		
	All	High-Skill	Medium-Skill	Low-Skill
	(1)	(2)	(3)	(4)
OLS:				
Δ Robots	-0.443	-0.031	-0.302	-0.11
	(0.07)***	(0.017)*	(0.049)***	(0.04)***
	[0.012]***	[0.005]***	[0.013]***	[0.007]***
2SLS: Baseline IV				
Δ Robots	-0.499	-0.11	-0.185	-0.204
	(0.11)***	(0.037)***	(0.086)**	(0.072)***
	[0.019]***	[0.005]***	[0.018]***	[0.011]***
First-Stage F:	29.77	29.77	29.77	29.77
Contribution to total effect:		22.04%	37.07%	40.88%
Period Fixed Effects	x	x	x	x
Region Fixed Effects	x	x	x	x
Demographic Controls	x	x	x	x
Regional Characteristics	x	x	x	x
Labor Demand Shifts	x	x	x	x
Detailed Industry Structure	x	x	x	x
Commuting Zones	158	158	158	158
Periods	2	2	2	2
Observations	316	316	316	316

Notes: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets, and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). All specifications include a set of region 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 population in 68 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product and the unemployment rate, as well as the start-of-period degree of urbanization. Labor Demand Shifts include changes in import- and export-exposure and ICT-intensity. 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) and the public sector. 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 working age population. Hence all skill group based variables have a common denominator and thus sum up to the aggregated population change. All regressions are weighted by start-of-period working age population.

Together these two groups account for around 78% percent of all migratory responses to the robotization shock.

6 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 known in the context of general labor demand shocks, the impact of industrial robotization on internal migration flows only recently received some attention. Also the question were internal migrants move after a shock 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 US. 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 to 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 these internal out-migration flows in rural areas are primarily 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. Exploring heterogeneous effects by population subgroups further shows that these rural-to-urban migration flows are primarily driven by those individuals that bare the strongest incidence of the robotization shock, namely young and medium- to low-skilled individuals.

References

Acemoglu, Daron, David H. Autor, David Dorn, Gordon H. Hanson, and Brendan Price. 2016. "Import Competition and the Great U.S. Employment Sag of the 2000s." *Journal of Labor Economics* 34 (S1):S141–S198.

Acemoglu, Daron and Pascual Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy* 128 (6):2188–2244.

———. 2022. "Demographics and Automation." *Review of Economic Studies* 89 (1):1–44.

Adao, Rodrigo, Michal Kolesár, and Eduardo Morales. 2019. "Shift-Share Designs: Theory and Inference." *The Quarterly Journal of Economics* 134 (4):1949–2010.

Autor, David and Mark G. Duggan. 2003. "The rise in the disability rolls and the decline in unemployment." *The Quarterly Journal of Economics* 118 (1):157–206.

Autor, David H. and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5):1553–1597.

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103 (6):2121–2168.

———. 2015. "Untangling Trade and Technology: Evidence from Local Labour Markets." *The Economic Journal* 125 (584):621–646.

———. 2021. "On the Persistence of the China Shock." *NBER Working Paper 29401* .

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists." *The Review of Economics and Statistics* 90 (2):300–323.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics* 118 (4):1279–1333.

Bartik, Timothy J. 1991. "Who benefits from state and local economic development policies?" .

Bjerke, Lina and Charlotta Mellander. 2017. "Moving home again? Never! The locational choices of graduates in Sweden." *The Annals of Regional Science* 59 (3):707–729.

Blanchard, Olivier J. and Lawrence F. Katz. 1992. "Regional Evolutions." *Brookings Papers on Economic Activity* 23 (1):1–76.

Bonfiglioli, Alessandra, Rosario Crinò, Harald Fadinger, and Gino Gancia. 2020. "Robot imports and firm-level outcomes." .

Borusyak, Kirill, Rafael Dix-Carneiro, and Brian K Kovak. 2022. "Understanding Migration Responses to Local Shocks." .

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2022. "Quasi-Experimental Shift-Share Research Designs." *Review of Economic Studies* 89 (1):181–213.

Bound, John and Harry J. Holzer. 2000. "Demand Shifts, Population Adjustments, and Labor Market Outcomes during the 1980s." *Journal of Labor Economics* 18 (1):20–54.

Brueckner, Jan K and Somik V Lall. 2015. "Cities in developing countries: fueled by rural–urban migration, lacking in tenure security, and short of affordable housing." *Handbook of regional and urban economics* 5:1399–1455.

Cadena, Brian C. and Brian K. Kovak. 2016. "Immigrants Equilibrate Local Labor Markets: Evidence from the Great Recession." *American Economic Journal: Applied Economics* 8 (1):257–290.

Card, David. 2001. "Immigrant inflows, native outflows, and the local labor market impacts of higher immigration." *Journal of Labor Economics* 19 (1):22–64.

Dauth, Wolfgang, Sebastian Findeisen, and Jens Suedekum. 2014. "The Rise of the East and the Far East: German Labor Markets and Trade Integration." *Journal of the European Economic Association* 12 (6):1643–1675.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner. 2021. "The adjustment of labor markets to robots." *Journal of the European Economic Association* 19 (6):3104–3153.

Dax, Thomas and Michael Fischer. 2018. "An Alternative Policy Approach to Rural Development in Regions Facing Population Decline." *European Planning Studies* 26 (2):297–315.

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

Faber, Marius, Andrés Sarto, and Marco Tabellini. 2021. "Local Shocks and Internal Migration: The Disparate Effects of Robots and Chinese Imports in the US." .

Foote, Andrew, Michel Grosz, and Ann Stevens. 2019. "Locate Your Nearest Exit: Mass Layoffs and Local Labor Market Response." *ILR Review* 72 (1):101–126.

Franz, Christian, Marcel Fratzscher, and Alexander S Kritikos. 2018. "German right-wing party AfD finds more support in rural areas with aging populations." *DIW Weekly Report* 8 (7/8):69–79.

Gathmann, Christina, Ines Helm, and Uta Schönberg. 2018. "Spillover Effects of Mass Layoffs." *Journal of the European Economic Association* 18 (1):427–468.

Goldsmith-Pinkham, Isaac Paul, Sorkin, and Henry Swift. 2020. "Bartik instruments: What, When, Why, and How." *American Economic Review* 110 (8):2586–2624.

Goos, Maarten and Alan Manning. 2007. "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." *The Review of Economics and Statistics* 89 (1):118–133.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review* 104 (8):2509–2526.

Graetz, Georg and Guy Michaels. 2018. "Robots at Work." *The Review of Economics and Statistics* 100 (5):753–768.

Greenland, Andrew, John Lopresti, and Peter McHenry. 2019. "Import Competition and Internal Migration." *Review of Economics and Statistics* 101 (1):44–59.

Greenstone, Michael, Alexandre Mas, and Hoai-Luu Nguyen. 2020. "Do Credit Market Shocks Affect the Real Economy? Quasi-experimental Evidence from the Great Recession and "Normal" Economic Times." *American Economic Journal: Economic Policy* 12 (1).

Helm, Ines. 2019. "National Industry Trade Shocks, Local Labour Markets, and Agglomeration Spillovers." *The Review of Economic Studies* 87 (3):1399–1431.

Hummels, David, Rasmus JÃ¸rgensen, Jakob Munch, and Chong Xiang. 2014. "The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data." *American Economic Review* 104 (6).

Huttunen, Kristiina, Jarle Møen, and Kjell G. Salvanes. 2018. "Job Loss and Regional Mobility." *Journal of Labor Economics* 36 (2):479–509.

Johnson, Kenneth M., Layton M. Field, and Dudley L. Poston Jr. 2015. "More Deaths Than Births: Subnational Natural Decrease in Europe and the United States." *Population and Developement Review* 41 (4):651–680.

Johnson, Kenneth M. and Daniel T. Lichter. 2019. "Rural Depopulation: Growth and Decline Processes over the Past Century." *Rural Sociology* 84 (1):3–27.

Kenny, Michael and Davide Luca. 2021. "The urban-rural polarisation of political disenchantment: an investigation of social and political attitudes in 30 European countries." *Cambridge Journal of Regions, Economy and Society* 14 (3):565–582.

Klump, Rainer, Anne Jurkat, and Florian Schneider. 2021. "Tracking the rise of robots: A survey of the IFR database and its applications." .

Koch, Michael, Ilya Manuylov, and Marcel Smolka. 2021. "Robots and firms." *The Economic Journal* 131 (638):2553–2584.

Lagakos, David. 2020. "Urban-rural gaps in the developing world: Does internal migration offer opportunities?" *Journal of Economic perspectives* 34 (3):174–92.

Lagakos, David, Ahmed Mushfiq Mobarak, and Michael E Waugh. 2018. "The welfare effects of encouraging rural-urban migration." *NBER Working Paper 24193* .

Lee, Neil, Katy Morris, and Thomas Kemeny. 2018. "Immobility and the Brexit vote." *Cambridge Journal of Regions, Economy and Society* 11 (1):143–163.

Notowidigdo, Matthew J. 2020. "The Incidence of Local Labor Demand Shocks." *Journal of Labor Economics* 38 (3):687–725.

Peri, Giovanni and Akira Sasahara. 2019. "The impact of global warming on rural-Urban migrations: Evidence from global big data." *NBER Working Paper 25728* .

Rickardsson, Jonna. 2021. "The urban–rural divide in radical right populist support: the role of residents characteristics, urbanization trends and public service supply." *The Annals of Regional Science* 67 (1):211–242.

Scala, Dante J. and Kenneth M. Johnson. 2017. "Political polarization along the rural-urban continuum? The geography of the presidential vote, 2000–2016." *The ANNALS of the American Academy of Political and Social Science* 672 (1):162–184.

Tolbert, Charles M. and Molly Sizer. 1996. "US Commuting Zones and Labor Market Areas: A 1990 Update." *Economic Research Service Staff Paper 9614* .

Veneri, Paolo and Vicente Ruiz. 2016. "Urban-To-Rural Population Growth Linkages: Evidence from OECD Tl3 Regions." *Journal of Regional Science* 56 (1):3–24.

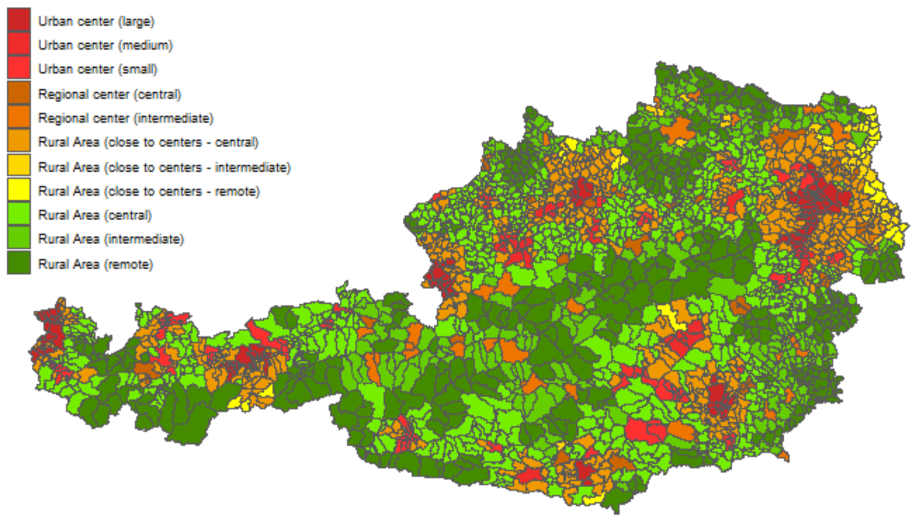
Wuthnow, Robert. 2018. *The Left Behind: Decline and Rage in Rural America.* Princeton University Press.

Zhao, Yaohui. 1999. "Leaving the countryside: rural-to-urban migration decisions in China." *American Economic Review* 89 (2):281–286.

Zweimüller, Josef, Rudolf Winter-Ebmer, Rafael Lalive, Andreas Kuhn, Jean-Philippe Wuellrich, Oliver Ruf, and Simon Büchi. 2009. "Austrian Social Security Database." *Working Paper No. 0903, NRN: The Austrian Center for Labor Economics and the Analysis of the Welfare State.* .

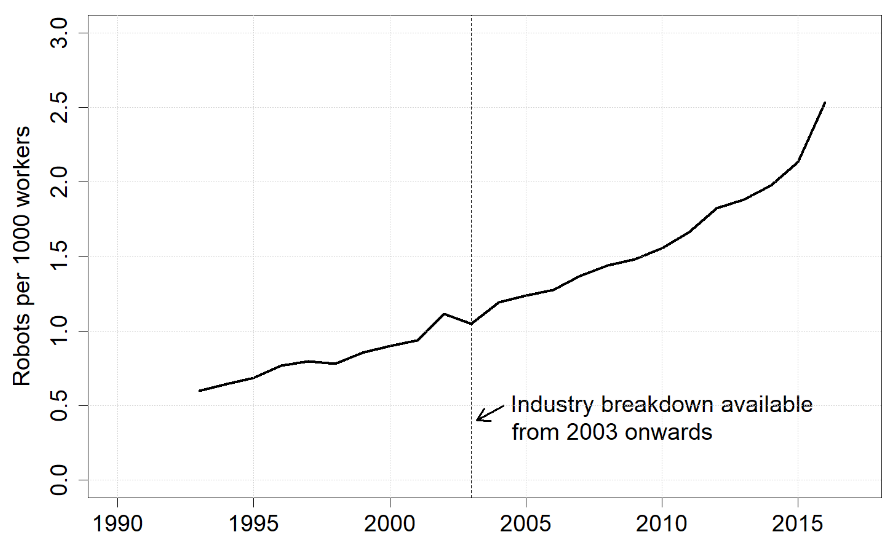
Appendix A Additional Descriptives & Results:

Figure A1: Urban-Rural Classification from Statistics Austria (2021)



Source: Statistics Austria

Figure A2: Change in robot density 1993-2016



Source: International Federation of Robotics (IFR), own calculations

Table A1: Robotization and Employment - Additional Results

	By Sector		By Occupation	
	Manuf.	Non-Manuf.	Blue Collar	White Collar
	(1)	(2)	(3)	(4)
Panel A: Δ log(Employment) $\times$ 100				
Δ Robots	-4.343	-0.031	-2.328	0.388
	(1.683)**	(1.178)	(0.913)**	(1.431)
	[0.299]***	[0.282]	[0.14]***	[0.345]
First-Stage F:	32.78	32.78	32.78	32.78
Panel B: %-change in Employment $\times$ 100				
Δ Robots	-5.438	0.028	-2.134	-0.245
	(1.585)***	(1.159)	(0.946)**	(1.358)
	[0.3]***	[0.265]	[0.154]***	[0.314]
First-Stage F:	32.78	32.78	32.78	32.78
Panel C: Separations (in % of initial employment) $\times$ 100				
Δ Robots	-8.006		-15.938	
	(2.771)***		(4.712)***	
	[0.53]***		[1.322]***	
First-Stage F:	32.78		32.78	
Panel D: New Hirings (in % of initial employment) $\times$ 100				
Δ Robots	-13.444		-18.072	
	(3.757)***		(5.054)***	
	[0.668]***		[1.373]***	
First-Stage F:	32.78		32.78	
Period Fixed Effects	x	x	x	x
Region Fixed Effects	x	x	x	x
Demographic Controls	x	x	x	x
Regional Characteristics	x	x	x	x
Labor Supply Shifts	x	x	x	x
Labor Demand Shifts	x	x	x	x
Detailed Industry Structure	x	x	x	x
Commuting Zones	158	158	158	158
Periods	2	2	2	2
Observations	316	316	316	316

Notes: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). All specifications include a set of region 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 (demographic controls relating to the age-group 0-14 are not included in employment regressions). Regional characteristics control for the start-of-period logarithm of the gross regional product 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) and the public sector. All regressions are weighted by start-of-period working-age population.

Table A2: Robotization and Employment - Shock Incidence by Age Groups

	Total Effect	By Age-group		
		Age 16-34	Age 35 to 49	Age 50 and older
	(1)	(2)	(3)	(4)
Panel A: %-change in Manufacturing Employment × 100				
Δ Robots	-5.438	-2.21	-1.517	-1.711
	(1.585)***	(0.745)***	(0.772)*	(0.592)***
	[0.3]***	[0.155]***	[0.135]***	[0.141]***
First-Stage F:	32.78	32.78	32.78	32.78
Relative contribution to total effect:		40.64%	27.9%	31.46%
Panel B: %-change in Blue Collar Employment × 100				
Δ Robots	-2.134	-0.973	-0.591	-0.57
	(0.946)**	(0.466)**	(0.469)	(0.271)**
	[0.154]***	[0.106]***	[0.086]***	[0.041]***
First-Stage F:	32.78	32.78	32.78	32.78
Relative contribution to total effect:		45.6%	27.69%	26.71%
Period Fixed Effects	x	x	x	x
Region Fixed Effects	x	x	x	x
Demographic Controls	x	x	x	x
Regional Characteristics	x	x	x	x
Labor Supply Shifts	x	x	x	x
Labor Demand Shifts	x	x	x	x
Detailed Industry Structure	x	x	x	x
Commuting Zones		158	158	158
Periods		2	2	2
Observations		316	316	316

Notes: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). All specifications include a set of region 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 (demographic controls relating to the age-group 0-14 are not included in employment regressions). Regional characteristics control for the start-of-period logarithm of the gross regional product 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) and the public sector. All regressions are weighted by start-of-period working-age population.

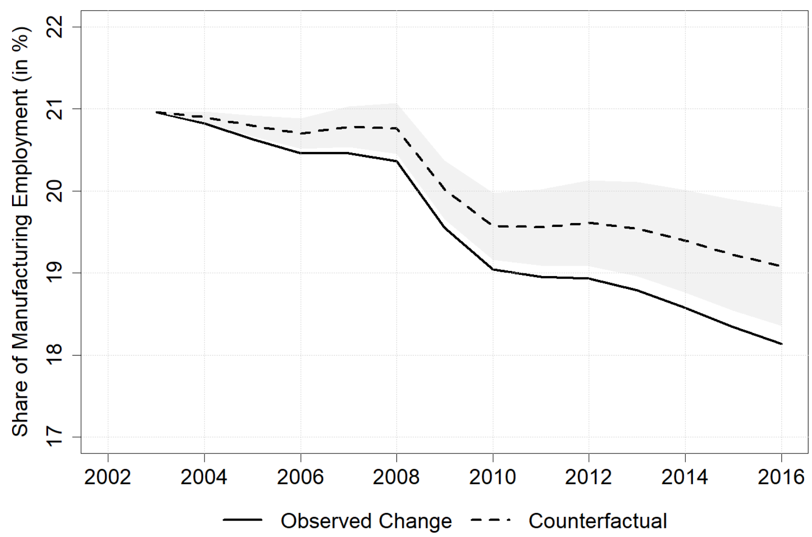
Table A3: Robotization and Internal Migration (2003-2016) - Alternative migration measure

	(1)	(2)	(3)	(4)	(5)
Panel A: Dependent Variable: Δ log(working-age population) $\times 100$					
OLS:					
Δ Robots	-0.384	-0.382	-0.375	-0.388	-0.393
	(0.059)***	(0.059)***	(0.061)***	(0.061)***	(0.067)***
	[0.017]***	[0.016]***	[0.016]***	[0.015]***	[0.016]***
2SLS:					
Δ Robots	-0.314	-0.338	-0.319	-0.327	-0.375
	(0.091)***	(0.098)***	(0.099)***	(0.101)***	(0.101)***
	[0.021]***	[0.018]***	[0.02]***	[0.02]***	[0.018]***
Panel B: Dependent Variable: Δ log(rural working-age population) $\times 100$					
OLS:					
Δ Robots	-0.414	-0.411	-0.429	-0.434	-0.454
	(0.061)***	(0.064)***	(0.065)***	(0.064)***	(0.071)***
	[0.012]***	[0.014]***	[0.013]***	[0.013]***	[0.011]***
2SLS:					
Δ Robots	-0.361	-0.376	-0.448	-0.457	-0.502
	(0.101)***	(0.106)***	(0.111)***	(0.113)***	(0.108)***
	[0.022]***	[0.018]***	[0.022]***	[0.021]***	[0.019]***
First Stage Results:	0.011	0.011	0.011	0.011	0.011
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
	[0.0003]***	[0.0003]***	[0.0003]***	[0.0003]***	[0.0002]***
First Stage F-Statistic:	37.09	34.58	27.94	27.58	29.77
Period Fixed Effects	x	x	x	x	x
Region Fixed Effects	x	x	x	x	x
Demographic Controls	x	x	x	x	x
Regional Characteristics		x	x	x	x
Labor Demand Shifts			x	x	x
Manufacturing Share				x	
Detailed Industry Structure					x
Commuting Zones	158	158	158	158	158
Periods	2	2	2	2	2
Observations	316	316	316	316	316

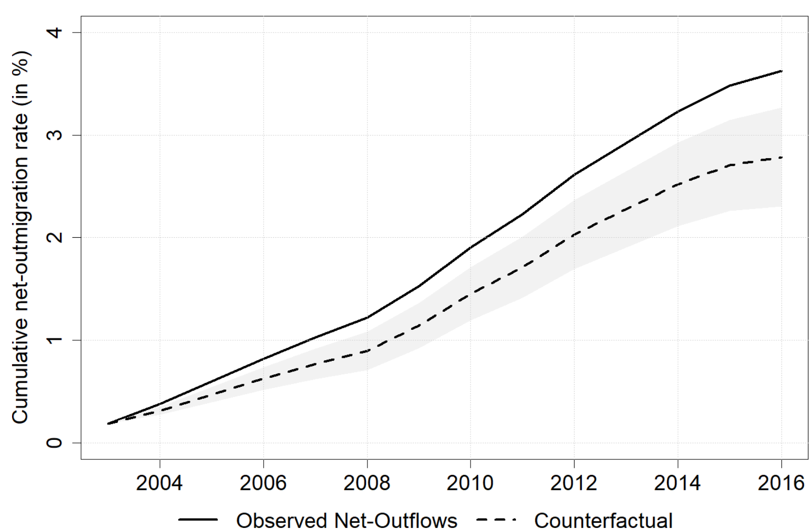
Notes: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). All specifications include a set of region 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 population in 68 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product 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) and the public sector. All regressions are weighted by start-of-period working-age population.

Figure A3: Benchmarking of robotization effects:

(a) Manufacturing Share



(b) Cummulated net-outmigration rates
Working-age population (age 15 to 64)



Notes: The counterfactual evolutions of the manufacturing share and the cummulated net out-migration rates are calculated using the observed change in robots per 1000 workers (1.485 - Figure A2). In Panel (a) this value is multiplied with the estimated effect of one additional robot per 1000 workers on manufacturing employment (-4.343 - Table 4, column 6) , while in Panel (b) it is multiplied with the estimated effect of one additional robot on the rural-to-urban net out-migration rates of the working-age population (0.565 - Table 6, column 4). The resulting contributions of industrial robots to changes in manufacturing employment and net-outmigration rates are then spread out evenly over the entire observational period and added to the observed trends to construct the counterfactuals. The grey area corresponds to 95% confidence intervals (computed from the conventional heteroskedasticity robust standard errors).

Appendix B Additional Robustness Checks:

Table A4: Robustness Check: Alternative definition of rural areas:

	Total	External	Internal		
			All	Rural to Urban	Rural to Rural
	(1)	(2)	(3)	(4)	(5)
OLS:					
Δ Robots	0.162	-0.004	0.166	0.12	0.046
	(0.159)	(0.023)	(0.175)	(0.094)	(0.089)
	[0.038]***	[0.005]	[0.042]***	[0.021]***	[0.023]**
2SLS:					
Δ Robots	0.977	-0.068	1.044	0.615	0.429
	(0.299)***	(0.046)	(0.333)***	(0.17)***	(0.182)**
	[0.061]***	[0.009]***	[0.068]***	[0.035]***	[0.037]***
First-Stage F:	29.77	29.77	29.77	29.77	29.77
Period Fixed Effects	x	x	x	x	x
Region Fixed Effects	x	x	x	x	x
Demographic Controls	x	x	x	x	x
Regional Characteristics	x	x	x	x	x
Labor Demand Shifts	x	x	x	x	x
Detailed 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: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets, and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). All specifications include a set of region 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 population in 68 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product and the unemployment rate, as well as the start-of-period degree of urbanization. Labor Demand Shifts include changes in import- and export-exposure and ICT-intensity. 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) and the public sector. All regressions are weighted by start-of-period working-age population.

Table A5: Correlation between employment shares of different age groups in Austria and countries used to construct instrument

	Share of total hours worked by:		
	Young	Middle	Old
	(1)	(2)	(3)
Average:	1.326	0.73	1.516
	(0.195)***	(0.226)***	(0.159)***
Canada:	0.447	0.358	0.913
	(0.42)	(0.152)**	(0.486)*
Denmark:	0.483	0.024	0.58
	(0.249)*	(0.121)	(0.221)**
Finland:	1.396	-0.541	0.507
	(0.145)***	(0.553)	(0.073)***
Italy:	0.488	0.265	0.78
	(0.135)***	(0.074)***	(0.103)***
Spain:	1.18	0.632	0.916
	(0.202)***	(0.103)***	(0.43)*
United Kingdom:	1.891	1.054	0.999
	(0.651)**	(0.252)***	(0.489)*
United States:	0.735	0.406	1.285
	(0.306)**	(0.175)**	(0.436)**
Industries:		16	

Notes: * < 0.10, ** < 0.05, *** < 0.01. Estimates are from regressions of employment shares (by age group) in Austria on the corresponding employment shares in other countries. The explanatory variable in the first regression ("Average") is computed as an unweighted mean over all available countries. Data on industry level shares of hours worked by age group are from the EU-KLEMS March 2008 release. Industry level correlations have been estimated using 2003 data. Data on industry level age composition for France, Mexico, Norway and Sweden is not available. Robust standard errors are shown in brackets.

Table A6: Alternative Instrumental Variable

	OLS	2SLS	
		Baseline IV	Exclude €-Area
	(1)	(2)	(3)
Panel A: Δ log(manufacturing employment)			
Δ Robots	-0.885	-4.343	-3.061
	(1.333)	(1.683)**	(1.527)**
	[0.438]**	[0.299]***	[0.224]***
F-Statistic:		32.78	58.02
Panel B: Net-outflow			
Δ Robots	0.155	1.055	1.105
	(0.165)	(0.323)***	(0.257)***
	[0.043]***	[0.071]***	[0.058]***
F-Statistic:		29.77	53.95
Panel C: Net-outflow (rural areas)			
Δ Robots	0.141	0.953	0.852
	(0.164)	(0.307)***	(0.241)***
	[0.037]***	[0.061]***	[0.05]***
F-Statistic:		29.77	53.95
Panel D: Net-outflow (rural to urban)			
Δ Robots	0.057	0.565	0.435
	(0.09)	(0.162)***	(0.129)***
	[0.02]***	[0.031]***	[0.026]***
F-Statistic:		29.77	53.95
Period Fixed Effects	x	x	x
Region Fixed Effects	x	x	x
Demographic Controls	x	x	x
Regional Characteristics	x	x	x
Labor Demand Shifts	x	x	x
Labor Supply Shifts	x	x	x
Detailed Industry Structure	x	x	x
Commuting Zones	158	158	158
Periods	2	2	2
Observations	316	316	316

Notes: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets, and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). All specifications include a set of region 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 population in 68 age-gender-education-nationality cells. Regional characteristics control for the start-of-period logarithm of the gross regional product and the unemployment rate, as well as the start-of-period degree of urbanization. Labor Demand Shifts include changes in import- and export-exposure and ICT-intensity. 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) and the public sector. All regressions are weighted by start-of-period working-age population.

Online Appendix

Online Appendix C Commuting Zones:

This Section describes the construction of the commuting zones used as units of observation during the analysis. Thereby I strictly follow the methodology described in Tolbert and Sizer (1996) and Dorn (2009).

The construction of commuting zones requires data on the commuting ties between municipalities. This data is taken from the register based Austrian census 2011 (available at Statistics Austria), and includes detailed information on municipality-to-municipality commuting flows.

Denote municipalities with $k = 1, ..., K$. Then a $K \times K$ commuting-matrix is constructed, whereby rows i indicate the municipality of residence and columns j indicate the municipality of work. Each element of this commuting matrix therefore contains the number of workers who live in municipality i and work in municipality j, with the main diagonal indicating the number of workers who work in their residential municipality (i.e. do not commute). This commuting matrix is converted into a symmetric flow matrix. Following Tolbert and Sizer (1996), each element of this flow matrix is constructed as:

$$P_{ij} = P_{ji} = \frac{f_{ij} + f_{ji}}{\min(L_i, L_j)} \tag{9}$$

where f_{ij} denotes the absolute number of workers living in municipality i who commute to municipality j, and L_i denotes the residential labor force of municipality i. Hence each element of the flow matrix P computes as the sum of shared commuters between i and j, divided by the smaller residential labor force. As is explained in detail in Tolbert and Sizer (1996), the symmetric flow matrix P is characterized as a similarity matrix, where a higher value of P_{ij} indicates a stronger commuting relationship between i and j. As the clustering algorithm (explained in detail below) requires a dissimilarity (or distance) matrix as input, the symmetric flow matrix is converted into a distance matrix D, whereby each element of this matrix computes as:

$$D_{ij} = D_{ji} = \begin{cases} 1 - P_{ij} & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases} \tag{10}$$

In this distance matrix, a lower value of D_{ij} indicates stronger commuting ties (i.e. less distance) between municipalities i and j. In the main diagonal, where $i = j$, the distance is set to zero.[28]

To arrive at the desired commuting zones, a Hierarchical Cluster Algorithm is applied to the distance matrix D.[29] This algorithm clusters elements of the distance matrix D, based on their average distance to each other, starting with the closest pair, and ending with one large cluster of all units. The algorithm stops clustering, once the average between cluster distance reaches a predefined threshold h. For the estimation of commuting zones for the US Tolbert and Sizer (1996) use an average between cluster distance of $h = 0.98$.

Table A7 compares clustered Austrian commuting zones for different threshold values

[28] As Tolbert and Sizer (1996) mention in footnote 4 on page 12 of their paper, in some rare cases (i.e. whenever the sum of shared commuters between i and j is greater than the smaller one of the residential labor forces), P_{ij} exceeds one. This would imply a negative distance between i and j in the distance matrix D. To avoid this, I follow Tolbert and Sizer (1996) and set $D_{ij} = 0.001$ whenever this is the case.

[29] This type of algorithm is often used in machine learning applications and belongs to the broader class of unsupervised learning algorithms.

h, political districts and municipalities. As is to be expected, municipalities themselves perform rather poorly at containing commuter flows within their boarders with only about 47.3% of workers working in their residential municipality. Political districts, which are pre-defined administrative units, perform a little better. They contain around 65.6% of all commuters within the borders of 94 units (whereby the 23 districts of the capital Vienna are aggregated to a single observation).

Table A7: Comparison of different local labor market (LLM) definitions

LLM	Commuters within LLM	N
Municipalities:	47.30%	2090
Political Districts:	65.62%	94
Commuting Zones:		
h = 0.98	70.07%	238
h = 0.9825	71.57%	197
h = 0.985	72.75%	158
h = 0.9875	74.18%	124
h = 0.99	75.31%	100

Note: Data on commuting flows is taken from the 2011 registry based census (available at Statistics Austria). To match municipality level data with other data sources used in the subsequent analysis, 2011 municipality structure has been mapped to the 2017 municipality structure. In cases were this mapping was ambiguous (i.e. when municipalities were split during reforms), some municipalities had to be aggregated to arrive at an municipality structure that is consistent over all used data sources. Therefore the number of municipalities slightly deviates from official sources.

Comparing the performance of municipalities and political districts to clustered commuting zones, shows that the clustered commuting zones for all used thresholds h perform markedly better at containing commuting flows. For example the commuting zone for the clustering threshold $h = 0.98$ (i.e. the same threshold as in Tolbert and Sizer, 1996) captures about 70% of commuting flows within its clusters. Compared to pre-defined political districts, it does this much more efficiently, as it captures a larger fraction of commuters (70% vs. 65.6%) in a higher number of clusters (238 vs. 94). Clustered commuting zones thus perform markedly better at controlling for spatial shock spillovers, while also resulting in a higher number of available observations. This comes as no surprise, as the horizontal clustering algorithm is specifically designed to cluster regions according to their commuting ties.

For the main part of the analysis, I rely on commuting zones clustered up to an average between cluster distance of $h = 0.985$. This threshold is slightly more restrictive than the one used by Tolbert and Sizer (1996) for the US in that it requires a greater average between cluster distance.

Robustness of results to different clustering thresholds h

To asses the influence of the tuning parameter h on the estimation results Tables A8 and A9 show corresponding estimations for several different values of this tuning parameter. Here Table A8 uses the baseline instrumental variable, and Table A9 uses the instrument were all Euro-Area countries are excluded from the computation. The very first configuration of the tuning constant ($h = 0.98$, column 2) corresponds to the configuration used for the clustering of US commuting zones in Tolbert and Sizer (1996) and Dorn (2009). All following configurations are more restrictive in that they allow weaker between-cluster commuting ties and thus result in a lower number of clusters. The baseline configuration which is used during the primary part of the analysis ($h = 0.985$) is presented in column 4.

As is visible from Tables A8 and A9, the primary results of the analysis are robust to different configurations of the clustering algorithm. Here it stands out, that more thoroughly controlling for spatial spillover effects (via higher configurations of h) mostly leads to an increase in effect size and precision. Since commuting zones which are clustered using higher values of the tuning constant h perform better at containing commuters within their borders, this indicates the presence of spatial spillover effects which potentially bias the estimates. This is further corroborated by Moran's I test for

Table A8: Local Labor Market Definition (Baseline IV)

	(1)	(2)	(3)	(4)	(5)	(6)
				Baseline		
LLM Definition:	Districts	h = 0.98	h = 0.9825	h = 0.985	h = 0.9875	h = 0.99
Commuters within LLM:	65.62 %	70.07 %	71.57 %	72.75 %	74.18 %	75.31 %
Panel A: Δ log(manufacturing employment)						
Δ Robots	2.455	-5.407	-4.679	-4.343	-1.909	0.898
	(1.082)**	(0.902)***	(0.792)***	(1.683)**	(1.421)	(3.173)
	[0.616]***	[0.2]***	[0.176]***	[0.299]***	[0.32]***	[0.748]
First-Stage F:	26.24	80.54	78.69	32.78	28.85	2.11
Moran's I:	0.012	-0.032	0.002	0.031	-0.04	-0.019
(p-Value)	(0.739)	(0.14)	(0.845)	(0.174)	(0.177)	(0.683)
Panel B: Net-outflow (all)						
Δ Robots	-0.159	0.051	0.388	1.055	0.242	0.172
	(0.127)	(0.164)	(0.177)**	(0.323)***	(0.314)	(0.438)
	[0.025]***	[0.033]	[0.035]***	[0.071]***	[0.077]***	[0.074]**
First-Stage F:	13.22	78.31	80.9	29.77	17.73	2.77
Moran's I:	-0.109	0.023	-0.076	-0.026	0.008	0.033
(p-Value)	(0.039)**	(0.198)	(0.002)***	(0.37)	(0.686)	(0.234)
Panel C: Net-outflow (rural areas only)						
Δ Robots	0.082	0.055	0.433	1.02	0.461	0.007
	(0.102)	(0.168)	(0.188)**	(0.342)***	(0.324)	(0.505)
	[0.031]***	[0.034]	[0.031]***	[0.069]***	[0.076]***	[0.094]
First-Stage F:	13.22	78.31	80.9	29.77	17.73	2.77
Moran's I:	0.074	0.01	-0.08	-0.028	0.002	0.024
(p-Value)	(0.121)	(0.529)	(0.001)***	(0.333)	(0.853)	(0.38)
Panel D: Net-outflow (rural to urban)						
Δ Robots	-0.07	0.023	0.23	0.565	0.483	-0.213
	(0.054)	(0.08)	(0.087)***	(0.162)***	(0.14)***	(0.236)
	[0.009]***	[0.019]	[0.013]***	[0.031]***	[0.03]***	[0.054]***
First-Stage F:	13.22	78.31	80.9	29.77	17.73	2.77
Moran's I:	0.01	0.039	-0.058	-0.039	0.018	0.023
(p-Value)	(0.748)	(0.042)**	(0.02)**	(0.173)	(0.45)	(0.397)
Full Controls	x	x	x	x	x	x
Regions	94	238	197	158	124	100
Periods	2	2	2	2	2	2
Observations	188	476	394	316	248	200

Notes: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets, and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. All specifications include a full set of control variables. All regressions are weighted by start-of-period working-age population.

Table A9: Local Labor Market Definition (Alternative IV)

	(1)	(2)	(3)	(4)	(5)	(6)
				Baseline		
LLM Definition:	Districts	h = 0.98	h = 0.9825	h = 0.985	h = 0.9875	h = 0.99
Commuters within LLM:	65.62 %	70.07 %	71.57 %	72.75 %	74.18 %	75.31 %
Panel A: Δ log(manufacturing employment)						
Δ Robots	1.788	-5.681	-4.622	-3.061	-2.618	-7.61
	(1.065)	(0.705)***	(0.719)***	(1.527)**	(1.657)	(2.268)***
	[0.586]***	[0.185]***	[0.129]***	[0.224]***	[0.345]***	[0.55]***
First-Stage F:	50.25	158.56	179.06	58.02	42.02	4.16
Moran's I:	0.026	-0.032	0.002	0.031	-0.043	-0.032
(p-Value)	(0.535)	(0.143)	(0.853)	(0.183)	(0.145)	(0.419)
Panel B: Net-outflow (all)						
Δ Robots	-0.2	0.3	0.48	1.105	0.769	0.573
	(0.111)	(0.127)**	(0.16)***	(0.257)***	(0.27)***	(0.291)*
	[0.023]***	[0.024]***	[0.032]***	[0.058]***	[0.054]***	[0.051]***
First-Stage F:	32.09	153.92	168.11	53.95	29.09	6.09
Moran's I:	-0.103	0.018	-0.076	-0.027	0.006	0.033
(p-Value)	(0.051)*	(0.293)	(0.002)***	(0.366)	(0.745)	(0.231)
Panel C: Net-outflow (rural areas only)						
Δ Robots	0	0.286	0.484	0.934	0.728	0.286
	(0.086)	(0.141)**	(0.172)***	(0.27)***	(0.282)**	(0.334)
	[0.026]	[0.025]***	[0.023]***	[0.056]***	[0.052]***	[0.072]***
First-Stage F:	32.09	153.92	168.11	53.95	29.09	6.09
Moran's I:	0.054	0.006	-0.08	-0.028	0.003	0.023
(p-Value)	(0.241)	(0.667)	(0.001)***	(0.341)	(0.804)	(0.385)
Panel D: Net-outflow (rural to urban)						
Δ Robots	-0.067	0.114	0.223	0.435	0.433	-0.016
	(0.047)	(0.069)	(0.079)***	(0.129)***	(0.125)***	(0.161)
	[0.008]***	[0.015]***	[0.01]***	[0.026]***	[0.022]***	[0.037]
First-Stage F:	32.09	153.92	168.11	53.95	29.09	6.09
Moran's I:	0.012	0.037	-0.058	-0.036	0.018	0.022
(p-Value)	(0.721)	(0.057)*	(0.02)**	(0.215)	(0.454)	(0.425)
Full Controls	x	x	x	x	x	x
Regions	94	238	197	158	124	100
Periods	2	2	2	2	2	2
Observations	188	476	394	316	248	200

Notes: * < 0.10, ** < 0.05, *** < 0.01. Conventional robust standard errors are shown in round brackets, and shift-share robust standard errors from Adao, Kolesár, and Morales (2019) are shown in square brackets. All specifications include a full set of control variables. All regressions are weighted by start-of-period working-age population.

spatial autocorrelation in the residuals which indicates the presence of spatial autocorrelation when using political districts (column 1) and less restrictive configurations of the clustering algorithm (columns 2 and 3). Importantly Moran's I test fails to reject the null of no spatial autocorrelation for the configuration of the clustering algorithm that is used during the primary part of the analysis ($h = 0.985$, column 4), which suggests that all results in the main part of the paper are unaffected by spatial autocorrelation.

Increasing the value of h also has an impact on the first stage regression, as the strength of the instrument declines with increasing h. Therefore the first stage F-statistic drops below 10 when increasing h to 0.99.

Online Appendix D Shift-share standard errors:

The shift-share robust standard errors proposed by Adao, Kolesár, and Morales (2019) rely on asymptotic properties related to the number of industry shocks that are available to compute the shift-share variables. Correspondingly they may be downward biased, and thus overreject, in applications where the number of available industries is small. A possible downward bias due to an insufficient number of industry shocks is of particular concern in this application, because the IFR-data only contains information on 26 industries. This concern is further corroborated, since the AKM-standard errors are generally smaller than conventional heteroskedasticity robust standard errors.

To address this concern, I apply an adjusted computation for the AKM-standard errors that uses the fact that each of the 26 IFR-industries is itself comprised of several sub-industries.

Let any industry $i = 1, ..., I$ be composed of several sub-industries j such that $j = 1, ..., J \in i$. Then the shift-share variable for region r can be re-written as:

$$\Delta Robots_r = \sum_i \frac{Emp_{ir}}{Emp_r} \frac{\Delta Robots_i}{Emp_i} \tag{11}$$

$$= \sum_i \left(\sum_{j \in i} \frac{Emp_{jr}}{Emp_r} \right) \frac{\Delta Robots_i}{Emp_i} \tag{12}$$

because the employment share of industry i in region r is simply the sum of the employment shares of its sub-industries.

To arrive at a shift-share expression for predicted regional exposure that uses the more detailed sub-industry based exposure shares one needs to assume that within industry i all sub-industries experience identical changes in robot density. Formally this assumption can be expressed as:

$$\frac{\Delta Robots_j}{Emp_j} = \frac{\Delta Robots_i}{Emp_i} \quad \forall \quad j \in i \tag{13}$$

In other words, this assumption states that every sub-industry j experiences the same change in robots per worker, as is observed for the aggregated industry i. Using this assumption allows to re-write the shift-share expression in equation 11 as:

$$\Delta Robots_r = \sum_i \sum_{j \in i} \frac{Emp_{jr}}{Emp_r} \frac{\Delta Robots_j}{Emp_j} \tag{14}$$

Notice that predicted robot exposure computed from expressions 11 and 14 result in the same value for regional robot exposure $\Delta Robots_r$. The only difference between the two expression is that the first is calculated from industry-level exposure shares, while the second is calculated using more detailed sub-industry level exposure shares (and imposing the assumption laid out in equation 13).

Therefore the same shift-share variable can be constructed from the exposure shares of the aggregated industry itself:

$$\frac{Emp_{ir}}{Emp_r} \tag{15}$$

or from the more detailed exposure shares of all sub-industries:

$$\frac{Emp_{jr}}{Emp_r} \tag{16}$$

whereby the second way results in a more detailed matrix of exposure shares which can be used in the estimation of the AKM-standard errors.

Table A10 compares the AKM-standard error computation as proposed by Adao, Kolesár, and Morales (2019) with standard error estimates for the described adjustment. Table A11 lists all available IFR-industries alongside the corresponding NACE Rev. 2 sub-industries used for the adjusted estimation. For illustrative purposes this comparison is carried out using estimations on the log-change in manufacturing employment. Other dependent variables result in a very similar picture (these results are available upon request). The comparison is performed for both variations of the AKM-standard error proposed in Adao, Kolesár, and Morales (2019), whereby the first one ('AKM') corresponds to the default[30], and the second version ('AKM0') corresponds to an estimate where the null is imposed in the estimation[31]. To account for the panel structure of the data the baseline estimates for both the AKM- and the AKM0-standard error cluster the available industries at the level of more aggregated industry categories (as is recommended for panel settings in Adao, Kolesár, and Morales, 2019).

Because the adjustment described in equations 11 to 14 clearly violates the assumption of mutual independence of the robotization shocks (assumption 2 in Adao, Kolesár,

[30] Equations 26 (OLS) and 36 (2SLS) in Adao, Kolesár, and Morales (2019).

[31] Equation 27 (OLS) and comment below equation 36 (2SLS) in Adao, Kolesár, and Morales (2019).

Table A10: Local Labor Market Definition

								Increase in SE	
								Average	Full Specification
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
OLS:									
Δ Robots	-0.551	-3.921	-3.711	-2.841	-4.137	-2.743	-0.885		
AKM - W-matrix: standard (clustered)	(0.045)	(0.041)	(0.077)	(0.113)	(0.107)	(0.057)	(0.032)		
AKM - W-matrix: sub-sectors (clustered)	[0.361]	[0.38]	[0.518]	[0.622]	[0.521]	[0.411]	[0.474]	+ 706%	+ 1381%
AKM - W-matrix: sub-sectors (unclustered)	{0.333}	{0.337}	{0.45}	{0.462}	{0.476}	{0.413}	{0.438}	+ 628%	+ 1269%
AKM0 - W-matrix: standard (clustered)	(0.045)	(0.041)	(0.077)	(0.114)	(0.107)	(0.057)	(0.032)		
AKM0 - W-matrix: sub-sectors (clustered)	[0.362]	[0.382]	[0.521]	[0.627]	[0.526]	[0.415]	[0.478]	+ 646%	+ 1394%
AKM0 - W-matrix: sub-sectors (unclustered)	{0.333}	{0.338}	{0.45}	{0.463}	{0.477}	{0.414}	{0.439}	+ 628%	+ 1272%
2SLS:									
Δ Robots	-1.185	-5.984	-6.254	-3.823	-4.006	-3.599	-4.343		
AKM - W-matrix: standard (clustered)	(0.241)	(0.301)	(0.312)	(0.252)	(0.21)	(0.137)	(0.095)		
AKM - W-matrix: sub-sectors (clustered)	[4.337]	[0.952]	[0.809]	[0.554]	[0.476]	[0.328]	[0.237]	+ 373%	+ 149%
AKM - W-matrix: sub-sectors (unclustered)	{3.862}	{0.713}	{0.626}	{0.509}	{0.495}	{0.394}	{0.299}	+ 340%	+ 215%
AKM0 - W-matrix: standard (clustered)	(0.243)	(0.301)	(0.313)	(0.252)	(0.21)	(0.137)	(0.095)		
AKM0 - W-matrix: sub-sectors (clustered)	[4.337]	[0.952]	[0.809]	[0.554]	[0.476]	[0.328]	[0.237]	+ 371%	+ 149%
AKM0 - W-matrix: sub-sectors (unclustered)	{4.048}	{0.717}	{0.629}	{0.512}	{0.498}	{0.395}	{0.3}	+ 350%	+ 216%
Period Fixed Effects	x	x	x	x	x	x	x		
Region Fixed Effects	x	x	x	x	x	x	x		
Demographic Controls		x	x	x	x	x	x		
Regional Characteristics			x	x	x	x	x		
Labor Demand Shifts				x	x	x	x		
Labor Supply Shifts					x	x	x		
Manufacturing Share						x			
Detailed Industry Structure							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: Significance stars omitted for readability. Units of observation are 158 clustered commuting zones (for details see Online Appendix C). All specifications include a set of region 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 (demographic controls relating to the age-group 0-14 are not included in employment regressions). Regional characteristics control for the start-of-period logarithm of the gross regional product 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) and the public sector. All regressions are weighted by start-of-period working-age population.

and Morales, 2019), as the sub-industry shocks are perfectly correlated, standard error estimations for the adjusted case are again clustered by more aggregated industries (as described in equation 37 in Adao, Kolesár, and Morales, 2019). Since the clustered version of the AKM-standard error only requires shocks to be independent across industry clusters but not within, this clustering should alleviate problems arising from the inherent dependence of the industry shock built into the described adjustment.

As can be seen in column 8 of Table A10, the adjustment described in equations 11 to 14 results in markedly higher standard error estimates. Both the clustered and unclustered versions of the adjustment result in standard error estimates that are on average between around 340% and 380% larger than in the unadjusted case for the 2SLS estimations. These results suggest that the baseline AKM-standard errors are indeed downward biased due to the insufficient number of industry level robotization shocks. Including additional control variables appears to somewhat alleviate this issue, however also in the specification including all available control variables the adjusted standard error estimates in the 2SLS estimation are still between around 150% and 220% larger than in the unadjusted case.

Interestingly the unclustered version of the adjustment result in a stronger increase in the size of the estimated standard error (+216%) than the clustered version (+149%), while there is almost no difference between the AKM and the AKM0 standard error.

Given the estimation results in Table A10, I apply the described adjustment to all estimations of the AKM-standard error throughout the analysis, as this results in more conservative standard error estimates. I do this to mitigate concerns about a possible downward bias in these standard errors due to the small number of industry level observations. Since the unclustered version of the adjustment results in more conservative estimates, I do not cluster by more aggregated industries. Given that there is little difference between the AKM and AKM0 standard errors in Table A10, I use the baseline AKM-standard errors. Additionally all estimations in the main part of the paper also report conventional heteroskedasticity robust standard errors, as these standard errors are generally larger than the (adjusted or unadjusted) AKM-standard errors.

Table A11:
Correspondence between IFR and NACE Rev. 2 used in the adjustment of the AKM-standard erros

IFR		NACE Rev. 2	
Code	Name	Code	Name
Manufacturing industries:			
s10_12	Food products, beverages and tobacco	C 10	Food products
		C 11	Beverages
		C 12	Tobacco products
s13_15	Textiles, leather, wearing apparel	C 13	Textiles
		C 14	Wearing apparel
		C 15	Leather and related products
s16	Wood, products of wood (incl. wood furniture) and products of cork	C 16	Wood, products of wood and cork, (excl. furniture) Articles of straw and plaiting materials
		C 3101	Office and shop furniture
		C 3102	Kitchen furniture
		C 3109	Other Furniture
s17_18	Paper and paper products, publishing & printing	C 17	Paper and paper products
		C 18	Printing and reproduction of recorded media
s19	Chemical products, pharmaceuticals, cosmetics	C 204	Soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations
		C 21	Basic pharmaceutical products and pharmaceutical preparations
s20_21	Unspecified chemical, petrolium products	C 19	Coke and refined petroleum products
		C 201	Basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms
		C 202	Pesticides and other agrochemical products
		C 203	Paints, varnishes and similar coatings, printing ink and mastics
		C 205	Other chemical products
		C 206	Man-made fibres
s22	Rubber and plastic products without auto parts	C 221	Rubber products
		C 222	Plastic products
s23	Glass, ceramics, stone, mineral products n.e.c.	C 231	Glass and glass products
		C 232	Refractory products
		C 233	Clay building materials
		C 234	Other porcelain and ceramic products
		C 235	Cement, lime and plaster
		C 236	Articles of concrete, cement and plaster
		C 237	Cutting, shaping and finishing of stone
		C 239	Abrasive products and non-metallic mineral products n.e.c.
s24	Basic metals (iron, steel, aluminium, copper, chrome)	C 241	Basic iron and steel and of ferro-alloys
		C 242	Tubes, pipes, hollow profiles and related fittings, of steel
		C 243	Products of first processing of steel
		C 244	Basic precious and other non-ferrous metals
		C 245	Casting of metals
s25	Metal products (without automotive part), except machinery and equipmen t	C 251	Structural metal products
		C 252	Tanks, reservoirs and containers of metal
		C 253	Steam generators, except central heating hot water boilers
		C 254	Weapons and ammunition
		C 255	Forging, pressing, stamping and roll-forming of metal powder metallurgy

Source: International Federation of Robotics

Table A9:
Correspondence between IFR and NACE Rev. 2 used in the adjustment of the AKM-standard erros (continued)

IFR		NACE Rev. 2	
Code	Name	Code	Name
		C 256	Treatment and coating of metals; machining
		C 257	Cutlery, tools and general hardware
		C 259	Other fabricated metal products
s260_261	Electronic components/devices and Semiconductors, LCD, LED (incl. solar cells and solar thermal collectors)	C 261	Electronic components and boards
s262	Computers and peripheral equipment	C 262	Computers and peripheral equipment
s263	Info communication equipment domestic and professional (TV, radio, CD, DVD-Players, pagers, mobile phones, VTR etc.) without automotive parts	C 263	Communication equipment
		C 264	Consumer electronics
s265	Medical, precision and optical instruments	C 265	Instruments and appliances for measuring, testing and navigation; watches and clocks
		C 266	Irradiation, electromedical and electrotherapeutic equipment
		C 267	Optical instruments and photographic equipment
s271	Electrical machinery and apparatus n.e.c. (without automotive parts)	C 271	Electric motors, generators, transformers and electricity distribution and control apparatus
		C 272	Batteries and accumulators
		C 273	Wiring and wiring devices
		C 274	Electric lighting equipment
s275	Household/domestic appliances	C 275	Domestic appliances
s279	Electrical/electronics unspecified	C 279	Other electrical equipment
s28	Industrial machinery	C 281	
		C 281	General-purpose machinery
		C 282	Other general-purpose machinery
		C 283	Agricultural and forestry machinery
		C 284	Metal forming machinery and machine tools
		C 289	Other special-purpose machinery
s29	Motor vehicles, motor vehicle engines and bodies	C 291	Motor vehicles
		C 292	Bodies (coachwork) for motor vehicles; trailers
		C 293	Parts and accessories for motor vehicles
s30	Other transport equipment	C 301	Ships and Boats
		C 302	Railway locomotives and rolling stock
		C 303	Air and spacecraft and related machinery
		C 304	Military fighting vehicles
		C 309	Transport equipment n.e.c.
s91	Other Manufacturing		
Non-Manufacturing industries:			
sA	Agriculture, hunting and forestry, fishing	A	Agriculture, Forestry, Fishing
sB	Mining and quarrying	B	Mining and quarrying
sDE	Electricity, gas and water supply	D	Electricity, gas, steam and air conditioning supply
		E	Water supply; sewerage, waste management and remediation
sF	Construction	F	Construction
sP	Education, research and development	P	Education
		M 72	Scientific research and development

Source: International Federation of Robotics