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Alexander M. Danzer, Carsten Feuerbaum, Fabian Gaessler

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Labor Supply and Automation Innovation

Abstract

While economic theory suggests substitutability between labor and capital, little evidence exists regarding the causal effect of labor supply on inventing labor-saving technologies. We analyze the impact of exogenous changes in regional labor supply on automation innovation by exploiting an immigrant placement policy in Germany during the 1990s and 2000s. Difference-in-differences estimates indicate that one additional worker per 1,000 manual and unskilled workers reduces automation innovation by 0.05 patents. The effect is most pronounced two years after immigration and confined to industries containing many low-skilled workers. Labor market tightness and external demand are plausible mechanisms for the labor-innovation nexus.

JEL-Codes: O310, O330, J610.

Keywords: labor supply, automation, innovation, patents, labor market tightness, quasi-experiment.

Alexander M. Danzer
KU Eichstaett-Ingolstadt / Germany
alexander.danzer@ku.de

Carsten Feuerbaum
KU Eichstaett-Ingolstadt / Germany
carsten.feuerbaum@ku.de

Fabian Gaessler
Max Planck Institute for Innovation and Competition, Munich / Germany
fabian.gaessler@ip.mpg.de

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1 Introduction

Are man and machine substitutes? Empirically, the labor share in national income has been falling since the 1980s and one potential explanation may be the increased capital intensity of production, i.e., labor-saving technological progress (Salomons et al., 2018; Karabarbounis and Neiman, 2014). This observation revives an older theoretical debate on whether labor supply can affect firms' investments into labor-saving innovation (Habakkuk, 1962; Hicks, 1932). In a more recent theoretical contribution, Acemoglu (2010) suggests that labor scarcity may induce technological progress if new technologies are *strongly labor saving*.[1] The substitutability between labor and capital should be particularly relevant in jobs where automation innovation is technically feasible and efficiency enhancing. Despite the topic's economic and societal relevance, empirical studies on the response of automation innovation to changes in labor supply have remained scarce.

This paper provides first evidence on the causal effect of regional labor supply on automation innovation by firms – i.e., the development of labor-saving technologies. For identification, we rely on plausibly exogenous variation in immigration, which has been found to affect regional wages and employment (e.g., Card, 1990; Borjas, 1994; Dustmann et al., 2008, 2017; Peri and Sparber, 2009). Our analysis takes advantage of the quasi-experimental placement of ethnic Germans across German regions during the 1990s and 2000s.[2] Following the collapse of the Soviet Union, approximately 2.5 million ethnic Germans entered Germany between 1990 and 2006. Most of the new German citizens came from the low end of the skill distribution and competed with the resident labor force for low-skilled manual jobs. To ensure a more even distribution of these immigrants across regions, most German states introduced an allocation policy, which became binding in 1996/97. We exploit this allocation policy to disentangle the effect of positive labor supply shocks on automation innovation from potential bias that would occur if immigrants self-selected into regions. The dispersion of migrants across Germany thus provides a unique setting for causal inference.

We analyze the effect of labor supply on automation innovation in a difference-in-differences framework. The approach compares automation innovation in region-year pairs with differential labor supply shocks resulting from the quasi-experimental placement of ethnic Germans. The empirical analysis is based on a newly constructed panel data set at the labor market-year level. Our main outcome variables are novel measures of automation innovation, based on geo-coded patent data from the European Patent Office that are matched to labor market regions using the OECD REGPAT Database (Maraut et al., 2008). While patents are assigned to specific technology classes during examination, the bibliographic information does not reveal automation vs. non-automation inventions. We therefore identify automation patents by relying on text-based classification algorithms. The key explanatory variable (labor supply) is operationalized as the lagged exogenous ethnic German inflow divided by the total workforce in the previous year. Regional controls include GDP per capita, the unemployment rate, and precise measures of the skill and occupation composition of the

[1] *Strongly labor saving* implies that technological advances decrease the marginal product of labor.

[2] Glitz (2012) is the first to exploit the placement of the ethnic Germans for investigating the labor market effects of labor supply shocks.

workforce based on high-quality administrative data from the Institute for Employment Research (IAB). By including region fixed effects and time fixed effects, we account for time-invariant systematic differences across regions and for nationwide time trends in automation innovation. Our identification uses a pure spatial approach that captures the total automation innovation effect of labor supply shocks at the regional level, similar to Boustan et al. (2010) and Dustmann et al. (2017).[3] It rests on the common trends assumption for which we provide empirical support.

We find that the exogenous labor supply shock has a statistically significant negative effect on automation innovation activities in the respective region: an increase by one ethnic German per 1,000 workers of *any skill* level leads to a decline in the regional share of automation innovation by 0.75 percentage points and in the level of automation innovation by 4.3 percent. Since the labor supply shock mostly affects the lower end of the skill distribution, we also express the effect size relative to the stock of *manual* and *unskilled* workers in the respective region: an increase by one ethnic German per 1,000 manual and unskilled workers reduces the number of automation patents by 0.41 percent. This equals a loss of about 0.05 automation patents for the median region. With an average of 22.8 ethnic Germans per 1,000 manual and unskilled workers, the reduction in automation patents is economically significant. In contrast, we do not find any significant effects of labor inflows on the level of non-automation innovation ruling out a product demand effect of labor supply shocks.

The impact on automation innovation is concentrated in the first and second year after the labor supply shock, in mechanical engineering and among corporate patent applicants. Our results indicate that small and young firms react more strongly than large and old firms. We find that the substitution between workers and automation innovation is much stronger in regions where labor is scarce compared to regions plagued by unemployment. These findings are in line with the established notion that labor inflows relax labor supply shortages in tight markets, but have little impact on labor abundant markets. We also illustrate that the effect originates from industries that employ large numbers of low- and un-skilled workers. Finally, we find suggestive evidence that not only internal but also external demand drives these R&D responses. A variety of robustness checks regarding the estimation technique, lag structures, the weighting of the data, the observation period, regional subgroups, and alternative measures of automation innovation corroborate our causal interpretation.

The contributions of our paper are twofold: First, our study provides causal evidence on the regional effects of labor supply on automation innovation in a current setting. We, hence, contribute empirically to a predominantly theoretical literature that relates relative factor supplies to the direction of technological change (e.g., Acemoglu, 2002, 2007; Hanlon, 2015; Kiley, 1999). The few existing empirical tests are from contemporary history and remain inconclusive: San (2019) finds increased invention activities in the US farming industry due to labor shortages following the exclusion of Mexican workers in the 1960s. In contrast, Doran and Yoon (2019) study the effect of US mass immigration in the early 20th century and find a *positive* relationship between low-skilled

[3]The regionality of effects is rationalized by evidence according to which production activity and innovative activity tend to cluster in the same regions (e.g., Paci and Usai, 2000).

worker inflows and the overall rate of innovation. Using cross-country variation on wages and firm-level data on distinct patenting activities, the results from Dechezleprêtre et al. (2019) suggest that an increase in low-skilled wages increases automation innovation. Our paper also relates to the literature on the role of factor endowments for technology adoption (e.g., Zeira, 1998). Prior research suggests that firms absorb shifts in regional labor supply by switching to the most cost-efficient production technology (e.g., Hanson and Slaughter, 2002; Dustmann and Glitz, 2015; Zator, 2019). In fact, Clemens et al. (2018), Lewis (2011), Imbert et al. (2019), and Monras (2019) find that low-skilled labor supply explains firm adoption of production technologies. We complement these findings and show that firms do not only *adopt* but also *develop* these technologies as evidenced by their increased automation patenting activities. Lastly, we complement the recent literature concerning the effect of immigration on the overall level of innovation (e.g., Hornung, 2014; Hunt and Gauthier-Loiselle, 2010; Kerr et al., 2015; Moser et al., 2014). While most previous studies analyze the effect of high-skilled immigration, we add a labor replacement perspective based on low-skilled immigration.

Second, a distinguishing feature of our work is that we explore the mechanism of how labor supply affects automation innovation. Prior research shows that the inflows of ethnic Germans had no effect on wages (Glitz, 2012), a result which is compatible with Germany's strong labor market regulation and powerful unions. In the paper we open the black box of the labor-innovation nexus by separately adressing the market for labor and for innovation. First, focussing on the labor market side we analyze the ease of establishing employment based on variation in pre-existing labor market tightness across a large number of labor market regions. Second, focussing on the innovation side we investigate whether internal (i.e., in-house) or external (i.e., market) demand drives the innovation response of firms.

The remainder of this paper is structured as follows: Section 2 describes the institutional background of the quasi-experimental placement of ethnic Germans in the 1990s and 2000s. Section 3 presents the data sets used in the empirical part of the paper and the underlying patent classification algorithm. Section 4 describes the econometric model and provides empirical support for the identifying assumption. We present the results in Section 5 and robustness analyses in Section 6. Section 7 concludes.

2 Institutional Background: Germany's Migration Placement Policy

After the fall of the Iron Curtain, Germany experienced a massive permanent resettlement of ethnic Germans from Eastern Europe (Klose, 1996). Approximately 2.5 million ethnic Germans – around 3.1 percent of Germany's population and 6.7 percent of its workforce – immigrated between 1990 and 2006 (Bundesverwaltungsamt, 2019). The incoming ethnic Germans were descendants of German speaking emigrants to Eastern Europe in the 18th and 19th centuries (Bade, 1990).[4] Prospective ethnic German immigrants had to apply for visa at the German embassy in their home country and provide proof of German ancestry. Successful applicants were granted entry into Germany subject to annual immigration quotas (from 1993: 225,000, from 1999: 100,000). Annual inflows of ethnic Germans to Germany amounted to about 200,000 per year until 1995, before they fell to around 100,000 per year thereafter (see Figure A-1 on inflows from the Former Soviet Union).[5]

Upon arrival in Germany, these immigrants were sent to central admission centers and naturalized, implying that they could immediately take up work (Dietz, 2006; Ohliger, 2008). To prevent the emergence of residential enclaves, the government had enacted a regional allocation policy for ethnic Germans in 1989; however, the rule remained inoperative until 1996. During these early years many ethnic Germans self-selected into clusters of co-ethnics, so that newly arrived ethnic Germans comprised 20 percent or more of the population in some regions (Klose, 1996). In consequence, most West German federal states except Bavaria and Rhineland-Palatinate made the allocation rule compulsory from March 1996, with Lower Saxony following in April 1997 and Hesse in January 2002. Figure 1 highlights the West German states which implemented the Assigned Place of Residence Act (with thick edging).[6] The policy assigned immigrants to one of the federal states according to historical state quotas that were originally developed for budget rules (*Königsteiner Schlüssel*[7]). Within the respective states, incoming ethnic Germans were further allocated to counties according to relative population size.[8] Immigrants were unable to choose their destination in Germany and their allocation was not determined by labor market considerations, such as educational endowments (see Glitz, 2012, for more details). After their placement, immigrants were bound to stay in their allocated county for at least three years; non-compliance was heavily sanctioned with the loss of most welfare benefits. Therefore, compliance with the rules was very high, actual immigration matched the allocated quotas well (Dietz, 2006) and the policy was considered successful (Federal Constitutional Court (1 BvR 1266/00, Rn. 1-56)).

The majority of incoming ethnic Germans was of working age and with working experience in their countries of origin. Their predominant work experience referred to manual occupations, such as farmers, laborers, transport workers, operatives and craft workers, according to official an-

[4] Many ancestors had followed a resettlement offer by Russian Empress Catherine the Great in 1763 (granting land and religious freedoms).

[5] Between 1992 and 2006, 95.7 percent of ethnic Germans originated from the successor states of the USSR (Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Russian Federation, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan). This share increased to over 98 percent after the implementation of the placement policy in 1996.

[6] See Appendix Table B-2 for details regarding the analysis sample and the implementation of the assigned place of residence act.

[7] The state quotas are based on population size (with weight 1/3) and tax revenues (with weight 2/3). A comparable rule for the UK is the Barnett Formula.

[8] Meeting these quotas was of utmost priority, but anecdotal evidence suggests that the allocation was relaxed in particular cases: ethnic Germans could be exempted if they were able to provide proof of registered employment *and* sufficient housing in a different county *and* were willing to waive social benefits. No data exist on the number of immigrants using this exemption, but only 11 percent of ethnic Germans did not receive any kind of social benefits during the first three years after arrival, according to Haug and Sauer (2007). Consequently, the number of exemptions was certainly small.

nual statistics published by the *Bundesverwaltungsamt*. Most arrivals were low-skilled or had poor prospects of receiving recognition for their outdated skills which had been acquired in a different economic system (Koller, 1993; Bundesverwaltungsamt, 2019). The few formally high-skilled migrants faced considerable barriers to the recognition of their qualifications and experienced significant skill downgrading (e.g., Eckstein and Weiss, 2004; Danzer and Dietz, 2014). Despite their German ancestry, many immigrants had a limited account of the German language. Over the period 1992 to 2002 the share of immigrants with working experience and their occupational distribution were quite stable, suggesting a constant quality of immigration cohorts (Figures A-2b and A-2a).

To summarize, the immigration of ethnic Germans provides a quasi-experimental setting, which helps overcoming the potential bias from the self-selection of immigrants into specific regions: In the absence of a placement policy immigrants might have either chosen regions with declining trends in (labor-replacing) automation innovation or booming regions with high levels of automation innovation, depending on their belief about labor market conditions. The resultant reverse causality would bias the empirical estimates. In line with our considerations, earlier studies have documented the exogeneity of regional inflows of ethnic Germans with respect to regional conditions of the labor market (Glitz, 2012), crime (Piopiunik and Ruhose, 2017), or the capacity to innovate (Jahn and Steinhardt, 2016). In Section 4 we provide empirical support for the identifying assumption that immigrant inflows can be considered exogenous to regional automation innovation.

3 Data

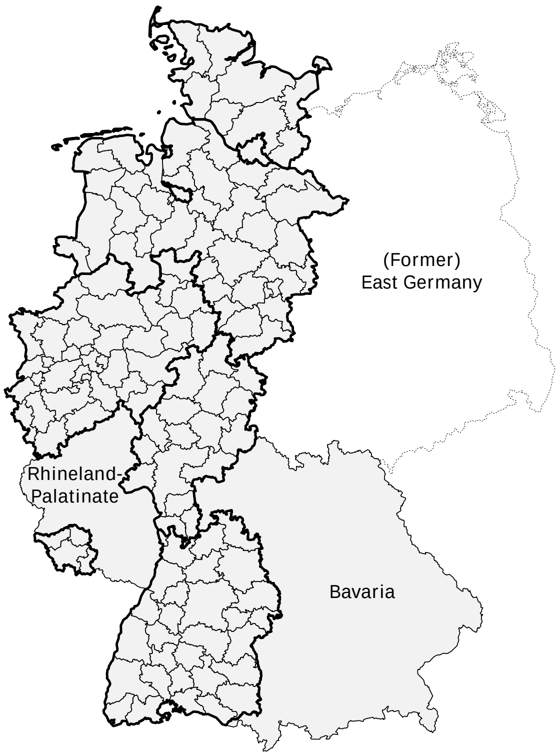
Our analysis exploits a balanced regional panel with yearly information spanning the time period 1992-2006; it covers the pre-allocation period from 1992 to 1995 and the period of legally enforced allocation thereafter.[9] The research is staged at the level of German labor market regions (*Arbeitsmarktregionen*), following Glitz (2012). These labor market regions comprise one or several counties and have been designed – based on commuter flows – to capture regional labor markets (Federal Office for Building and Regional Planning, 2019). Following prior studies we restrict our analysis to labor markets in West Germany, since East Germany experienced severe adjustment processes following the German reunification. The sample also excludes states without binding allocation policy (Bavaria and Rhineland-Palatinate).[10] Our analysis sample contains 127 labor market regions for 15 years.[11] The data combine regionalized information on automation innovation, immigrant inflows and regional economic conditions from several data sources.

[9] We do not analyze the years before 1992, because the selection of ethnic Germans was different before the collapse of the Soviet Union (1991). Also, regional data on migrant inflows are not systematically available before 1992. After 2006 the number of incoming ethnic Germans was negligible.

[10] No regional data on ethnic German inflows were recorded for the state of Bavaria (Glitz, 2012). With Baden-Württemberg and North Rhine-Westphalia our sample includes the most innovative and most populous federal states.

[11] For details on the assignment of labor market regions to the analysis sample, see Table B-2 in the Appendix. We exclude the labor market region of Ulm from our analysis because it is partly in the state of Bavaria, which did not implement the placement policy.

Figure 1: West German states with allocation policy



Notes: The black lines denote state or labor market region borders. With the exception of Bavaria and Rhineland-Palatinate all states in West Germany introduced the allocation policy. See Appendix Table B-2 for details on the analysis sample. Figure based on a shapefile of the Federal Republic of Germany from Eurostat and a reference file on counties and labor market regions from the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR).

3.1 Automation Innovation

The automation innovation measure is based on all patent applications filed at the European Patent Office (EP patents) by inventors located in the West German allocation states with a priority date between 1992 and 2010. The priority date reflects the filing date of the first application in case several applications have been submitted for the same invention at different patent offices; this ensures the best approximation for the date of the inventive activity (e.g., OECD, 2009). The focus on EP patents has, first, the advantage that it features Europe-wide instead of domestic patent protection. Accordingly, the underlying inventions tend to be of comparatively higher economic value. Second, practically all EP patents feature English descriptions, regardless of their origin; this renders language-specific adjustments of our text-based method unneccessary.[12] We rely on the text and

[12]If not directly available, we draw on English publications within the same DOCDB patent family available from other patent offices, where English is the official language (e.g., the USPTO and the UKIPO). For more than 99.86 percent of the patent applications the English abstract is available in PATSTAT. Patent applications with a missing English abstract are excluded for the construction of the regional measures of automation innovation.

bibliographic data as provided by the PATSTAT database (2017 Autumn Edition). While our main analysis focusses on patent applications of corporate entities, we also investigate patents with at least one non-corporate applicant (e.g., a natural person or a university).[13]

Classification of Patents

We classify patent applications into automation vs. non-automation innovations by searching the invention descriptions for word stems related to automation. First, we pre-process the English patent abstracts to reduce the high-dimensionality of text features, following standard text mining procedures: this involves tokenizing, case-folding each alphabetic token into lowercase and removing punctuation, numbers and stop words. The idea is that the relevant information in words is stored in their linguistic root, not in their grammatical form. Words are mapped to their linguistic root using the English version of a commonly employed stemming algorithm (Porter et al., 1980). For instance, the words "automate" and "automation" are transformed to their common word stem "automat". Second, the actual classification is based on a simple Boolean search algorithm: if a pre-processed English abstract contains one of the eight stemmed substrings "automat", "execut", "detect", "input", "system", "display", "output" or "inform", we classify the patent application as an automation patent, and as a non-automation patent otherwise.[14] Even though this classification method does not rely on any sophisticated semantic-based analysis, it performs well in manual checks.[15] In robustness tests, we show that our main findings are robust to variations in the set of automation keywords (with one, six or ten substrings).

We assign each automation and non-automation patent to one of five main technology areas: "Chemistry", "Electrical Engineering", "Instruments", "Mechanical Engineering" and "Other Technology Areas". For this purpose, we map the 34 International Patent Classification (IPC) codes to the five main technology areas using the concordance table developed by the Fraunhofer ISI and the Observatoire des Sciences et des Technologies in cooperation with the French Patent Office (Schmoch, 2008). This allows us to explore the effects of labor supply shocks on automation innovation across the five technology areas. For illustrative purposes, Figure A-4 presents the share of automation patents across technology areas for all eight automation keywords appearing in the patent abstracts.

To assess the accuracy of our classification method we, first, cross-check our sample of EP patents with overlapping classified US patents data from Mann and Püttmann (2018).[16] Both automation

[13]We identify corporate vs. non-corporate entities with the sector categorization provided by PATSTAT. We consider applicants as corporate entity if they are labeled as either "Company", "Company Gov Non-Profit" or "Company Hospital". Non-corporate entities are labeled as "hospital", "individual", "governmental non-profit university", "governmental non-profit" or "university". In the very rare case of missing applicant entity, we assume that the applicant entity is corporate.

[14]The set of keywords is borrowed from Mann and Püttmann (2018), who created a manually labelled training data set of 560 granted patents to eventually classify all USPTO patents as automation vs. non-automation inventions.

[15]Table B-21 presents examples of automation patents with their full English abstract.

[16]We can link 41 percent of the EP patents in our data set to their equivalent in the US data set through a common DOCDB patent family number.

indicators are highly correlated: our measure is equal to theirs in 77.3 percent of cases, with a correlation coefficient of 0.45.[17] Second, we consider whether the share of automation innovation across 34 IPC classes is consistent with common perception of automatability. Indeed, the share of automation innovation is high in IPC classes that involve high levels of automation such as “IT Methods”, “Telecom” and “Transportation”, but low in classes such as “Organic Chemistry” and “Polymers” (Figure A-3).

Figure A-5 shows the annual number of patent applications related to automation and non-automation between 1992 and 2006. Although there was a general rise in the total number of patents, the increase was particularly strong for automation inventions. The number of automation patents has increased from about 1,500 per year in 1992 to more than 4,500 in 2006. Figure A-6 presents the share of automation patents by main technology areas over time. The shares of automation patents differ considerably between areas but remain fairly stable during our observation period.

Regionalization of Patents

We assign all patent applications to regions using the inventors’ region of residence as inferred from the geocoded address information in the OECD REGPAT Database (March 2018 edition).[18] If a patent application lists multiple inventors, we divide the respective patent application equally among all the inventors’ regions of residence using fractional counts.[19] Then, we construct a labor market region-year panel data set on the number of automation and non-automation patent applications for the years 1992 to 2010, based on the priority year of patent applications.[20] The map in Figure A-8 shows the geographic distribution of the regional share of automation patents in all patents, i.e., the relative incidence of automation innovation across labor market regions, for the period 1992 to 2006.

3.2 Ethnic German Inflows and Other Regional Data

The key explanatory variable comprises official annual regional inflows of ethnic German immigrants, as reported by the federal admission centers.[21] The variable is defined as the ethnic German inflow in $t-2$ divided by the regional workforce in $t-3$ (in thousands). We allow for two lags in

[17] Note that the out-of-sample error rate of the algorithm by Mann and Püttmann (2018) is 22.6 percent, thereby putting an upper bound to the correlation with our measure. Overall, our automation patent classification shows a lower recall rate, which renders our approach more conservative than theirs.

[18] Note that we merge the labor market regions “Osterode” and “Goettingen” to make the patent data compatible with the regional data on education groups and skill groups.

[19] This also applies to patent applications with foreign co-inventors.

[20] We assign NUTS3 regions to labor market regions using a reference file from the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR).

[21] While we use the inflow data made available by Glitz (2012) and Piopiunik and Ruhose (2017), the original data are provided by the federal admission centers for the years 1992 to 2001. The official data from 2002 to 2006 are provided by the Bundesarbeitsgemeinschaft Evangelische Jugendsozialarbeit e.V., Jugendmigrationsdienste.

order to reflect the delayed impact of labor supply shocks on innovation and patenting. Since immigrants were locked into their initially assigned region for the first three years, our operationalization does not introduce any potentially spurious post-placement mobility of ethnic Germans.

We supplement the panel data set with a rich set of regional control variables:[22] the size of the labor force and the share of unemployed workers are from the German Employment Office, population size, gross domestic product (GDP), and different measures of gross value added (GVA) are from the Working Group Regional Accounts VGRdL[23], and the regional share of the stock of non-natives are from INKAR online and from Glitz (2012).[24] We amend the data set with regional shares of older age workers (> 55 years), three skill groups, and twelve occupation groups using employment data from the Institute for Employment Research (IAB) Establishment History Panel: skill groups (medium skilled, high skilled, engineers and scientists) proxy for regional innovative capacity and R&D personnel while occupation groups account for the regional industrial structure. Since recent research has shown that population ageing might stimulate the adoption of automation technologies (Acemoglu and Restrepo, 2019; Zator, 2019), we also include a control variable for the share of older workers. Since the IAB data use the *full population* of all establishments with at least one employee subject to security contributions in Germany,[25] the data provide precise measures of these regional groups.

3.3 Descriptive Statistics

Table 1 reports summary statistics for the region-year panel data set. On average, 91.8 patent applications are filed per labor market region in a given year. Out of these, 24.0 patents are categorized as automation patents. The large standard deviation of 56.9 reflects the substantial variation in the automation innovation capacity across Germany, with several high performing regions. We log-transform the patent count variables for the empirical analysis to account for this right-skewed distribution.[26] The average share of automation patents in total patents per region is 23.0 percent.[27] The average annual ethnic German inflow equals 535.9 immigrants per region. This corresponds to an inflow rate of 3.89 ethnic Germans per 1,000 workers in a region over the whole period.

Table 1 also reports summary statistics on lagged regional control variables such as population size, the overall share of the non-native population (average 8.5 percent), GDP per capita (average 23,000 EUR), and the unemployment rate (average 10 percent). The table further reports fractions of older workers, of three different skills groups and of twelve occupation groups.

[22] See Table B-1 for an overview of regional characteristics and their sources.

[23] The statistical offices of all German states and the Federal Statistical Office are members of the Working Group Regional Accounts VGRdL.

[24] The data from Glitz (2012) are based on the German Statistical Office. These and INKAR online exhibit a very high degree of consistency for the overlapping years.

[25] From 1999 onwards, the data set also covers marginally employed persons.

[26] Since a very small number of regions contains zero filed patent applications in a given year, we add plus one to every region-year observation before log-transforming the variables.

[27] The share of automation patents is not available for two observations because there were zero patent applications in two region-year pairs.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min	Max	N
Innovation					
Patents	91.77	172.13	0.00	1938.92	1849
Log Patents	3.81	1.19	0.00	7.57	1849
Automation patents	24.00	56.94	0.00	718.72	1849
Log Automation patents	2.40	1.22	0.00	6.58	1849
Automation patents / patents	23.01	11.14	0.00	88.89	1847
Non-automation patents	67.77	118.09	0.00	1251.35	1849
Log Non-automation patents	3.55	1.16	0.00	7.13	1849
Ethnic German Inflows					
$\text{Inflow}_{\text{t-2}}$	535.92	666.64	0.00	7342.00	1849
$\text{Inflow rate}_{\text{t-2}}$	3.89	3.57	0.00	39.31	1849
Population and Economic Indicators					
$\text{Log Population}_{\text{t-3}}$	12.51	0.73	11.27	14.83	1849
$\text{Share of non-natives}_{\text{t-3}}$	8.49	3.47	1.88	25.64	1849
$\text{GDP per capita (in thous. €)}_{\text{t-3}}$	22.95	4.84	12.07	44.78	1849
$\text{GVA total}_{\text{t-3}}$	8.61	0.84	6.94	11.46	1849
$\text{GVA production}_{\text{t-3}}$	7.52	0.82	5.89	10.32	1849
$\text{GVA services}_{\text{t-3}}$	8.14	0.90	6.43	11.23	1849
Labor Market					
$\text{Log Labor Force}_{\text{t-3}}$	11.65	0.74	10.37	14.03	1849
$\text{Unemployment rate}_{\text{t-3}}$	0.10	0.03	0.03	0.18	1849
$\text{Share age} > 55_{\text{t-3}}$	0.11	0.02	0.06	0.17	1849
Skill Groups					
$\text{Share medium skilled}_{\text{t-3}}$	0.73	0.03	0.61	0.81	1849
$\text{Share high skilled}_{\text{t-3}}$	0.07	0.03	0.03	0.18	1849
$\text{Share research and development}_{\text{t-3}}$	0.02	0.01	0.00	0.06	1849
Occupation Groups					
$\text{Share agricultural}_{\text{t-3}}$	0.02	0.01	0.01	0.09	1849
$\text{Share unskilled manual}_{\text{t-3}}$	0.16	0.05	0.05	0.35	1849
$\text{Share unskilled services}_{\text{t-3}}$	0.15	0.04	0.09	0.28	1849
$\text{Share unskilled commercial and admin.}_{\text{t-3}}$	0.09	0.01	0.06	0.16	1849
$\text{Share skilled manual}_{\text{t-3}}$	0.17	0.03	0.09	0.27	1849
$\text{Share skilled services}_{\text{t-3}}$	0.05	0.01	0.03	0.08	1849
$\text{Share skilled commercial and admin.}_{\text{t-3}}$	0.18	0.03	0.10	0.32	1849
$\text{Share technicians}_{\text{t-3}}$	0.05	0.01	0.02	0.13	1849
$\text{Share semiprofessions}_{\text{t-3}}$	0.06	0.01	0.03	0.10	1849
$\text{Share engineers}_{\text{t-3}}$	0.02	0.01	0.01	0.07	1849
$\text{Share professions}_{\text{t-3}}$	0.01	0.01	0.00	0.04	1849
$\text{Share managers}_{\text{t-3}}$	0.02	0.01	0.01	0.05	1849

Notes: Summary statistics of the region-year panel data set computed for the period 1994 to 2008. Automation patents: number of automation patents filed in year t. Automation patents / patents: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Non-automation patents: number of non-automation patents filed in year t. $\text{Inflow}_{\text{t-2}}$: ethnic German inflows in $t-2$. $\text{Inflow rate}_{\text{t-2}}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

4 Empirical Framework

We estimate the impact of labor supply on innovation using a difference-in-differences design, based on the quasi-exogenous placement of ethnic Germans over time. The panel structure of our data set allows us to observe regional innovative activities and inflows of ethnic German in consecutive years before and after the introduction of the binding allocation policy. The allocation policy followed a staggered roll-out, starting in the year 1996 for 76, in the year 1997 for 34 and in the year 2002 for 17 labor market regions.[28]

We estimate the following OLS model with region and time fixed effects at the region-year level:

$$\begin{aligned} y_{rt} = \beta_0 \; + \; \beta_1 \frac{I_{rt-2}}{L_{rt-3}} \; + \; \beta_2 \, P_{rt-2} \\ + \; \beta_3 \, P_{rt-2} \times \frac{I_{rt-2}}{L_{rt-3}} \; + \; X'_{rt-3} \, \vartheta \; + \; \delta_r \; + \; \tau_t \; + \; \eta_{rt} \; + \; \epsilon_{rt}, \end{aligned} \tag{1}$$

where the dependent variable y_{rt} is either (i) the share of automation innovation $\frac{A_{rt}}{N_{rt}}$ filed in region r in year t, (ii) the level of automation innovation in logs $\ln(A_{rt}+1)$, or (iii) the level of non-automation innovation in logs $\ln(NA_{rt}+1)$. We estimate both, intensity effects (i) and scale effects (ii/iii) since low numbers of total patents in some regions might introduce measurement error in the estimated share (i). Also, the effect on the share of automation patents is sensitive to changes in the total number of patents (i.e., the denominator of (i)) over time.

The continuous treatment $\frac{I_{rt-2}}{L_{rt-3}}$ corresponds to the lagged region-year specific inflow of ethnic Germans to region r in year $t-2$ divided by the pre-existing workforce in $t-3$.[29] As advocated by Dustmann et al. (2016), we employ a pure spatial approach relating automation innovation to immigrant inflows. Our approach covers the *total* innovation effect of immigration-induced labor supply shocks at the regional level taking into account complementarities across regional skill groups. This approach is also immune to misclassification due to skill downgrading.[30] P_{rt-2} is a dummy variable that equals 1 if the state-wide allocation policy was binding in region r in $t-2$.

Our estimation includes a rich set of regional time-variant control variables X'_{rt-3} such as population size, the overall share of the non-native population, the unemployment rate, GDP per capita, different variables on gross value added, the share of employees older than 55, three skill groups and twelve occupation groups. By including region-fixed effects δ_r, we control for time-invariant unobserved factors across regions such as the general capacity to innovate in automation technologies. We account for the national time trend in innovation by including time-fixed effects τ_t. Finally, we include year-by-state fixed effects η_{rt} to account for systematic changes in automation innovation

[28]See Table B-2 for details on the regional analysis sample and the state-level implementation of the assigned place of residence act. While the allocation policy remained in effect until 2009, regional data on ethnic German inflows are not available for the years after 2006.

[29]Note that we also investigate the robustness of results by employing alternative lag structures ranging from t to $t-3$. Alternative empirical models with an overlapping data structure (Section 6.3) or poisson regressions (Section 6.4) yield similar results.

[30]Note that the occurrence of skill downgrading is particularly pronounced in the first years after arrival of immigrants (Dustmann et al., 2017).

that are common to all regions within the same state over time, such as state-level support infrastructure or subsidies. The error term is ϵ_{rt}. We cluster standard errors at the level of labor market regions to account for correlations within regions over time. Region-year observations are weighted with pre-determined regional population sizes as of 1991.[31]

Our regression models identify the effect of labor supply shocks on automation innovation from the variation of ethnic German inflows into a region over time. The coefficient β_1 captures the effect of the potentially endogenous inflows before the introduction of the binding placement policy. The coefficient that is associated with the interaction term of treatment intensity and allocation policy dummy, β_3, corresponds to the effect difference between the inflows before the binding allocation period and the inflows during the binding allocation period. The sum of the coefficients β_1 and β_3 captures the total effect of the immigration-induced labor supply shocks during the binding allocation period. If the positive labor supply shocks reduced automation innovation, we expect negative values for the sum of β_1 and β_3. We report the total effects and the corresponding p-values in all tables.

The identification strategy hinges on the common trends assumption: It implies that in the absence of the labor supply shock all regions are on the same path of automation innovation over time. This requires the inflows of ethnic Germans to be exogenous with respect to unobserved factors that influence automation innovation. Prior research has elaborately shown that the inflows of ethnic Germans were exogenous to the regional labor market and to the overall regional innovative capacity (Glitz, 2012; Jahn and Steinhardt, 2016). To lend credibility to the identifying assumption, we need to rule out reverse causality as well as deviations in the pre-treatment period. Regarding the first, allocated migrant inflows should be unrelated to concurrent automation innovation since firms are unlikely to respond by immediately changing their patenting activities. In Section 5.1 we show that the share of automation innovation as well as the levels of automation and of non-automation innovation are indeed not associated with allocated inflows of the same year. Regarding the second, we assess pre-trends in an event study analysis. The lack of significant pre-trends in Section 5.1 solidifies our approach.

5 Results

In this section, we present our main results (Section 5.1) and examine potential mechanisms (Section 5.2). To shed light on two potential channels of how the labor market affects innovation we explore heterogeneity with respect to labor market tightness and to the origin of the demand for automation innovation.

[31] Alternatively, weighting observations with regional GDP in 1991 yields similar results.

5.1 Main Results

Table 2 shows that the effect of labor supply on the regional share of automation innovation is negative and highly significantly different from zero, irrespective of the chosen specification. Notably, the magnitudes of the estimated coefficients increase only modestly when we include year-by-state fixed effects (column 2) and time-variant regional controls (column 3). The results are also robust to controlling for the regional time-variant shares of twelve occupation groups and three skill groups (column 4). The fact that the coefficients barely change across specifications is consistent with prior research showing that the inflows are orthogonal to regional (labor market) conditions (Glitz, 2012). The total effect (reported at the bottom of the table) suggests that increasing the inflow rate by one ethnic German per 1,000 employed workers leads to a significant decline in the share of automation patents by around 0.75 percentage points (column 4, full specification). Overall, the results indicate that an exogenous increase in the low skilled workforce significantly shifts the direction of technological change away from automation innovation.

We repeat the analysis with the level of automation innovation: in line with the negative impact on the share of automation, we also find negative effects of the exogenous inflow on the number of automation patents (Table 3, column 1-4). The total effect suggests that an increase in the inflow rate by one ethnic German per 1,000 workers of *any skill* level is followed by a decline in the number of automation patents by 4.3 percent (column 4, full specification). Since the labor supply shock mostly affects the lower end of the skill distribution, we also express the effect size relative to the stock of *manual* and *unskilled* workers in the respective region (roughly 16 percent of the total workforce): an increase in the inflow rate by one ethnic German per 1,000 manual and unskilled workers reduces the number of automation patents by 0.41 percent. This equals a loss of about 0.05 automation patents for the median region (out of 11.7 automation patents per year). With an average annual inflow rate of about 22.8 ethnic Germans per 1,000 manual and unskilled workers during the binding allocation period, the total reduction of automation patents of about 1.1 patents is economically meaningful. While these estimates are not directly comparable to other studies, we confirm Dechezleprêtre et al. (2019) and San (2019) in concluding that automation innovation is quite responsive to changes in labor supply.

Finally, we run the empirical analysis with the level of non-automation innovation as outcome (Table 3, column 5-8). The estimates of the total automation innovation effect are very close to zero and statistically insignificant indicating that non-automation did not adjust to the regional labor supply shocks.

The findings suggest that regional labor supply shocks play a critical role in the direction of technological progress. They are consistent with theoretical predictions that labor scarcity will encourage labor-saving innovation. The insignificant effects of the labor supply shock on non-automation innovation serve as empirical evidence against alternative explanations, according to which systematic unobserved dynamics may drive the results regarding automation innovation (e.g., differential product demand or trends in regional exports).

Table 2: Effect of labor supply on the share of automation innovation

Dep. Var.:	Automation patents / patents			
	(1)	(2)	(3)	(4)
Inflow rate$_{t\text{-}2}$	0.069	0.106	0.110	0.139
	(0.112)	(0.105)	(0.132)	(0.132)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	−0.766***	−0.907***	−0.884***	−0.896***
	(0.193)	(0.206)	(0.208)	(0.211)
Log Population$_{t\text{-}3}$			−47.652*	−65.640**
			(26.891)	(31.622)
Log Labor force$_{t\text{-}3}$			22.653	18.834
			(15.172)	(16.523)
Unemployment rate$_{t\text{-}3}$			−15.026	−13.729
			(36.732)	(36.853)
Share of non-natives$_{t\text{-}3}$			0.085	−0.116
			(0.241)	(0.231)
GDP per capita$_{t\text{-}3}$			−0.228	−0.957
			(0.490)	(0.663)
GVA total$_{t\text{-}3}$			33.700	26.945
			(24.359)	(24.431)
GVA production$_{t\text{-}3}$			−7.165	−1.229
			(6.476)	(6.912)
GVA services$_{t\text{-}3}$			−16.391	4.003
			(11.700)	(13.373)
Share age > 55$_{t\text{-}3}$			−81.685	−5.282
			(53.888)	(60.548)
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Year-by-State fixed effects	No	Yes	Yes	Yes
Occupation + Skill groups	No	No	No	Yes
Observations	1847	1847	1847	1847
R-squared	0.556	0.581	0.584	0.591
Within R-squared	0.007	0.009	0.015	0.033
Total effect	−0.697	−0.801	−0.774	−0.757
P-value	0.000	0.000	0.000	0.001

Notes: OLS regressions. Dependent variable: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table 3: Effect of labor supply on the level of (non-)automation innovation

Dep. Var.:	Automation patents				Non-Automation patents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inflow rate$_{t\text{-}2}$	−0.008	−0.007	−0.005	−0.007	−0.015***	−0.016***	−0.011*	−0.015**
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	−0.046***	−0.048***	−0.041***	−0.035**	−0.005	0.004	0.008	0.014
	(0.015)	(0.015)	(0.015)	(0.015)	(0.010)	(0.009)	(0.009)	(0.008)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-State fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Occupation + Skill groups	No	No	No	Yes	No	No	No	Yes
Observations	1849	1849	1849	1849	1849	1849	1849	1849
R-squared	0.953	0.955	0.956	0.958	0.972	0.975	0.975	0.977
Within R-squared	0.014	0.014	0.037	0.070	0.016	0.017	0.042	0.089
Total effect	−0.054	−0.055	−0.046	−0.043	−0.019	−0.012	−0.003	−0.001
P-value	0.000	0.000	0.003	0.004	0.059	0.208	0.721	0.904

Notes: OLS regressions. Dependent variable: Column 1-4: number of automation patents filed in year t (entered in logs). Column 5-8: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Dynamics of the Effect

The dynamics of the innovation response to labor supply shocks comprises the *response time* to the shock (i.e., how soon will a firm adjust its innovation activity to the given shock?) as well as the *effect persistence* (i.e., how long does a given shock affect the innovation actitiy?). This section sheds light on both dimensions.

Response time. To explore the empirically most pertinent innovation response we estimate the following OLS models with different lag structures at the region-year level:

$$\begin{aligned} y_{rt} = \beta_0 \;+\; \beta_1 \,\frac{I_{rt-k}}{L_{rt-k-1}} \;+\; \beta_2 \, P_{rt-k} \\ +\; \beta_3 \, P_{rt-k} \times \frac{I_{rt-k}}{L_{rt-k-1}} \;+\; X'_{rt-k-1}\,\vartheta \;+\; \delta_r \;+\; \tau_t \;+\; \eta_{rt} \;+\; \epsilon_{rt}, \end{aligned} \tag{2}$$

where y_{rt} is either (i) the share of automation innovation $\frac{A_{rt}}{N_{rt}}$ filed in region r in year t, (ii) the level of automation innovation in logs $\ln(A_{rt}+1)$, or (iii) the level of non-automation innovation in logs $\ln(NA_{rt}+1)$. $\frac{I_{rt-k}}{L_{rt-k-1}}$ corresponds to the inflow of ethnic Germans in year $t-k$ divided by the size of the workforce in the previous year. X'_{rt-k-1} corresponds to the full set of control variables in $t-k-1$. Since the optimal choice of the lag structure $k \in \{0,1,2,3\}$ is *a priori* unclear, we evaluate the effect for each of the inflows in the years t, $t-1$, $t-2$, and $t-3$ in Table 4.

We find a significantly negative effect of labor supply on the share and level of automation innovation for the inflow years $t-1$ and $t-2$ (Table 4). In contrast, we find neither significant effects for the year of treatment t nor for the more distant year $t-3$. These results suggest that the impact of the positive labor supply shock on automation innovation materializes in the first and second year and, hence, soon but not immediately after the exogenous shock. By contrast, we find no significant negative results for the level of non-automation irrespective of the chosen lag structure (Table B-3 in the Appendix). Based on these findings, our preferred specification features a response time of $t-2$ for the remaining results of the paper.

Table 4: Effect of labor supply on automation innovation – alternative lag structure

Dep. Var.:	Automation patents / patents				Automation patents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inflow rate$_t$	0.131				−0.004			
	(0.121)				(0.008)			
Allocation$_t$ × Inflow rate$_t$	−0.112				0.000			
	(0.244)				(0.015)			
Inflow rate$_{t\text{-}1}$		0.049				−0.009		
		(0.138)				(0.007)		
Allocation$_{t\text{-}1}$ × Inflow rate$_{t\text{-}1}$		−0.743***				−0.025*		
		(0.223)				(0.014)		
Inflow rate$_{t\text{-}2}$			0.139				−0.007	
			(0.132)				(0.007)	
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$			−0.896***				−0.035**	
			(0.211)				(0.015)	
Inflow rate$_{t\text{-}3}$				0.039				−0.009
				(0.113)				(0.006)
Allocation$_{t\text{-}3}$ × Inflow rate$_{t\text{-}3}$				−0.133				−0.001
				(0.217)				(0.015)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1847	1847	1847	1847	1849	1849	1849	1849
R-squared	0.581	0.579	0.591	0.582	0.957	0.958	0.958	0.957
Within R-squared	0.034	0.035	0.033	0.021	0.083	0.077	0.070	0.047
Total effect	0.019	−0.694	−0.757	−0.094	−0.004	−0.034	−0.043	−0.010
P-value	0.939	0.002	0.001	0.657	0.792	0.015	0.004	0.501

Notes: OLS regressions. Dependent variable: Column 1-4: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Column 5-8: number of automation patents filed in year t (entered in logs). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Effect persistence. Regarding the persistence of labor supply effects on automation innovation, we implement an event study design by regressing y_{rt}, i.e., the level of automation innovation $\ln(A_{rt}+1)$ or the level of non-automation innovation $\ln(NA_{rt}+1)$, on the lagged inflow rates interacted with time dummies. More precisely, we estimate the following specification:

$$y_{rt} = \alpha_0 + \sum_{j=-6}^{6} \beta_j \, D_{rt}^{j-2} \times \frac{I_{rt-2}}{L_{rt-3}} \\ + X'_{rt-3}\,\vartheta + \delta_r + \tau_t + \eta_{rt} + q_{rt} + \epsilon_{rt}, \tag{3}$$

where D_{rt}^{j-2} is a set of dummies indicating that the binding allocation policy is introduced $j-2$ years away. The corresponding coefficient vector of interest is β_j. We normalize the coefficient β_{-6} to zero and, hence, express the dynamic treatment effects relative to this pre-treatment year. Relative year fixed effects are denoted by q_{rt}. We bin time dummies at the endpoints of the event window following the literature (see e.g., Schmidheiny and Siegloch, 2019). To increase the precision of the estimates, we use two-year intervals allowing for three lead and four lag effects. The coefficient β_0 refers to the labor supply shocks from the first two years of the binding placement policy.

Figure 2a and Figure 2b display the estimated lead and lag effects on the level of automation patents and non-automation patents. As evident in Figure 2a, we find significant negative effects on automation innovation during the years following the introduction of the binding placement policy. The effect on automation innovation is confined to the first five years after the labor supply shock. The estimated coefficient in $t = 6$ is insignificant and close to zero suggesting that the negative automation innovation response is only transient. By contrast, the level of non-automation innovation is not significantly affected in any of the time periods.

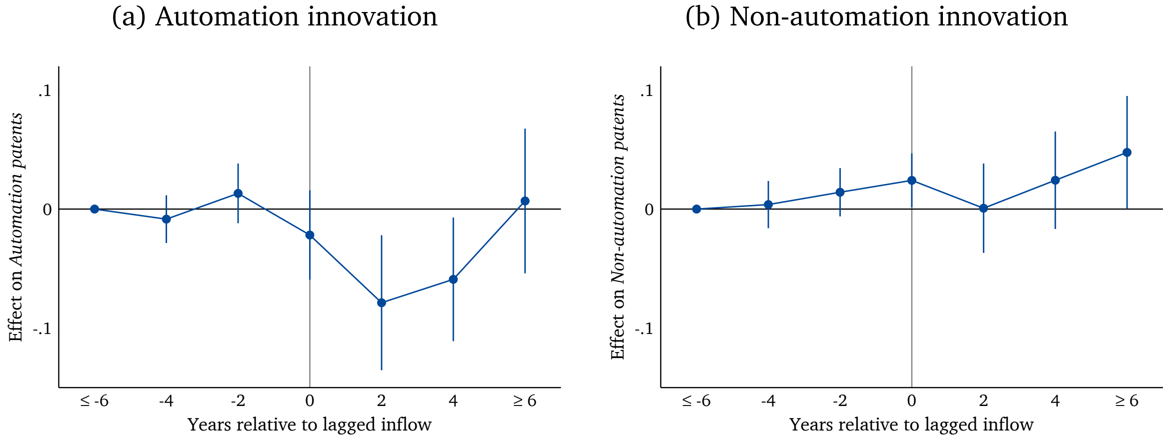
The flat pre-period trends and the insignificant lead coefficients for the level of automation innovation (Figure 2a) and the level of non-automation innovation (Figure 2b) corroborate the common trends assumption underlying our difference-in-differences analysis and, hence, the causal interpretation of our estimates.

Results by Technology Area

Production technologies differ across economic sectors and automation innovation is more likely to replace manual labor in some technology areas (such as mechanical engineering) than in others. Figure A-7 visualizes the number of low- und unskilled workers across five major technology areas in Germany over time (Chemistry, Electrical Engineering, Instruments, Mechanical Engineering, and Other Fields).[32] Industries in mechanical engineering and chemistry employ the largest numbers of low- und unskilled workers. Jobs in these industries are at comparably great risk of automatability. At the same time, these industries are also strongly exposed to the labor supply shock given that close

[32] To this end, we calculate the size of the workforce in industries related to the different main technology areas using data from the Institute for Employment Research (IAB) and concordance tables between industries and technologies by Dorner and Harhoff (2018).

Figure 2: Effect of labor supply on innovation – event study



Notes: Figure displays the event study estimates and the 95 percent confidence bands based on equation 4. Dependent variable is the number of automation patents (non-automation patents) in the left-hand (right-hand) figure. The outcomes are regressed on the ethnic inflow rates interacted with year dummies indicating that the binding allocation policy is introduced two years in the past. Full set of time-variant controls, fixed effects (region, time, year-by-state) and relative year fixed effects included. Standard errors clustered at the regional level.

to 60 percent of ethnic German immigrants had prior work experience in low-skilled and manual occupations such as farmer, laborer, transport worker, operative and craft worker (see Figure A-2b).

We assess the innovation response to the labor supply shock across across the five technology areas by running separate regressions with the share of automation innovation within each area as dependent variable. That is, the average "Share of automation patents (Mechanical Engineering)" corresponds to the regional number of automation patents in mechanical engineering divided by the total number of patents in mechanical engineering. Beside the share of automation innovation (panel A of Table 5) we also assess the level of automation innovation (panel B) and level of non-automation innovation within each technology area (not reported). The effect is especially pronounced in the area of mechanical engineering where an increase in the inflow rate by one ethnic German per 1,000 workers is associated with a decline in the share of automation innovation by 0.55 percentage points (column 4, Panel A). We also find some evidence for negative effects on automation innovation related to chemistry. In contrast, there are neither systematic and significant effects for any other technology area nor for the number of non-automation innovation in general (not reported). To summarize, the labor supply effect on automation innovation is concentrated in technology areas that are especially susceptible to automatization.

Table 5: Effect of labor supply on automation innovation by technology area

Main Technology Area:	Chemistry	Electrical Engineering	Instruments	Mechanical Engineering	Other Fields
Dep. Var.:	Automation patents / patents				
	(1)	(2)	(3)	(4)	(5)
Inflow rate$_{t\text{-}2}$	−0.113	0.113	0.089	0.369*	−0.100
	(0.162)	(0.418)	(0.565)	(0.215)	(0.276)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	−0.772**	−0.359	−1.274	−0.916***	−0.705
	(0.332)	(0.650)	(0.994)	(0.299)	(0.580)
Observations	1798	1690	1666	1837	1667
R-squared	0.236	0.350	0.293	0.391	0.215
Within R-squared	0.015	0.024	0.017	0.029	0.022
Total effect	−0.885	−0.246	−1.185	−0.547	−0.805
P-value	0.009	0.707	0.174	0.079	0.202
Dep var mean	12.067	40.059	41.915	20.287	15.882
Dep. Var.:	Automation patents				
	(6)	(7)	(8)	(9)	(10)
Inflow rate$_{t\text{-}2}$	−0.003	0.005	0.005	−0.004	−0.007
	(0.007)	(0.009)	(0.010)	(0.008)	(0.007)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	−0.021	−0.039*	−0.018	−0.035**	−0.013
	(0.015)	(0.020)	(0.023)	(0.016)	(0.021)
Observations	1849	1849	1849	1849	1849
R-squared	0.913	0.929	0.906	0.927	0.785
Within R-squared	0.073	0.086	0.058	0.052	0.036
Total effect	−0.024	−0.033	−0.013	−0.039	−0.020
P-value	0.107	0.076	0.520	0.017	0.369
Dep var mean	0.752	1.255	1.152	1.547	0.527
Region and year fixed effects	Yes	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Occupation + skill groups	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. Dependent variables: Panel A: number of automation patents filed in year t which are in a specific technology area divided by the total number of patents filed in year t in that technology area (multiplied by 100). Panel B: number of automation patents filed in year t which are in a specific technology area (entered in logs). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Firm Characteristics

We examine the responsiveness of different types of innovators to the labor supply shock – by firm type, size, age, and by the regional concentration of a firm's innovative activities. We, first, distinguish between corporate entities and non-corporate entities, such as universities, governmental institutions, or natural persons. These entities differ with respect to their objective function (in simplified terms: profit maximizing vs. non-profit maximizing goals) and their exposure to competition. We therefore expect them to vary in their response to the labor supply shock. Since the labor-automation link should be most relevant for firms under cost pressure, we hypothesize that corporate entities respond substantially stronger than non-corporate entities. Unlike for corporations (on which we focus in our main analyis) we find no statistically significant effect of the labor supply shock on the share and the absolute number of automation patents among non-corporate entities (Figure 3a and 3b). In line with our hypothesis, only corporations seem to adjust their automation innovation activities to the labor supply shock.

We next explore potential heterogeneity in innovation responses between firms of different sizes, ages, and regional innovation concentrations. To operationalize the subgroup analysis, we split the sample of patents at the respective medians of the three variables size, age and regional innovation concentration, stratified by technology area and year. We proxy firm size with the cumulative number of previously filed patents, firm age with the number of years since the first patent filed (after the cut-off year 1979), and regional innovation concentration with the number of distinct inventor regions of all patents of a given firm (not plant).[33] While these variables constitute crude approximations of the actual firm characteristics, we find indicative evidence for heterogeneous firm responses.

From an innovation perspective, smaller and younger firms tend to exhibit greater innovative flexibility and, hence, may respond more elastically to labor supply shocks. From a labor perspective, the inflow of low-skilled immigrants may specifically help smaller and younger firms which tend to pay lower wages. Regarding the regional concentration of a firm's innovative activities, there might be a stronger reaction of regional firms to regional labor supply shocks. However, since our regionality measure does not include the location of manufacturing plants, it provides a rather unreliable differentiation.

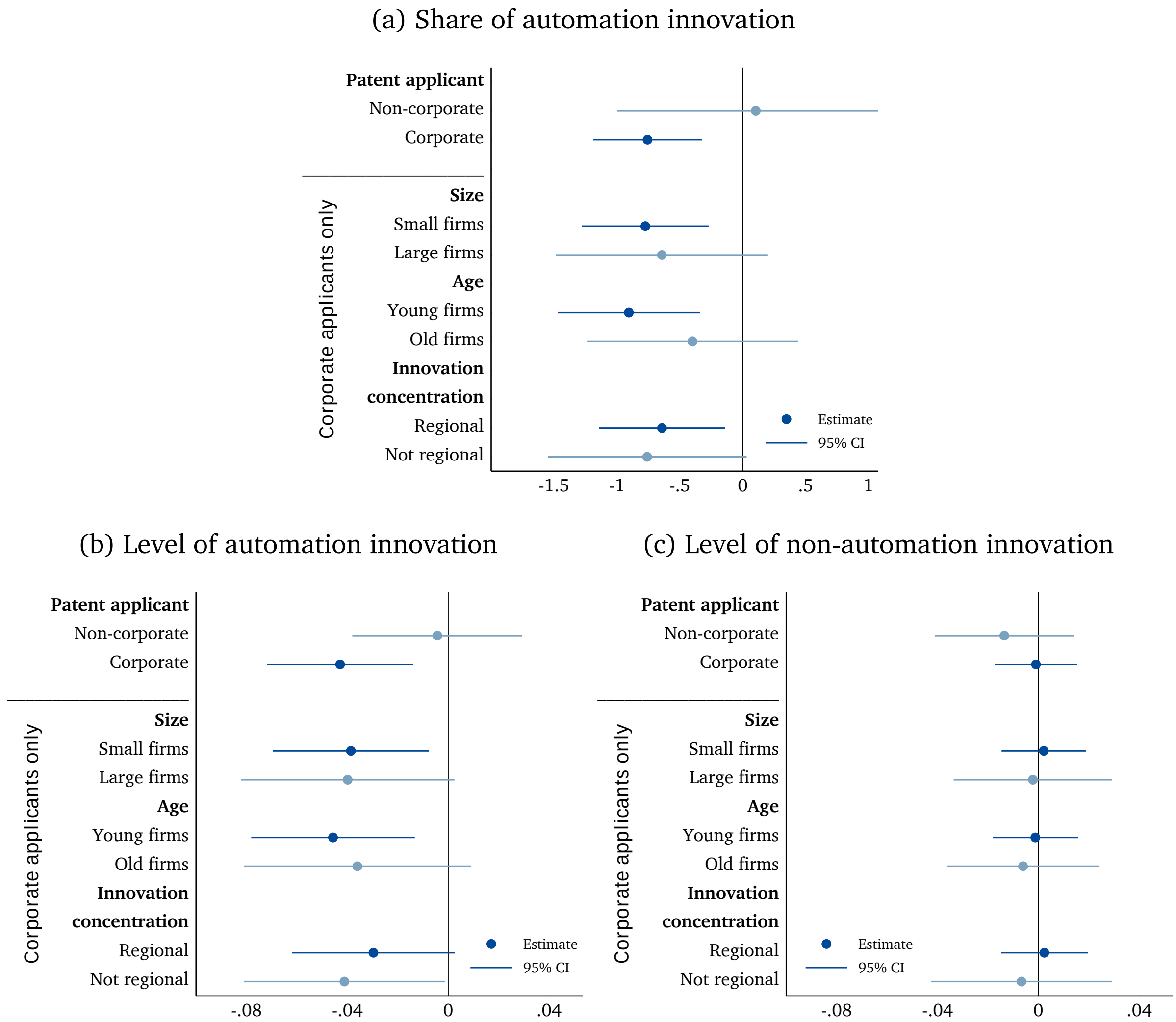
Figure 3 presents the combined effect of $\hat{\beta}_1$ and $\hat{\beta}_3$ in regressions of equation 3 on the share of automation innovation and the level of (non-)automation innovation, based on two lags.[34] We find a significant negative effect on automation innovation (share and level) by small firms and young firms. In contrast, the effects are smaller (in absolute size) and/or less precisely estimated for large firms and old firms. The comparatively stronger effects in small and young firms reflect standard considerations in innovation and labor economics. In line with the fuzzy regionality measure, we find almost no differences between firms with and without geographically concentrated innovation

[33] We rely on the PATSTAT standardized name (PSN ID) for the patent applicants to construct firm patent portfolios.

[34] The corresponding regression results can be found in Tables B-4, B-5 and B-6 in the Appendix.

activities. It bears mentioning that, again, we find no significant effects (or differences) for the level of non-automation in any subgroup.

Figure 3: Effect of labor supply on (non-)automation innovation by originator characteristics



Notes: This figure presents the combined effect of $\hat{\beta_1}$ and $\hat{\beta_3}$ in regressions of equation 2 on the share of automation innovation and the level of (non-)automation innovation, based on two lags. Figure 3a displays the estimated effects on the share of automation patents. Figure 3b (Figure 3c) displays the estimated effects on the level of automation patents (non-automation patents). The corresponding regression results can be found in Tables B-4, B-5 and B-6 in the Appendix. The samples of patents are split by type of applicant as well as at the respective medians of the three variables size, age and innovation concentration, stratified by technology area and year. Firm size is proxied by the cumulative number of previously filed patents, firm age by the number of years since the first patent filed (after the cut-off year 1979), and regional innovation concentration by the number of distinct inventor regions of all patents of a given firm.

5.2 Discussion of Mechanisms

An important contribution of our study is the analysis of mechanisms through which labor supply affects innovation. We differentiate between a labor market link (mediated through the tightness of the labor market) and a link operating through the market for innovation (based on external vs. internal sources of demand for innovation).

Labor Market Tightness

The strength of the labor supply effect on automation innovation will depend on regional labor market conditions: Labor inflows into regions that are characterized by labor scarcity may result in larger marginal effects on automation innovation since they effectively relax labor supply constraints and reduce firms' search costs for workers. Prior research has hinted at search costs of firms being higher in tight than in slack labor markets (Muehlemann and Leiser, 2018).[35] To the contrary, labor inflows may have smaller marginal effects on automation innovation in areas of labor abundance, i.e., in the presence of high unemployment. To shed light on effect heterogeneity by labor market conditions, we differentiate our analysis for tight and slack labor market regions.[36]

We split the sample at the 75-percentile of the unemployment rate as of the year 1995, i.e., the year before the exogenous placement of ethnic Germans was made compulsory.[37] The results in Table 6 indicate that there are strong negative effects of labor supply shocks on the share and level of automation innovation (columns 1 and 5) for regions with tight labor markets. At the same time, the negative effects of labor supply shocks on the share and level of automation innovation (columns 2 and 6) are small in magnitude and statistically insignificant in regions with high pre-determined unemployment, i.e., slack labor markets.

The heterogeneous results remain robust when using an alternative definition of labor market tightness, which is the 75-percentile of the unemployment rate in $t-3$, the year before the treatment (i.e., the labor supply shock in $t-2$). This definition captures the pre-existing labor scarcity more dynamically. While the results for labor supply shocks on automation innovation remain very similar in tight labor markets (columns 3 and 7), the total effects are close to zero in slack labor markets (columns 4 and 8). To test the robustness regarding unemployment thresholds, we present analogous regressions using the 50 pctl. (90 pctl.) of unemployment rates in Table B-17 (Table B-18). The results remain qualitatively similar.

We repeat the analysis using the level of non-automation innovation as outcome variable (Table B-19). There are no heterogenous effects of labor supply shocks on non-automation innovation by pre-existing labor market tightness. All effects are not statistically different from zero.

While labor supply shocks might influence automation innovation also through *wages*, adjustments are, in practice, hampered by wage rigidity (see for example Card et al. (1996)). In fact, the

[35]From the worker perspective, job-finding rates are higher in tight labor markets (Shimer, 2005).

[36]For similar categorization see Buchheim et al. (2019) and Nakamura and Steinsson (2014).

[37]As an exception, it refers to the year 1996 for regions in Lower Saxony, and to the year 2001 for regions in Hesse.

Table 6: Effect of labor supply on automation innovation by labor market tightness

Labor Market Tightness:	Tight $U_0 < 75$ pctl	Slack $U_0 \geq 75$ pctl	Tight $U_{t\text{-}3} < 75$ pctl	Slack $U_{t\text{-}3} \geq 75$ pctl
Dep. Var.:	Automation patents / patents			
	(1)	(2)	(3)	(4)
Inflow rate$_{t\text{-}2}$	0.038	0.130	−0.027	0.334
	(0.169)	(0.231)	(0.158)	(0.296)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	−0.981***	−0.600	−0.809***	−0.225
	(0.214)	(0.741)	(0.207)	(0.895)
Observations	1373	459	1371	457
R-squared	0.666	0.504	0.680	0.502
Within R-squared	0.055	0.078	0.057	0.085
Total effect	−0.943	−0.470	−0.836	0.109
P-value	0.000	0.481	0.001	0.888
Dep. Var.:	Automation patents			
	(5)	(6)	(7)	(8)
Inflow rate$_{t\text{-}2}$	−0.008	−0.010	−0.010	−0.003
	(0.007)	(0.015)	(0.007)	(0.020)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	−0.043***	−0.010	−0.042***	0.024
	(0.014)	(0.046)	(0.014)	(0.046)
Observations	1374	460	1371	459
R-squared	0.968	0.922	0.966	0.934
Within R-squared	0.075	0.173	0.087	0.159
Total effect	−0.051	−0.020	−0.052	0.020
P-value	0.001	0.659	0.001	0.617
Region and year fixed effects	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Occupation + skill groups	Yes	Yes	Yes	Yes

Notes: OLS regressions. Sample splits at the 75-percentile of the unemployment rate in the year before the binding placement (column 1-2 and 5-6) and at the 75-percentile of the unemployment rate in $t-3$ (column 3-4 and 7-8). Dependent variables: Panel A: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Panel B: number of automation patents filed in year t (entered in logs). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

German labor market is notoriously inflexible owing to strict labor market regulation and powerful unions.[38] Accordingly, Glitz (2012) and D'Amuri et al. (2010) find little to no effect of immigration on wages in Germany in the 1990s. Hence, wages are very unlikely to mediate the effect of labor supply on automation innovation in our setting.

In sum and consistent with search costs for firms playing a key role, labor supply shocks have larger marginal effects on automation innovation in tight labor markets.

Demand for Automation Innovation

In this section, we investigate the origin of the demand for automation innovation and whether the observed decrease in automation innovation activities can be plausibly rationalized with reduced *internal* demand (i.e., by the innovating firm) or *external* demand (i.e., by other firms). Since no data on the *internal* vs. *external* demand for automation technologies exist, we approach the issue in three steps: First, we leverage a process vs. product classification of patented technologies. Second, we investigate the physical distance between patents and their forward citations. Third, we analyze differences in firms' innovation responses depending on whether they are located in small or large labor markets.

First, process innovations relate to how goods or services are created whereas product innovations refer to the outcomes of such procedures. We assume that process innovations mostly reflect internal use, whereas product innovations predominantly reflect market activities (Klepper, 1996). Differences in the effect for process vs. product automation innovation may therefore indicate whether the regional labor supply shock is channeled through changes in internal or external demand for automation innovation. We test this empirically by classifying patents into process vs. product innovation using a method similar to Ganglmair and Reimers (2019).[39] On average 24.0 non-automation and 11.4 automation patents relating to processes have been filed in a region in a given year. The average share of automation patents that relate to process innovation corresponds to 28.0 percent. Table 7 reports the effects of the ethnic German inflows on automation innovation for process vs. product oriented innovation. Product automation innovation (columns 2, 4 and 6) seems to react more strongly than process automation (columns 1, 3 and 5). The latter estimates are less precisely estimated owing to the small share of patents in the process and automation category. In fact, firms may refrain from patenting process innovations which is intended for internal use and instead decide to avoid misappropriation through secrecy (cf. Levin et al., 1987; Ganglmair and Reimers, 2019). As a consequence, selection into patenting may lead to underestimating the true effect on automation process innovations. In sum, the results regarding process vs. product innovation suggest that innovation responses of firms are largely driven by lower external demand, i.e., by other firms demanding fewer automation technologies for adoption. This observation is in

[38]For example, the collective bargaining coverage in Germany was larger than 80 percent in 1990 and still 68 percent in 2000 (OECD, 2004). The level of unionisation is substantially higher in Germany compared to the US where the coverage of collective bargaining was only 14 percent in 2000.

[39]We search for the keywords "method", "process", and "procedure" in the patent claim text. For around 12 percent of patent applications there is no available patent claim text.

line with the existing literature which finds that low-skilled labor supply determines firms' decisions to adopt (new) production technologies from external suppliers (Clemens et al., 2018; Lewis, 2011; Imbert et al., 2019; Monras, 2019).

Second, we investigate the regionality of automation innovation. In light of national, if not global, product markets a *regional* demand-pull mechanism may seem surprising. Local firms can source automation technologies from firms outside their own region. Likewise, firms developing automation technologies can supply these to firms far away. Both considerations will dampen the relationship between local labor supply and local automation innovation. At the same time, the arguably high specificity of automation technologies and the need for continuous maintenance favor spatial proximity between inventor and user. The latter effect seems to dominate, given that the existing empirical evidence points to a considerable geographical bias of buyer-supplier relationships (Bernard et al., 2019) and technology transfer (Almeida and Kogut, 1999; Audretsch and Feldman, 1996). Also, the fact that we find significant effects in our regional approach suggests that supply of and demand for automation technologies are fairly regionalized.[40] A practical challenge relates to the difficulties in observing market activities as product purchases and technology licensing deals are often not disclosed to the public. One solution to exemplify the geographical bias in the market for technology is to analyze the geographical distance between the location of a cited patent and its citing patent. Roughly 50 percent of forward citations stem from within the same firm. Among the citations by external firms, almost one in four automation patents originates from within a proximity of 20 km (Figure 4). This is indicative of geographical bias in the technology market.[41]

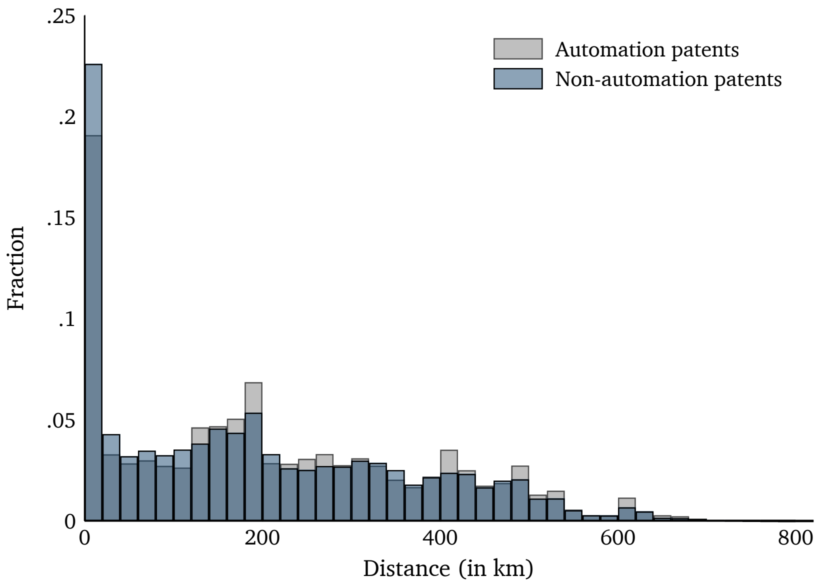
Third, we investigate regional external demand for automation innovation by focussing on the size of the labor market region. We therefore assume that large labor market regions exhibit a comparatively more vibrant economic environment and host many relevant economic partners for local firms. If regional external demand drives the effect on automation innovation, we would expect a stronger (weaker) effect of the local labor supply shock in large (small) labor market regions. We split our sample of regions into large and small labor markets, according to the median of the regional labor force as of the year 1991. Indeed, Table 8 shows that the effect on the share and the level of automation innovation is larger in magnitude and more precisely estimated for the sample of large labor market regions compared to the sample of small regions. This confirms that regional market size is an important factor for the pass-through of the labor supply shock.

In sum, our results suggest that environmental factors such as labor market tightness and regional external demand are important mechanisms of how labor supply shocks affect innovative activities.

[40] As our spatial approach does not capture potential spillovers, we likely underestimate the overall effect.

[41] Technology adoption does not necessarily lead to patented follow-on inventions. Also, citations may be the result of knowledge spillovers, which can be regionalized as well.

Figure 4: Distance between focal patent and citing patents



Notes: Histogram of citing distance for automation and non-automation patents in our sample. Bin width corresponds to 20 kilometers. Citing patents of foreign firms excluded. Self-citations excluded. Own calculations.

6 Robustness Analyses

In this section, we present additional results with value-weighted patent counts (Section 6.1) and alternative measures of automation innovation (Section 6.2). We also assess the labor supply-innovation nexus for the pre- and post-allocation period separately (Section 6.3). Moreover, we repeat our main analysis with an alternative poisson regression model (Section 6.4) and alternative samples (Section 6.5). All tests confirm the robustness of our previously reported findings.

6.1 Accounting for Patent Value

Some patents turn into highly successful applications while others remain close to irrelevance. To account for these differences in future patent value, we resort to a weighting scheme in which patents receive different impact depending on (1) their patent grant status[42] (Table B-7, column 1), (2) the size of their DOCDB patent family (column 2), or (3) the number of received US patent forward citations within the first 3 years after the granting date (column 3). The first weighting scheme restricts the sample to patents with successful examination, the second puts emphasis on how far-reaching the patent protection is across different jurisdictions, and the third accounts for the short- to medium-run impact of each patent on future innovative activities. Importantly, our weighting scheme combines quality assessments of the patent office (1), of the originator of each patented invention (2), and of other inventors (3). All estimated effects on the weighted share of

[42]While a granted patent application has a weight of one, a non-granted application has a weight of zero.

Table 7: Effect of labor supply on automation innovation by process and product innovation

Dep. Var.:	Automation patents / patents		Automation patents		Non-Automation patents	
	Process	Product	Process	Product	Process	Product
	(1)	(2)	(3)	(4)	(5)	(6)
Inflow rate$_{t-2}$	0.365	−0.039	0.006	−0.020***	−0.017**	−0.020***
	(0.234)	(0.146)	(0.008)	(0.008)	(0.008)	(0.007)
Allocation$_{t-2}$ × Inflow rate$_{t-2}$	−0.958**	−1.015***	−0.021	−0.041**	0.037***	0.011
	(0.402)	(0.294)	(0.017)	(0.017)	(0.013)	(0.009)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1835	1843	1849	1849	1849	1849
R-squared	0.512	0.326	0.940	0.932	0.959	0.964
Within R-squared	0.033	0.028	0.079	0.062	0.070	0.074
Total effect	−0.593	−1.054	−0.015	−0.062	0.020	−0.009
P-value	0.121	0.000	0.346	0.001	0.145	0.265
Dep var mean	27.991	20.016	1.684	1.750	2.473	2.970

Notes: OLS regressions. Dependent variables refer to patent applications that are related to processes (column 1, 3 and 5) and products (column 2, 4 and 6). Dependent variables: Column 1-2: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Column 3-4: number of automation patents filed in year t (entered in logs). Column 5-6: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t-2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t-2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

automation patents (Panel A) and the weighted number of automation patents (Panel B) confirm that the positive labor supply shock leads to a reduction in automation innovation. To the contrary, we do not find any significant effects on the weighted measures of the level of non-automation innovation (results not reported).

6.2 Alternative Measures of Automation Innovation

While the recent literature has successfully applied keyword search in patent texts (see e.g., Dechezleprêtre et al., 2019; Webb, 2019), the choice of relevant keywords can be disputed. Therefore, we examine the sensitivity of our findings to using three alternative keyword based measures of automation innovation (Table B-8). First, we construct one extended keyword measure by searching the pre-processed English abstracts for the following ten substrings: “automat", “execut", “detect",

Table 8: Effect of labor supply on automation innovation by labor market size

Dep. Var.:	Automation patents / patents		Automation patents		Non-Automation patents	
Labor market size of regions:	Small	Large	Small	Large	Small	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Inflow rate$_{t-2}$	0.085	0.112	0.001	−0.015*	−0.003	−0.021**
	(0.196)	(0.186)	(0.011)	(0.008)	(0.009)	(0.010)
Allocation$_{t-2}$ × Inflow rate$_{t-2}$	−0.588	−0.888***	−0.013	−0.039**	0.018	0.010
	(0.458)	(0.242)	(0.028)	(0.017)	(0.018)	(0.010)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes	Yes	Yes	Yes
Observations	931	901	933	901	933	901
R-squared	0.421	0.721	0.837	0.961	0.918	0.977
Within R-squared	0.027	0.074	0.060	0.117	0.093	0.129
Total effect	−0.503	−0.776	−0.011	−0.053	0.015	−0.010
P-value	0.224	0.007	0.650	0.004	0.305	0.339

Notes: OLS regressions. Sample splits at the 50-percentile of the size of the regional labor force in the year 1991. Dependent variables: Column 1-2: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Column 3-4: number of automation patents filed in year t (entered in logs). Column 5-6: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t-2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t-2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

“input", “system", “display", “output", “inform", “signal" and “sensor". Second, the reduced keyword measure utilizes the following six instead of eight keywords: “automat", “execut", “input", “system", “output" and “inform". Finally, we construct a very conservative classifier by searching only for the unambiguous keyword “automat”. As before, we classify the underlying patent application as an automation patent if one of the corresponding keywords appears in the English abstract. Reassuringly, the extended (10 substrings), the reduced (6 substrings) and the very conservative (1 substring) keyword classifications confirm our baseline results regarding the effect of labor supply shocks on the share of automation patents, the level of automation patents and the level of non-automation patents.

6.3 Separate Analyses for Post- vs. Pre-Binding-Allocation Periods

Our difference-in-differences approach exploits observations from before and after the introduction of the binding allocation rule. This goes beyond previous work by Glitz (2012) who exclusively focusses on the period since the implementation of the binding allocation rule in 1996. For better comparability we employ separate analyses for the pre- vs. post-binding-allocation periods in this section.[43] Initially, we estimate the following fixed effects model using only region-year pairs from the binding-allocation period starting in 1996:

$$y_{rt} = \beta_0 + \beta_1 \frac{I_{rt-2}}{L_{rt-3}} + X'_{rt-3}\vartheta + \delta_r + \tau_t + \eta_{rt} + \epsilon_{rt}, \tag{4}$$

where y_{rt} is either the regional share of automation patents or the level of automation (non-automation) patents in region r filed in year t. $\frac{I_{rt-2}}{L_{rt-3}}$ corresponds to the inflow of ethnic Germans in year $t-2$ divided by the size of the workforce in year $t-3$. We weight region-year observations with pre-determined regional population sizes as of 1995.

Table B-10 quantifies the effects of the supply shock induced by the inflow of ethnic Germans on the share of automation patents (column 1), the level of automation patents (column 2) and the level of non-automation patents (column 3). The significantly negative effects on automation innovation (zero effect for non-automation innovation) are of similar size to the difference-in-differences estimates; hence, the simple differences approach confirms findings from our baseline model. Also in line with expectations, we do not find any significant effects of the ethnic German inflows on automation or non-automation innovation using only observations from the pre-binding allocation period (see Table B-11).

As an additional robustness test, we use an overlapping observation model to avoid the arbitrariness in choosing a specific lag structure.[44] As a further advantage, the overlapping data structure exploits the data more efficiently (see e.g., Harri and Brorsen, 2009). We estimate the following model with region and time fixed effects at the region-year level:

$$y_{rt+z} = \beta_0 + \beta_1 \frac{\sum_{z=-2}^{0} I_{rt+z}}{L_{rt-3}} + X'_{rt-3}\vartheta + \delta_r + \tau_t + \eta_{rt} + \epsilon_{rt}, \tag{5}$$

where y_{rt+z} is either the regional share of automation patents $\frac{\sum_{z=0}^{2} A_{rt+z}}{\sum_{z=0}^{2} N_{rt+z}}$, the number of automation patents $\ln(\sum_{z=0}^{2} A_{rt+z}+1)$ or the number of non-automation patents $\ln(\sum_{z=0}^{2} NA_{rt+z}+1)$ filed over the period t to $t+2$ in region r. Our main explanatory variable $\frac{\sum_{z=-2}^{0} I_{rt+z}}{L_{rt-3}}$ corresponds to the cumulative inflow of ethnic Germans allocated to region r over the period $t-2$ to t, divided by the workforce in $t-3$. We include regional time-variant control variables X'_{rt-3} and cluster standard errors at the regional level to account for correlations between regions over time. Given the overlapping data

[43] See Table B-2 in the Appendix for details regarding the region-year pairs from the binding allocation period.

[44] See also Glitz and Meyersson (2020) who use a similar overlapping observations model in their primary specification. Note that the method is not suitable for our main difference-in-differences specification.

structure, we additionally report p-values based on the wild cluster bootstrap-t method by Cameron et al. (2008) to account for within-group dependence in estimating standard errors with a limited number of clusters.

According to Table B-12, one additional ethnic German immigrant per 1,000 workers induces a decline in the share of automation patents (number of automation patents) by 0.29 percentage points (1.8 percent). Both conventional p-values and p-values based on the wild cluster bootstrap-t method indicate that these effects are significant. At first glance, the estimated effects seem smaller than our difference-in-differences results; however, these estimates capture the effect of labor supply shocks over a three-year period from t to $t+2$. Multiplying the coefficients by three yields results quite similar to Table B-10. Once again, the ethnic German inflows have no effect on the level of non-automation innovation (column 3).

6.4 Alternative Estimation Model: Poisson Regression

As the number of patents is originally categorized as count data, we test the robustness of our OLS level findings with Poisson quasi-maximum likelihood regressions:

$$\begin{aligned} y_{rt} = \exp\bigg(& \gamma_0 + \gamma_1 \frac{I_{rt-2}}{L_{rt-3}} + \gamma_2 P_{rt-2} \\ & + \gamma_3 P_{rt-2} \times \frac{I_{rt-2}}{L_{rt-3}} + X'_{rt-3}\vartheta + \delta_r + \tau_t + \eta_{rt} \bigg) + \epsilon_{rt}, \end{aligned} \tag{6}$$

where y_{rt} denotes the natural number of filed automation patents A_{rt} or non-automation patents NA_{rt} in region r and year t. $\frac{I_{rt-2}}{L_{rt-3}}$ corresponds to the number of ethnic German inflows in region r and year $t-2$ divided by the workforce in the previous year. X'_{rt-3} represents a vector of the full set of control variables in year $t-3$. Again, we control for region fixed effects δ_r, time fixed effects τ_t and year-by-state fixed effects η_{rt}. We obtain the estimates using a Poisson pseudo-likelihood regression with multiple levels of fixed effects, following Correia et al. (2019). We continue to cluster standard errors at the regional level.

The results in Table B-9 confirm our main findings that the level of automation patents (column 1) declines in response to regional labor supply shocks. Once again, the level of non-automation patents remains unaffected by these shocks (column 2).

6.5 Alternative Samples

Omitting Specific Regions

At the national level there is substantial heterogeneity in innovative activities across regions: while only 13 patent applications were, for instance, filed in the labor market region "Hameln" in 1991 (i.e., prior to the migration allocation), the corresponding number is 613 for the labor market region "Stuttgart". To test whether our baseline results are driven by regions with unusually high or low levels of innovation, we rerun our regressions omitting those observations. More precisely, we exclude any region-year data points from our sample if the pre-determined regional number of filed patent applications in 1991 is below (above) the 10th (90th) percentile. Our results are robust to these omissions (Table B-13). The estimated effects of the ethnic German inflow rate on the share of automation patents (columns 1-2) and the level of automation patents (columns 3-4) are sizeable and significant across all specifications. Similar to our full-sample analysis, we find negligible and insignificant effects on the level of non-automation innovation (columns 5-6).

We also investigate whether our results are robust to excluding regions that signed the so-called Gifhorn declaration. In the first years after the breakdown of the Soviet Union, a small number of regions in Germany had received disproportionate large inflows of ethnic Germans. In 1995, these regions signed the Gifhorn declaration requesting a mandatory equal distribution of ethnic Germans across regions (Niedersächsische Landeszentrale für Politische Bildung, 2002).[45] After the implementation of the binding allocation policy, fewer incoming ethnic Germans were allocated to these seven regions. Results without Gifhorn regions mirror the key findings on the effects of labor supply on the share (Table B-14, column 1) and level of automation patents (column 2). We again estimate a zero effect of labor supply shocks on the level of non-automation innovation (column 3). This confirms that our results are not sensitive to the exclusion of specific regions from the estimation sample.

Addressing Outliers

To test whether our results are sensitive to outliers in the ethnic inflow rate, we winsorize the inflow rate by replacing very low (high) values with the 5th (95th) percentile value. Once again, we confirm a negative effect of the labor supply shocks on both outcomes of automation innovation (columns 1-2 of Table B-15) and an insignificant zero effect on non-automation innovation (column 3).

Excluding Transition Years

The fact that the mandatory migrant allocation rule was implemented during the years may blur the true labor supply effect since our data set contains annualized information: the states of Baden-Wuerttemberg, Bremen, Hamburg, North Rhine-Westphalia and Schleswig-Holstein introduced the policy on March 1, 1996, the Saarland on March 11, 1996, and Lower Saxony on April 4, 1997. As a consequence, the labor supply shocks during these transition years may remain partly endogenous. Consequently, we run a robustness check excluding those region-year pairs during which the binding allocation policy was implemented. Table B-16 shows that the results are robust to the omission of transition years.

[45]The following counties signed the Gifhorn declaration: Wolfsburg, Salzgitter, Gifhorn, Nienburg/Weser, Cloppenburg, Emsland and Osnabrück.

7 Conclusion

Economic theory suggests substitutability between inputs: Labor can be replaced by capital through investments in labor-saving automation innovation. Exploiting the placement of predominantly low-skilled ethnic German immigrants across German regions, we analyze the effect of plausibly exogenous labor supply shocks on automation innovation. Our difference-in-differences estimates rely on regional variation in immigrant inflows as well as variation over time induced by a compulsory migrant allocation policy. While we provide support for the causal interpretation and, hence, internal validity of our estimates, we acknowledge that our specific setting does not necessarily allow a generalization of our results. We find that the greater availability of workers reduce regional automation innovation in relative and absolute terms. The effects are concentrated in industries containing a high share of low- and unskilled workers (mechanical engineering and chemistry). The degree of substitution between labor supply and automation innovation is moderated by predetermined labor market tightness and by external demand: First, identical inflows have strong innovation displacement effects in tight labor markets, while effects are much weaker in regions with high unemployment. Second, we provide suggestive evidence that external demand for automation technologies slumps when workers become easily available. Taken together, our paper highlights the link between a larger pool of workers and the reduced pressure of firms to invent or buy cost-saving labor-replacing techniques.

Beside shedding light on the production function of firms, our research also hints at implications for the production function of entire economies. Shifts in automation innovation that are induced by changes in labor supply can influence the demand for and the relative remuneration of input factors in an economy. A reduction in automation innovation shifts the available production technologies towards more labor intensive production, so that firms will consequently hire more workers for automatable jobs. Accordingly, labor supply shocks can have redistributive effects in the relative remuneration of labor vs. capital. Two implications are noteworthy: First, positive low-skilled labor supply shocks can shield low-skilled workers from being replaced by machines when the overall production becomes more labor intensive. Such a potential feedback between labor and automation technologies complements the current research on the consequences of adopting automation technologies. Second, the fact that low-skilled immigrants can spur labor demand via reduced automation innovation is relevant for the politics of immigration. The negative automation innovation effect may counterbalance some of the increased labor market competition which native workers experience with immigrant workers. This can dampen the effects of immigration on wages and employment in the medium and long run.

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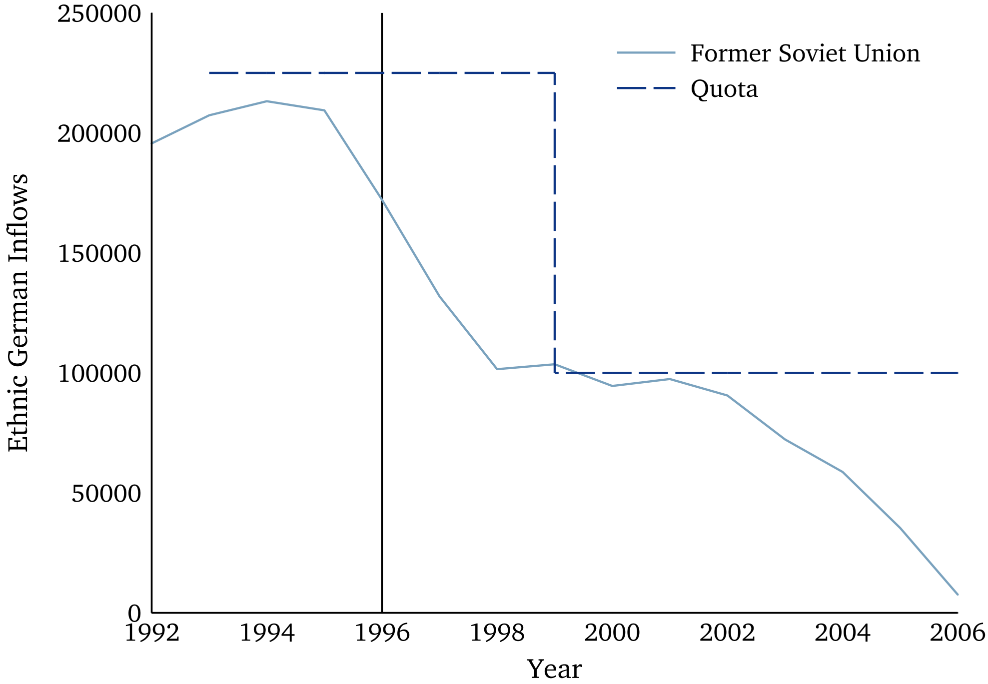
For Online Publication

A Appendix: Figures

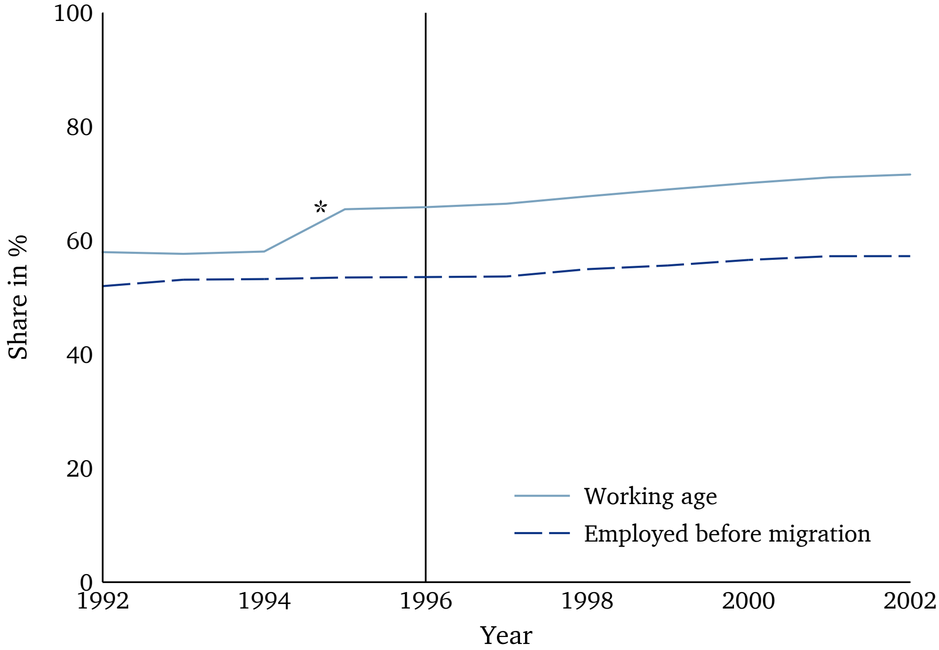
Figure A-1: Ethnic German inflows by arrival year



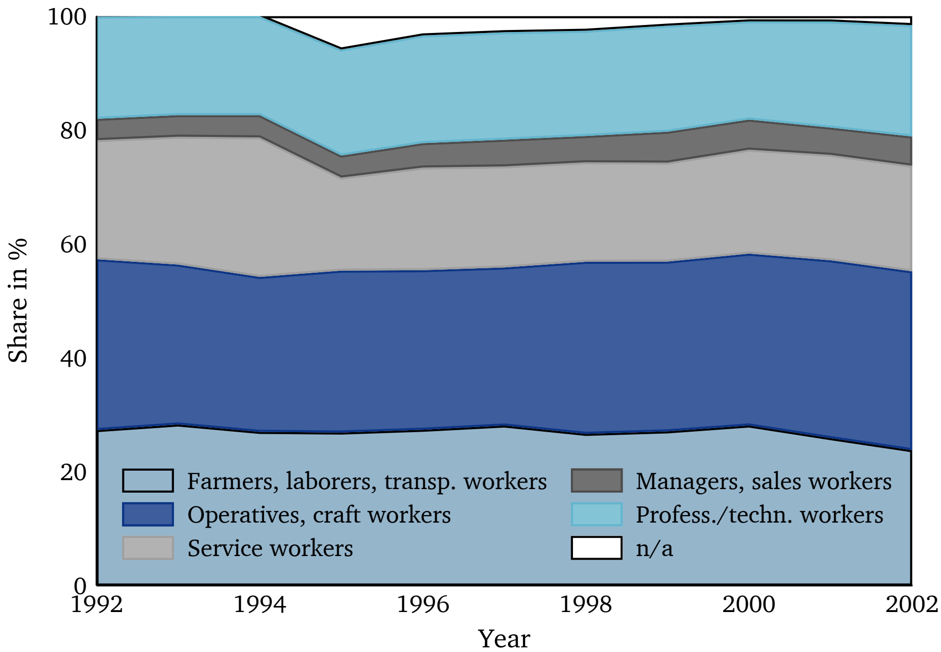
Notes: Annual ethnic German inflows from the former Soviet Union to Germany. More than 95.7 percent of the incoming ethnic Germans came from the former Soviet Union during the analysis period from 1992 to 2006. The following countries are part of the former Soviet Union: Armenia, Azerbaijan, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Russian Federation, Tajikistan, Turkmenistan, Ukraine, Uzbekistan and Belarus. The German authorities introduced a yearly quota of 225,000 ethnic Germans per year in 1993. This quota was further reduced in 1999 to 100,000 arrivals per year. All federal states in West Germany except Bavaria and Rhineland-Palatinate made the allocation policy binding after 1996. Most states adhered to the allocation policy from March 1996 with Lower Saxony following in April 1997 and Hesse in January 2002. Figure based on data from the German Federal Office of Administration (*Bundesverwaltungsamt*).

Figure A-2: Occupations and demographics of incoming ethnic Germans

(a) Employment before migration and working age by arrival year

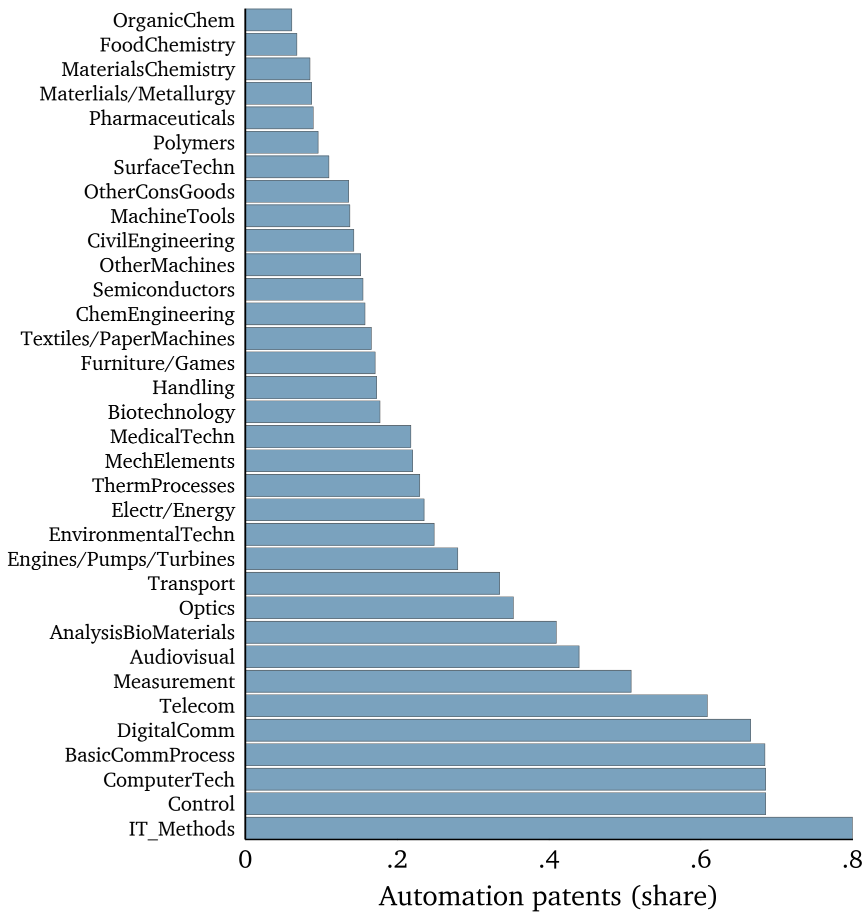


(b) Last occupation in country of origin by arrival year



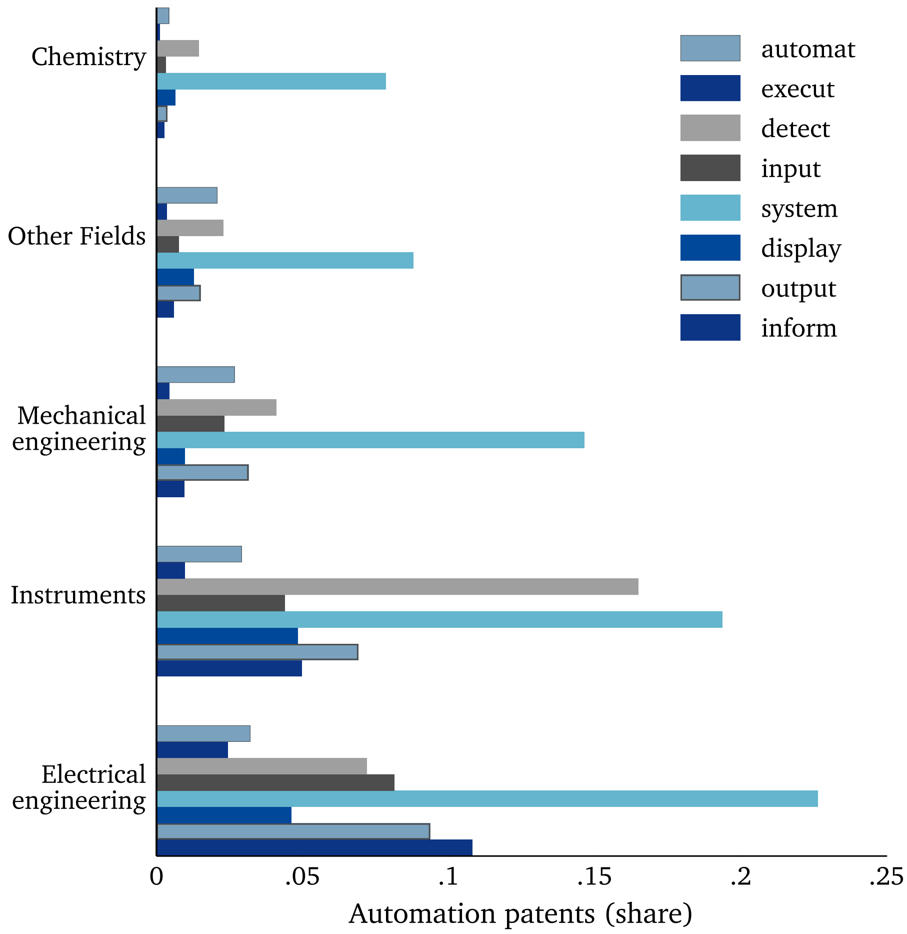
Notes: Top figure: Shares with respect to employment before migration and working age by arrival year. * refers to a change in the definition of working age (age between 18-64 (1992-1994) and 15-64 (1995-2002)). Bottom figure: Occupation shares of the last occupation in the country of origin of incoming ethnic Germans by arrival year. Own calculations based on data from Glitz (2012). Original data from the *Jahresstatistik für Aussiedler*, published annually by *Bundesverwaltungsamt*.

Figure A-3: Share of automation innovation by technology field



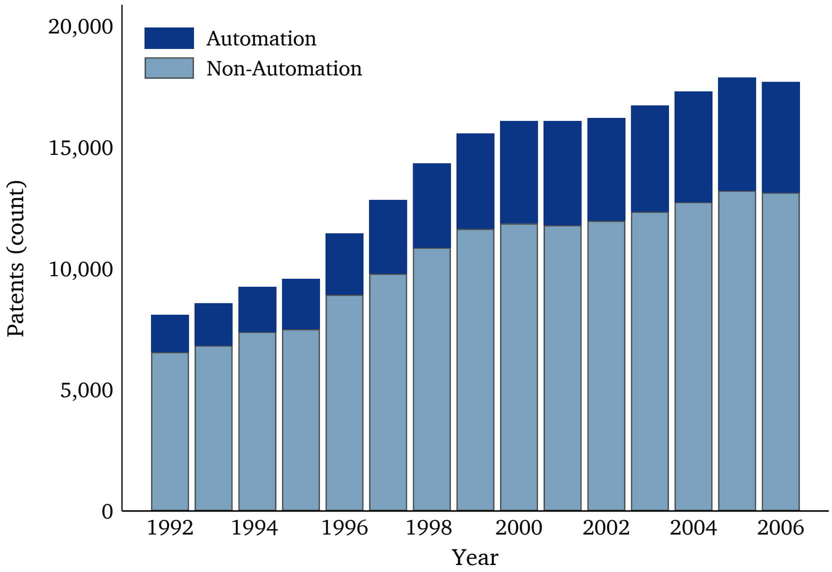
Notes: The share of automation patents across technology fields follows the International Patent Classification (IPC). Based on all patent applications filed at the European Patent Office by at least one inventor located in one of the allocation states with a priority date between 1992 and 2006. We classify patents into automation patents or non-automation patents by searching keywords related to automation in the pre-processed English abstracts. See text for more details on the classification and the technology areas which are constructed using IPC classes and a concordance table developed by the Fraunhofer ISI and the Observatoire des Sciences et des Technologies in cooperation with the French Patent Office (Schmoch, 2008). Source: PATSTAT, own calculations.

Figure A-4: Automation keywords by technology area



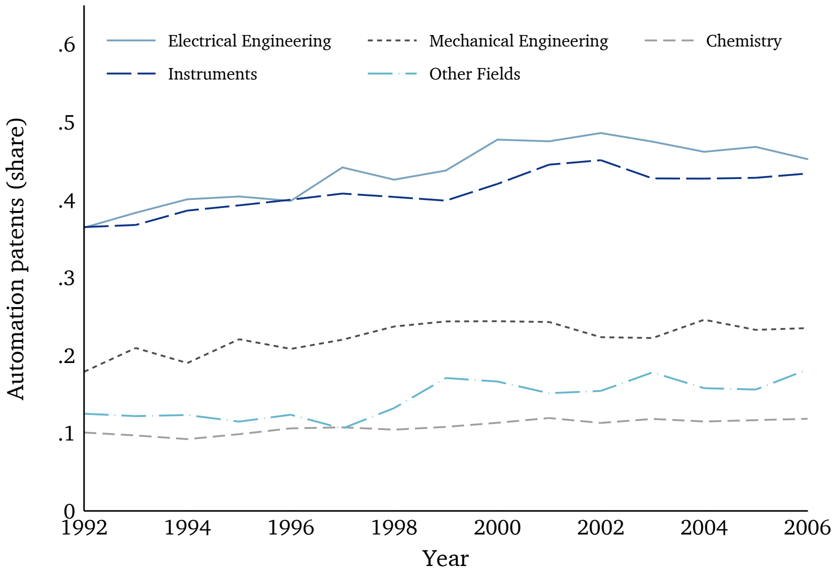
Notes: The share of patents by automation keywords appearing in the patent abstracts by technology area. Based on all patent applications filed at the European Patent Office by at least one inventor located in one of the allocation states with a priority date between 1992 and 2006. See text for more details on technology areas which are constructed using IPC classes and a concordance table developed by the Fraunhofer ISI and the Observatoire des Sciences et des Technologies in cooperation with the French Patent Office (Schmoch, 2008). Source: PATSTAT, own calculations.

Figure A-5: Number of automation and non-automation patents by year



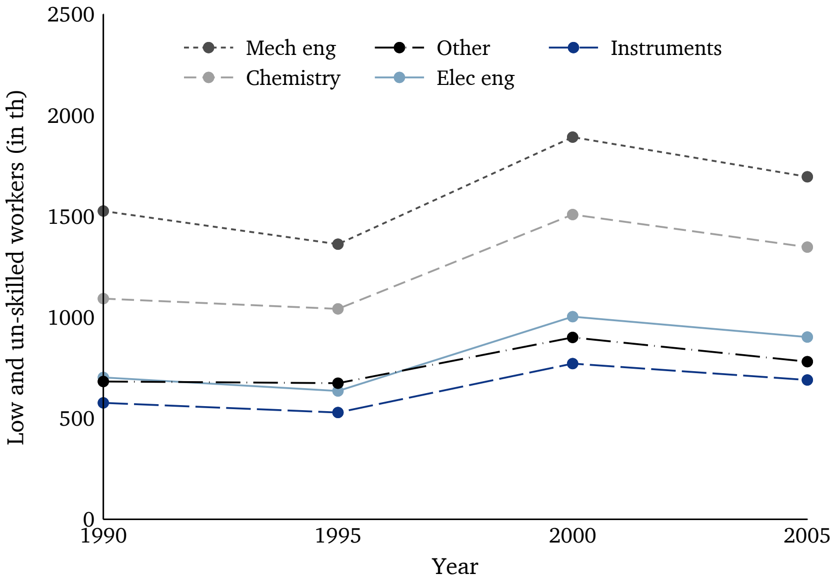
Notes: Figure shows the annual number of patent applications filed at the European Patent Office by at least one inventor located in one of the allocation states with a priority date between 1992 and 2006. We classify patents into automation patents or non-automation patents by searching keywords related to automation in the pre-processed English abstracts. See text for more details on the classification. Source: PATSTAT, own calculations.

Figure A-6: Share of automation patents by technology area



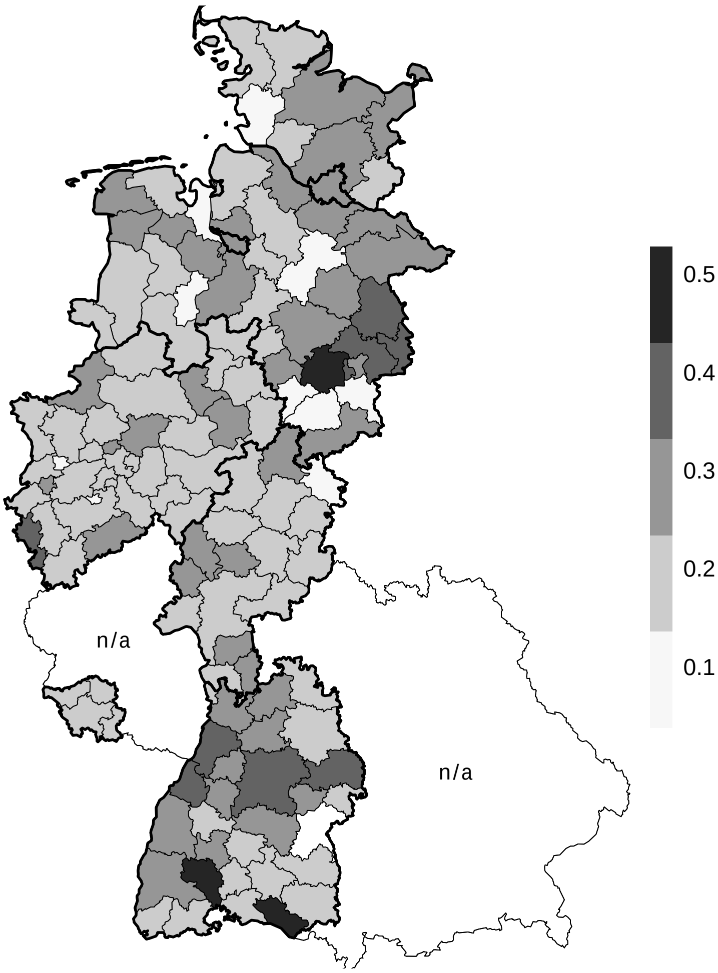
Notes: Figure shows the annual share of patent applications related to automation by technology area. Based on all patent applications filed at the European Patent Office by at least one inventor located in one of the allocation states with a priority date between 1992 and 2006. We classify patents into automation patents or non-automation patents by searching keywords related to automation in the pre-processed English abstracts. See text for more details on the classification. Source: PATSTAT, own calculations.

Figure A-7: Number of low-skilled workers by technology area



Notes: Figure shows the annual employment of unskilled and low skilled workers in industries related to specific technology areas. Own calculations based on concordance tables between industries and technologies by Dorner and Harhoff (2018) and employment data from the Institute for Employment Research.

Figure A-8: Share of automation patents across German regions



Notes: The share of automation patents across labor market regions in West German allocation states. Own calculations of the share of automation patents for 127 labor market regions. Based on all patent applications filed at the European Patent Office by at least one inventor located in one of the allocation states with a priority date between 1992 and 2006. The black lines denote state borders. Figure based on a shapefile of the Federal Republic of Germany from Eurostat and a reference file on counties and labor market regions from the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR).

B Appendix: Tables

Table B-1: Regional characteristics

Variable	Source and description
Ethnic inflows	Glitz (2012) and Piopiunik and Ruhose (2017), original data from 1992 to 2001 from the admission centers in each state and from 2002 to 2006 from Bundesarbeitsgemeinschaft Evangelische Jugendsozialarbeit e.V., Jugendmigrationsdienste.
Population	1992 and 1994-2008: Working Group Regional Accounts VGRdL. 1991 and 1993: Glitz (2012), original data from the German Statistical Office.
Share of non-natives	1995-2008: INKAR online. 1991-1994: Glitz (2012), original data from the German Statistical Office.
GDP, GVA, GVA production, GVA services	Working Group Regional Accounts VGRdL. We impute the 1993 values using the 1992 values and the 1993 national growth rate. We impute the 1991 values using the 1992 values and the 1992 national growth rate.
Labor force	Federal Employment Agency. The dependent labor force.
Unemployment rate	Federal Employment Agency. Based on the dependent labor force.
Skill groups	Establishment History Panel from the Institute for Employment (customized analysis, based on the population of establishments with at least one employee subject to social security in Germany). The shares of high skilled employees (with university degree or applied university degree), medium skilled employees (with school degree and vocational education but no higher degree) and the share of engineers and scientists (employees with a degree from a university or a university of applied sciences and with specific occupation classifications).
Occupation groups	Establishment History Panel from the Institute for Employment (customized analysis, based on the population of establishments with at least one employee subject to social security in Germany). The shares of 12 different occupation groups (agricultural, unskilled manual, unskilled services, unskilled commercial and admin., skilled manual, skilled services, skilled commercial and admin., technicians, semiprofessions, engineers, professions, managers).
Age > 55	Establishment History Panel from the Institute for Employment (customized analysis, based on the population of establishments with at least one employee subject to social security in Germany). The employment share of workers older than 55.

Table B-2: Analysis sample

Federal State of Germany	Labor Market Regions	Analysis Sample	Pre Binding Allocation	Binding Allocation			
		Region-Year Observations	Region-Year Observations	Region-Year Observations	Start Year	End Year	Implementation Date
Baden-Wuerttemberg	28	420	112	308	1996	2006	01.03.1996
Bremen[*]	0	0	0	0	1997	2006	01.03.1996
Hamburg[**]	0	0	0	0	1996	2006	01.03.1996
North Rhine-Westphalia	36	540	144	396	1996	2006	01.03.1996
Schleswig-Holstein	8	120	32	88	1996	2006	01.03.1996
Lower Saxony	34	505	170	335	1997	2006	07.04.1997
Saarland	4	60	16	44	1996	2006	11.03.1996
Hesse	17	204	119	85	2002	2006	01.01.2002
Total	127	1849	593	1256			

Notes: Analysis sample and the implementation of the assigned place of residence act. Regional level: labor market region. We have merged the regions "Osterode" and "Goettingen" into one region to make the data compatible with the regional employment data. We conservatively exclude the region "Ulm" because it is partly located in the state of Bavaria which did not implement the placement policy. The regions "Bremen" and "Bremerhaven" are partly in the state of Bremen and contain counties that are in Lower Saxony[*]. We conservatively include these regions only from 1997 onward when Lower Saxony implemented the allocation policy. The region "Hamburg" contains the state of Hamburg, three counties in Schleswig-Holstein and one county in Lower Saxony[**]. Since the counties in Schleswig-Holstein and the city of Hamburg are dominant, we follow Glitz (2012) and include this region from 1996 onward when Hamburg and Schleswig-Holstein adopted the placement policy. The region "Mannheim" contains also one county in Hesse. We conservatively include this region only from 2002 onward when Hesse implemented the allocation policy. For the construction of the state fixed effects and year-by-state fixed effects, we assign the region "Hamburg" to the state of Schleswig-Holstein, the regions "Bremen" and "Bremerhaven" to the state of Lower Saxony and the region "Mannheim" to the state of Hesse. Data on ethnic German inflows are not available for the region "Hannover" (Lower Saxony) for the years 2002-2006 and for regions within the state of Hesse for the years 1992-1994. To merge the inflow data with the patent data, we account for territorial reforms in the regions using historical files of changes between the various NUTS versions from Eurostat. There were only two territorial reforms in the labor market regions of the allocation states: in 2001, “Hannover, Kreisfreie Stadt" and “Hannover, Landkreis" were united into “Region Hannover.” Likewise in 2009, “Aachen, Kreisfreie Stadt" and “Aachen, Kreis" were united into “Städteregion Aachen."

Table B-3: Effect of labor supply on the level of non-automation innovation – alternative lag structure

Dep. Var.:	Non-Automation patents			
	(1)	(2)	(3)	(4)
Inflow rate$_t$	−0.013*			
	(0.007)			
Allocation$_t$ × Inflow rate$_t$	0.008			
	(0.009)			
Inflow rate$_{t-1}$		−0.014**		
		(0.007)		
Allocation$_{t-1}$ × Inflow rate$_{t-1}$		0.022**		
		(0.009)		
Inflow rate$_{t-2}$			−0.015**	
			(0.006)	
Allocation$_{t-2}$ × Inflow rate$_{t-2}$			0.014	
			(0.008)	
Inflow rate$_{t-3}$				−0.016***
				(0.005)
Allocation$_{t-3}$ × Inflow rate$_{t-3}$				0.008
				(0.010)
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes	Yes
Observations	1849	1849	1849	1849
R-squared	0.976	0.976	0.977	0.976
Within R-squared	0.117	0.096	0.089	0.056
Total effect	−0.005	0.008	−0.001	−0.007
P-value	0.638	0.461	0.904	0.423

Notes: OLS regressions. Dependent variable: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t-2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t-2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-4: Effect of labor supply on automation innovation by firm size

Dep. Var.:	Automation patents / patents			Automation patents			Non-Automation patents		
Applicant:	Small	Large	Non-corporate	Small	Large	Non-corporate	Small	Large	Non-corporate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Inflow rate$_{t\text{-}2}$	−0.069	0.210	−0.198	−0.012	0.002	0.007	−0.013**	−0.008	0.005
	(0.132)	(0.348)	(0.243)	(0.007)	(0.011)	(0.007)	(0.006)	(0.010)	(0.006)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	−0.705***	−0.854**	0.301	−0.027	−0.042*	−0.011	0.015*	0.006	−0.019
	(0.243)	(0.372)	(0.555)	(0.016)	(0.022)	(0.017)	(0.009)	(0.016)	(0.016)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1845	1814	1771	1849	1849	1849	1849	1849	1849
R-squared	0.399	0.484	0.155	0.933	0.943	0.840	0.966	0.955	0.910
Within R-squared	0.022	0.023	0.009	0.033	0.090	0.015	0.063	0.078	0.024
Total effect	−0.774	−0.643	0.103	−0.039	−0.040	−0.004	0.002	−0.002	−0.014
P-value	0.003	0.133	0.853	0.015	0.065	0.799	0.803	0.890	0.332
Dep var mean	21.100	26.025	21.267	1.904	1.656	0.819	3.100	2.512	1.691

Notes: OLS regressions. The samples of patents are split at the median size, stratified by technology area and year. Firm size is proxied by the cumulative number of previously filed patents of a given firm. Dependent variables constructed using patent applications filed by small firms (Column 1, 4, 7), large firms (Column 2, 5, 8), or non-coprorate applicants (Column 3, 6, 9): Column 1-3: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Column 4-6: number of automation patents filed in year t (entered in logs). Column 7-9: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-5: Effect of labor supply on automation innovation by firm age

Dep. Var.:	Automation patents / patents		Automation patents		Non-Automation patents	
Age:	Young	Old	Young	Old	Young	Old
	(1)	(2)	(3)	(4)	(5)	(6)
Inflow rate$_{t-2}$	−0.207	0.582**	−0.009	−0.006	−0.005	−0.025**
	(0.161)	(0.248)	(0.007)	(0.010)	(0.006)	(0.010)
Allocation$_{t-2}$ × Inflow rate$_{t-2}$	−0.699**	−0.983**	−0.036**	−0.030	0.004	0.019
	(0.288)	(0.377)	(0.017)	(0.022)	(0.009)	(0.015)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1839	1822	1849	1849	1849	1849
R-squared	0.380	0.470	0.933	0.928	0.962	0.951
Within R-squared	0.022	0.043	0.034	0.087	0.057	0.083
Total effect	−0.905	−0.401	−0.046	−0.036	−0.001	−0.006
P-value	0.002	0.347	0.006	0.115	0.886	0.689
Dep var mean	21.744	24.145	1.802	1.604	2.942	2.553

Notes: OLS regressions. The sample of patents are split at the median age, stratified by technology area and year. Firm age is proxied by the number of years since the firm first filed a patent (after the cut-off year 1979). Dependent variables constructed using patent applications from young firms (Column 1, 3, 5) or old firms (Column 2, 4, 6): Column 1-2: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Column 3-4: number of automation patents filed in year t (entered in logs). Column 5-6: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t-2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t-2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-6: Effect of labor supply on automation innovation by innovation concentration

Dep. Var.:	Automation patents / patents		Automation patents		Non-Automation patents	
Innovation concentration:	Regional	Not regional	Regional	Not regional	Regional	Not regional
	(1)	(2)	(3)	(4)	(5)	(6)
Inflow rate$_{t\text{-}2}$	−0.096	0.200	−0.015**	0.002	−0.013**	−0.010
	(0.138)	(0.320)	(0.008)	(0.011)	(0.006)	(0.009)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	−0.546**	−0.960**	−0.014	−0.043**	0.016*	0.003
	(0.258)	(0.369)	(0.017)	(0.020)	(0.009)	(0.019)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1843	1809	1849	1849	1849	1849
R-squared	0.383	0.432	0.927	0.936	0.962	0.955
Within R-squared	0.022	0.029	0.041	0.076	0.079	0.069
Total effect	−0.642	−0.760	−0.030	−0.041	0.002	−0.007
P-value	0.013	0.059	0.072	0.044	0.789	0.711
Dep var mean	20.982	26.437	1.827	1.565	3.019	2.385

Notes: OLS regressions. The sample of patents are split at the median innovation concentration, stratified by technology area and year. Innovation concentration is proxied by the number of distinct inventor regions of all patents of a given firm. Dependent variables constructed using patent applications from local firms (Column 1, 3, 5) or non-local firms (Column 2, 4, 6): Column 1-2: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Column 3-4: number of automation patents filed in year t (entered in logs). Column 5-6: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-7: Effect of labor supply on automation innovation (quality weighted)

Patent value weights:	Granted patents only	Weighted by family size	Weighted by fwd cites
Dep. Var.:	Automation patents / patents		
	(1)	(2)	(3)
Inflow rate$_{t-2}$	0.076	0.124	0.558*
	(0.151)	(0.151)	(0.294)
Allocation$_{t-2}$ × Inflow rate$_{t-2}$	−0.937***	−1.117***	−2.644***
	(0.232)	(0.230)	(0.498)
Observations	1846	1847	1823
R-squared	0.515	0.538	0.407
Within R-squared	0.028	0.027	0.034
Total effect	−0.860	−0.994	−2.086
P-value	0.000	0.000	0.000
Dep. Var.:	Automation patents		
	(4)	(5)	(6)
Inflow rate$_{t-2}$	−0.013*	−0.013	0.007
	(0.007)	(0.009)	(0.014)
Allocation$_{t-2}$ × Inflow rate$_{t-2}$	−0.037***	−0.046**	−0.115***
	(0.014)	(0.019)	(0.027)
Observations	1849	1849	1849
R-squared	0.949	0.927	0.897
Within R-squared	0.067	0.045	0.049
Total effect	−0.050	−0.059	−0.108
P-value	0.000	0.002	0.000
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes

Notes: OLS regressions. Each patent application is weighted with patent grant status (column 1 and 4), the number of patents within the same DOCDB family (column 2 and 5) or US patent citations within the first 3 years (column 3 and 6). Dependent variables: Panel A: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Panel B: number of automation patents filed in year t (entered in logs). Inflow rate$_{t-2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t-2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-8: Effect of labor supply on automation innovation – alternative sets of automation keywords

Dep. Var.:	Automation patents / patents			Automation patents			Non-Automation patents		
Set of Automation Keywords:	Extended	Reduced	automat	Extended	Reduced	automat	Extended	Reduced	automat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Inflow rate$_{t\text{-}2}$	0.176	0.112	0.068*	−0.006	−0.007	0.003	−0.015**	−0.014**	−0.013**
	(0.126)	(0.121)	(0.035)	(0.006)	(0.007)	(0.009)	(0.006)	(0.006)	(0.006)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	−0.958***	−0.882***	−0.302***	−0.034**	−0.042***	−0.085***	0.015*	0.013	0.005
	(0.212)	(0.201)	(0.063)	(0.014)	(0.015)	(0.015)	(0.008)	(0.009)	(0.010)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1847	1847	1847	1849	1849	1849	1849	1849	1849
R-squared	0.659	0.536	0.342	0.961	0.954	0.835	0.976	0.977	0.978
Within R-squared	0.036	0.033	0.040	0.072	0.069	0.073	0.088	0.092	0.098
Total effect	−0.781	−0.770	−0.234	−0.040	−0.049	−0.082	0.000	−0.001	−0.008
P-value	0.000	0.000	0.000	0.004	0.001	0.000	0.982	0.893	0.376
Dep var mean	26.710	19.582	2.248	2.531	2.259	0.731	3.500	3.594	3.787

Notes: OLS regressions. Dependent variables constructed using an extended (Column 1, 4, 7) or reduced set (Column 2, 5, 8) of automation keywords or the keyword "automat" (Column 3, 6, 9): Column 1-3: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Column 4-6: number of automation patents filed in year t (entered in logs). Column 7-9: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-9: Effect of labor supply on automation innovation – Poisson regressions

Dep. Var.:	Automation patents	Non-Automation patents
	(1)	(2)
Inflow $\text{rate}_{t\text{-}2}$	−0.012	−0.014**
	(0.008)	(0.007)
$\text{Allocation}_{t\text{-}2}$ × Inflow $\text{rate}_{t\text{-}2}$	−0.046***	0.008
	(0.016)	(0.008)
Region and year fixed effects	Yes	Yes
Year-by-State fixed effects	Yes	Yes
Controls	Yes	Yes
Occupation + Skill groups	Yes	Yes
Observations	1849	1849
Log-likelihood	-5147.551	-6758.882

Notes: Poisson pseudo-likelihood regression with multiple levels of fixed effects, as described by Correia et al. (2019). Table presents the estimated coefficients of the regressions. Dependent variables: Column 1: number of automation patents filed in year t. Column 2: number of non-automation patents filed in year t. Inflow $\text{rate}_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. $\text{Allocation}_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-10: Effect of labor supply on automation innovation – allocation period only

Dep. Var.:	Automation patents / patents	Automation patents	Non-Automation patents
	(1)	(2)	(3)
Inflow rate$_{t\text{-}2}$	−0.698***	−0.044***	−0.009
	(0.246)	(0.016)	(0.008)
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes
Observations	1256	1256	1256
R-squared	0.663	0.964	0.982
Within R-squared	0.044	0.083	0.094

Notes: OLS regressions. Throughout all regressions, we only include region-year pairs from the binding allocation period. Dependent variables: Column 1: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Column 2: number of automation patents filed in year t (entered in logs). Column 3: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-11: Effect of labor supply on automation innovation – non-binding allocation period only

Dep. Var.:	Automation patents / patents	Automation patents	Non-Automation patents
	(1)	(2)	(3)
Inflow rate$_{t\text{-}2}$	−0.003	−0.005	0.008
	(0.232)	(0.011)	(0.009)
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes
Observations	591	593	593
R-squared	0.601	0.968	0.984
Within R-squared	0.037	0.099	0.180

Notes: OLS regressions. Throughout all regressions, we only include region-year pairs from the non-binding allocation period. Dependent variables: Column 1: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Column 2: number of automation patents filed in year t (entered in logs). Column 3: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1995. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-12: Effect of labor supply on automation innovation – overlapping observations

Dep. Var.:	Automation patents / patents	Automation patents	Non-Automation patents
	(1)	(2)	(3)
OL Inflow rate$_{\text{t-2}}$	−0.295**	−0.018**	−0.001
	(0.117)	(0.009)	(0.005)
P-value wild cluster bootstrap	{0.024}	{0.052}	{0.863}
Region and year fixed effects	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes
Observations	1002	1002	1002
R^2 within	0.16	0.27	0.32

Notes: OLS regressions. Throughout all regressions, we only include region-year pairs from the binding allocation period. Dependent variables: Column 1: cumulated number of automation patents over the three-year period t to $t+2$ divided by the cumulated total number of patents over the three-year period t to $t+2$ (multiplied by 100). Column 2: cumulated number of automation patents over the three-year period t to $t+2$ (entered in logs). Column 3: cumulated number of non-automation patents over the three-year period t to $t+2$ (entered in logs). OL Inflow rate$_{\text{t-2}}$: cumulative ethnic German inflows over the three-year period $t-2$ to t scaled by the workforce in $t-3$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1995. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. P-values based on the wild cluster bootstrap-t method by Cameron et al. (2008) in curly parentheses. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-13: Effect of labor supply on automation innovation – regions with low or high innovative capacity excluded

Dep. Var.:	Automation patents / patents		Automation patents		Non-Automation patents	
Excluding regions with:	Low capacity	High capacity	Low capacity	High capacity	Low capacity	High capacity
	(1)	(2)	(3)	(4)	(5)	(6)
Inflow rate$_{t-2}$	0.084	0.050	−0.012*	−0.008	−0.019***	−0.008
	(0.144)	(0.143)	(0.007)	(0.007)	(0.007)	(0.006)
Allocation$_{t-2}$ × Inflow rate$_{t-2}$	−0.855***	−0.808***	−0.035**	−0.033*	0.014	0.009
	(0.212)	(0.241)	(0.015)	(0.017)	(0.009)	(0.009)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1669	1684	1669	1686	1669	1686
R-squared	0.643	0.535	0.957	0.903	0.976	0.944
Within R-squared	0.040	0.034	0.081	0.073	0.100	0.093
Total effect	−0.772	−0.758	−0.047	−0.041	−0.005	0.000
P-value	0.001	0.003	0.003	0.015	0.579	0.980

Notes: OLS regressions. We exclude regions in column 1, 3 and 5 (2, 4 and 6), if the pre-existing regional number of patent applications in 1991 is below (above) the 10 (90) percentile. Dependent variables: Column 1-2: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Column 3-4: number of automation patents filed in year t (entered in logs). Column 5-6: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t-2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t-2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-14: Effect of labor supply on automation innovation – Gifhorn regions excluded

Dep. Var.:	Automation patents / patents	Automation patents	Non-Automation patents
	(1)	(2)	(3)
Inflow rate$_{t\text{-}2}$	0.034	−0.010	−0.015**
	(0.161)	(0.008)	(0.007)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	−1.011***	−0.043***	0.014*
	(0.217)	(0.015)	(0.008)
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes
Observations	1757	1759	1759
R-squared	0.598	0.959	0.978
Within R-squared	0.038	0.064	0.067
Total effect	−0.977	−0.053	−0.001
P-value	0.000	0.001	0.865

Notes: OLS regressions. Throughout all regressions, we exclude regions that signed the Gifhorn declaration. Dependent variables: Column 1: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Column 2: number of automation patents filed in year t (entered in logs). Column 3: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-15: Effect of labor supply on automation innovation – winsorized inflow rate

Dep. Var.:	Automation patents / patents	Automation patents	Non-Automation patents
	(1)	(2)	(3)
Inflow $\text{rate}_{t\text{-}2}$	0.189	−0.006	−0.017*
	(0.187)	(0.011)	(0.009)
$\text{Allocation}_{t\text{-}2}$ × Inflow $\text{rate}_{t\text{-}2}$	−0.949***	−0.036**	0.016*
	(0.233)	(0.016)	(0.010)
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes
Observations	1847	1849	1849
R-squared	0.591	0.958	0.977
Within R-squared	0.033	0.070	0.086
Total effect	−0.760	−0.043	−0.001
P-value	0.001	0.004	0.910

Notes: OLS regressions. Dependent variables: Column 1: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Column 2: number of automation patents filed in year t (entered in logs). Column 3: number of non-automation patents filed in year t (entered in logs). Inflow $\text{rate}_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Inflow rates are winsorized at the 5th percentile and the 95th percentile. $\text{Allocation}_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-16: Effect of labor supply on automation innovation – transition years excluded

Dep. Var.:	Automation patents / patents	Automation patents	Non-Automation patents
	(1)	(2)	(3)
Inflow rate$_{t\text{-}2}$	0.113	−0.008	−0.013**
	(0.133)	(0.007)	(0.006)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	−1.003***	−0.040**	0.014
	(0.284)	(0.019)	(0.012)
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes
Observations	1737	1739	1739
R-squared	0.583	0.958	0.977
Within R-squared	0.032	0.066	0.086
Total effect	−0.891	−0.048	0.000
P-value	0.001	0.010	0.991

Notes: OLS regressions. Throughout all regressions, we exclude region-year pairs from transition years. Dependent variables: Column 1: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Column 2: number of automation patents filed in year t (entered in logs). Column 3: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-17: Effect of labor supply on automation innovation by labor market tightness (50 pctl split)

Labor Market Tightness:	Tight $U_0 < 50$ pctl	Slack $U_0 \geq 50$ pctl	Tight $U_{t\text{-}3} < 50$ pctl	Slack $U_{t\text{-}3} \geq 50$ pctl
Dep. Var.:	Automation patents / patents			
	(1)	(2)	(3)	(4)
Inflow rate$_{t\text{-}2}$	−0.228	0.176	−0.248	0.232
	(0.205)	(0.162)	(0.228)	(0.149)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	−0.482*	−0.701**	−0.615**	−0.723**
	(0.269)	(0.302)	(0.254)	(0.312)
Observations	885	947	891	926
R-squared	0.708	0.548	0.724	0.546
Within R-squared	0.075	0.045	0.075	0.046
Total effect	−0.709	−0.525	−0.862	−0.491
P-value	0.035	0.085	0.003	0.108
Dep. Var.:	Automation patents			
	(5)	(6)	(7)	(8)
Inflow rate$_{t\text{-}2}$	−0.019*	−0.006	−0.018	−0.005
	(0.011)	(0.009)	(0.012)	(0.009)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	−0.039*	−0.023	−0.045**	−0.023
	(0.019)	(0.020)	(0.017)	(0.020)
Observations	885	949	891	928
R-squared	0.972	0.948	0.974	0.944
Within R-squared	0.115	0.101	0.094	0.103
Total effect	−0.058	−0.028	−0.062	−0.028
P-value	0.008	0.161	0.001	0.177
Region and year fixed effects	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Occupation + skill groups	Yes	Yes	Yes	Yes

Notes: OLS regressions. Sample splits by the 50-percentile of the unemployment rate in the year before the binding placement (column 1-2 and 5-6) and by the 50-percentile of the unemployment rate in $t-3$ (column 3-4 and 7-8). Dependent variables: Panel A: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Panel B: number of automation patents filed in year t (entered in logs). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-18: Effect of labor supply on automation innovation by labor market tightness (90 pctl split)

Labor Market Tightness:	Tight $U_0 < 90$ pctl	Slack $U_0 \geq 90$ pctl	Tight $U_{t\text{-}3} < 90$ pctl	Slack $U_{t\text{-}3} \geq 90$ pctl
Dep. Var.:	Automation patents / patents			
	(1)	(2)	(3)	(4)
Inflow $\text{rate}_{t\text{-}2}$	0.080	−0.085	0.106	0.085
	(0.143)	(0.288)	(0.139)	(1.197)
$\text{Allocation}_{t\text{-}2}$ × Inflow $\text{rate}_{t\text{-}2}$	−0.945***	−0.339	−0.990***	1.426
	(0.212)	(1.811)	(0.226)	(2.347)
Observations	1653	194	1651	176
R-squared	0.650	0.326	0.643	0.466
Within R-squared	0.044	0.094	0.045	0.148
Total effect	−0.865	−0.424	−0.884	1.511
P-value	0.000	0.811	0.000	0.390
Dep. Var.:	Automation patents			
	(5)	(6)	(7)	(8)
Inflow $\text{rate}_{t\text{-}2}$	−0.005	−0.013	−0.003	−0.103*
	(0.006)	(0.011)	(0.006)	(0.051)
$\text{Allocation}_{t\text{-}2}$ × Inflow $\text{rate}_{t\text{-}2}$	−0.040***	−0.003	−0.045***	0.137*
	(0.015)	(0.074)	(0.015)	(0.069)
Observations	1654	195	1652	177
R-squared	0.960	0.871	0.962	0.943
Within R-squared	0.067	0.311	0.085	0.335
Total effect	−0.045	−0.017	−0.047	0.034
P-value	0.003	0.819	0.002	0.483
Region and year fixed effects	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Occupation + skill groups	Yes	Yes	Yes	Yes

Notes: OLS regressions. Sample splits by the 90-percentile of the unemployment rate in the year before the binding placement (column 1-2 and 5-6) and by the 90-percentile of the unemployment rate in $t-3$ (column 3-4 and 7-8). Dependent variables: Panel A: number of automation patents filed in year t divided by total number of patents filed in year t (multiplied by 100). Panel B: number of automation patents filed in year t (entered in logs). Inflow $\text{rate}_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. $\text{Allocation}_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-19: Effect of labor supply on non-automation innovation by labor market tightness

Dep. Var.:	Non-Automation patents			
Labor Market Tightness:	Tight $U_0 < 75$ pctl	Slack $U_0 \geq 75$ pctl	Tight $U_{t\text{-}3} < 75$ pctl	Slack $U_{t\text{-}3} \geq 75$ pctl
	(1)	(2)	(3)	(4)
Inflow rate$_{t\text{-}2}$	−0.011	−0.015	−0.011*	−0.012
	(0.007)	(0.016)	(0.006)	(0.017)
Allocation$_{t\text{-}2}$ × Inflow rate$_{t\text{-}2}$	0.012	0.003	0.006	0.025
	(0.009)	(0.032)	(0.010)	(0.027)
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Year-by-State fixed effects	Yes	Yes	Yes	Yes
Occupation + Skill groups	Yes	Yes	Yes	Yes
Observations	1374	460	1371	459
R-squared	0.983	0.955	0.983	0.964
Within R-squared	0.083	0.222	0.115	0.165
Total effect	0.001	−0.011	−0.005	0.013
P-value	0.874	0.690	0.572	0.484

Notes: OLS regressions. Sample splits by the 75-percentile of the unemployment rate in the year before the binding placement (column 1-2) and by the 75-percentile of the unemployment rate in $t-3$ (column 3-4). Dependent variable: number of non-automation patents filed in year t (entered in logs). Inflow rate$_{t\text{-}2}$: ethnic German inflows in $t-2$ scaled by the workforce in $t-3$. Allocation$_{t\text{-}2}$: dummy equal to 1 if the state-wide allocation policy was binding in $t-2$. Controls: log population, log labor force, unemployment rate, share of non-natives, GDP per capita, log gross value added total, log GVA production, log GVA services and Share age > 55. Occupation + skill groups: employment shares of 12 occupation groups and 3 skill groups. Regressions estimated at the region-year level, weighted by regional population in 1991. Standard errors clustered at the regional level in parentheses. Significance levels: * p<0.10, ** p<0.05,*** p<0.01. *Data sources*: Innovation variables based on PATSTAT data. For regional characteristics see Table B-1 in the Appendix.

Table B-20: Patent-level summary statistics

Variable	Mean	Std. Dev.	Min	Max	N
Main					
Automation patents	0.25	0.43	0.00	1.00	264061
Automation patents (Extended)	0.29	0.45	0.00	1.00	264061
Automation patents (Reduced)	0.21	0.41	0.00	1.00	264061
Automation patents (automat)	0.02	0.14	0.00	1.00	264061
Technology Areas					
Electrical	0.16	0.37	0.00	1.00	263858
Instruments	0.12	0.33	0.00	1.00	263858
Chemistry	0.28	0.45	0.00	1.00	263858
Mechanical	0.36	0.48	0.00	1.00	263858
Other	0.08	0.27	0.00	1.00	263858
Automation (Electrical)	0.07	0.26	0.00	1.00	263858
Automation (Instruments)	0.05	0.22	0.00	1.00	263858
Automation (Chemistry)	0.03	0.17	0.00	1.00	263858
Automation (Mechanical)	0.09	0.28	0.00	1.00	263858
Automation (Other)	0.01	0.11	0.00	1.00	263858
Quality Weights					
Granted	0.62	0.49	0.00	1.00	263915
Automation (Granted)	0.15	0.36	0.00	1.00	263915
DOCDB Family Size (weighted)	6.29	5.80	1.00	160.00	263915
Automation: DOCDB Family Size (weighted)	1.38	3.30	0.00	160.00	263915
DOCDB citations (weighted)	2.37	8.56	0.00	1388.00	263915
Automation: DOCDB citations (weighted)	0.72	5.83	0.00	1388.00	263915
Processes					
Process	0.46	0.50	0.00	1.00	231855
Non-Process	0.54	0.50	0.00	1.00	231855
Automation (Process)	0.13	0.34	0.00	1.00	231855
Automation (Non-Process)	0.12	0.32	0.00	1.00	231855
Automation (Process+Mechanical)	0.03	0.18	0.00	1.00	231855
Non-Automation (Process+Mechanical)	0.08	0.28	0.00	1.00	231855
Automation (Non-Process+Mechanical)	0.05	0.22	0.00	1.00	231855
Non-Automation (Non-Process+Mechanical)	0.20	0.40	0.00	1.00	231855

Notes: Summary statistics of patent applications with a priority year between 1990 and 2010 filed by inventors located in the allocation states. *Data source*: PATSTAT. The measures of automation innovation by one of five main technology areas are based on mapped IPC classes and the concordance table developed by the Fraunhofer ISI and the Observatoire des Sciences et des Technologies in cooperation with the French patent office (Schmoch, 2008). See text for more details regarding the classification of patents into automation and non-automation patents.

Table B-21: Examples of automation patents

EP application number	EP19940115956
Title	Method for controlling dryers in brick factories
Assignee	INNOVATHERM Prof Dr Leisenberg GmbH
Abstract	According to a method for controlling dryers in the ceramic industry, which are operated with an external and/or internal heating and are operated in conjunction with a tunnel furnace, and in which, by means of an empirical or mathematical model of the drying process, the state of drying-out of the chambers is approximately determined, the variation of the air condition values and/or of the convection capacity of the individual chambers is **automat**ically selected or calculated as a function of the products, the available drying time and the available furnace waste heat, from the point of view of a minimum total energy or energy cost expenditure, and is started as a drying programme. This mode of operation achieves an **automat**ic optimisation of the heat consumption in a targeted manner, using the prescribed boundary conditions, and, as a result, the costs of energy and personnel are reduced in a concern without large investment in terms of installation being necessary.
EP application number	EP20010969514
Title	Method and device for analysing chemical or biological samples
Assignee	BASF LYNX BIOSCIENCE AG
Abstract	The invention relates to a method and related device for analysing chemical or biological samples. Chemical or biological samples and/or targets (probes) are applied to an outer cylindrical lateral area of a carrier in the form of individual defined spots, or are loaded into bore holes in the form of liquid drops, said bore holes being recessed in the lateral area of the carrier. The carrier is introduced into a recess in the holder, said recess being essentially complementary to the cylindrical lateral area, the samples and/or targets are influenced by means of physical and/or chemical interactions, and the accordingly modified spots are then analysed. The invention also relates to the use of a novel carrier **system** for examining chemical or biological samples, which contrary to conventional planar biochips is characterised by a cylindrical geometry, whereby substances can be applied, immobilised for example, on the functionalised lateral area of the cylinder or in the radial bore holes recessed in the cylinder casing. An analysis **system** having clearly defined reaction volumes is implemented by co-operating with a complementary holder, said analysis **system** being easily standardised and highly **automat**ed.
EP application number	EP19990942756
Title	Method for **automat**ically controlling and selecting the bodies of slaughtered poultry
Assignee	CSB SYST SOFTWARE ENTWICKLUNG, Csb-System Software-Entwicklung & Unternehmensberatung AG
Abstract	The invention describes a method for **automat**ically controlling and selecting the bodies of slaughtered poultry. The invention aims at providing a very easy and cost-effective method for **automat**ically controlling and selecting the bodies of slaughtered poultry. According to the invention, said aim is achieved in that the body of the slaughtered poultry to be controlled is selected by conducting color analysis of the light reflected from the visible surface parts, said light being **detect**ed as a diffuse color mixing light eliminating spatial contours using a measuring technique, wherein the measured value is used for selection as integrating value for the totality of visible surface parts.

Notes: Source: PATSTAT.