Journal of Public Economics 235 (2024) 105136

Contents lists available at ScienceDirect

Journal of Public Economics

journal homepage: www.elsevier.com/locate/jpube

Labor supply and automation innovation: Evidence from an allocation policy☆

Alexander M. Danzer [a,b,c,d], Carsten Feuerbaum [a,h], Fabian Gaessler [e,f,g,h,*]

[a] KU Eichstaett-Ingolstadt, Germany
[b] IZA Bonn, Germany
[c] CReAM, University College London, United Kingdom
[d] CESifo, Munich, Germany
[e] Universitat Pompeu Fabra, Spain
[f] UPF Barcelona School of Management, Spain
[g] Barcelona School of Economics, Spain
[h] Max Planck Institute for Innovation and Competition, Munich, Germany

A R T I C L E I N F O

JEL classification:
J22
J61
O31
O33

Keywords:
Automation
Labor supply
Innovation
Patents
Germany

A B S T R A C T

Despite a longstanding interest in the potential substitution of labor and capital, limited empirical evidence exists regarding the causal relationship between labor supply and the development of labor-saving technologies. This study examines the impact of exogenous changes in regional labor supply on automation innovation by leveraging a German immigrant allocation policy during the 1990s and 2000s. The findings reveal that an increase in the low-skilled workforce reduces automation innovation, as measured by patents. This reduction is most pronounced for large firms within the manufacturing sector and primarily concerns process-related automation innovations. This suggests that the effect is channeled through changes in internal demand for automation innovation. Consistent with a labor scarcity mechanism, the effect is confined to tight labor markets.

1. Introduction

Are man and machine substitutes? This fundamental question pertains to a longstanding theoretical debate regarding the influence of labor supply on firms' investments in labor-saving (i.e., automation) innovation (Habakkuk, 1962; Hicks, 1932). In a recent theoretical contribution, Acemoglu (2010) suggests that labor scarcity could potentially drive technological progress if new technologies are *strongly labor-saving*. Consequently, examining the substitutability between labor and capital becomes particularly relevant in economic sectors where automation is both technically feasible and efficiency-enhancing. Despite this topic's economic and societal significance, empirical studies on the response of automation innovation to changes in labor supply have been limited.

This paper provides empirical evidence on the causal relationship between regional labor supply and automation innovation. To this end, we leverage an immigrant allocation policy in Germany, which provides plausibly exogenous variation in low-skilled labor supply across labor market regions. Our analysis exploits the immigration

☆ We acknowledge helpful comments and suggestions from Christoph Albert, Michele Battisti, Jen Brown, Marina Chugunova, Barbara Dietz, Bernhard Ganglmair, Albrecht Glitz, Dietmar Harhoff, Elke J. Jahn, Benjamin F. Jones, Dominika Langenmayr, Andrea Mina, Markus Nagler, Morten Olsen, Bettina Peters, Morgan Raux, Regina Riphahn, Michael Rose, Christopher T. Stanton, Max Steinhardt, Jan Stuhler, Teodora Tsankova, Fabian Waldinger, Bruce Weinberg, Rainer Widmann, Simon Wiederhold, Michal Zator, the co-editor David Seim, three anonymous referees, as well as the audiences at conferences and workshops in Bath, Glasgow, Herrsching, Ingolstadt, Jena, Leipzig, Manchester, Munich, Ohlstadt/Ammersee, Turino, Uppsala and Warwick. We gratefully thank Matthias Dorner, Alexander Patt, and the Institut für Arbeitsmarkt- und Berufsforschung (IAB) for providing us with employment data. We also thank Felix Poege and Vera Jahn for providing us with some regional data. Carsten Feuerbaum gratefully acknowledges funding through the International Doctoral Program Evidence-Based Economics of the Elite Network of Bavaria, Germany. Fabian Gaessler gratefully acknowledges financial support from the Deutsche Forschungsgemeinschaft, Germany through CRC TRR 190 "Rationality and Competition" and the Spanish Agencia Estatal de Investigación (AEI) through the Severo Ochoa Programme for Centres of Excellence in R&D (Barcelona School of Economics CEX2019-000915-S).

* Corresponding author at: Universitat Pompeu Fabra, Spain.
E-mail addresses: alexander.danzer@ku.de (A.M. Danzer), fabian.gaessler@upf.edu (F. Gaessler).

https://doi.org/10.1016/j.jpubeco.2024.105136
Received 1 May 2022; Received in revised form 29 February 2024; Accepted 6 May 2024
Available online 22 May 2024

of approximately 2.5 million ethnic Germans into West Germany following the collapse of the Soviet Union. These new German citizens predominantly originated from the lower end of the skill distribution and were willing to take on low-skilled manual jobs. Most West German states implemented an allocation policy in 1996/97 to achieve a more balanced distribution of these immigrants across regions. This restricted the ethnic Germans' ability to select regions based on their preference for particular labor market characteristics.

We examine the impact of labor supply on automation innovation in a difference-in-differences framework. Specifically, we construct a panel data set at the region-year level and compare how automation innovation activities evolve across regions as they experience different changes in labor supply due to the allocation of ethnic Germans. As a proxy for regional automation innovation activities, we use geocoded patents filed with the European Patent Office, which we categorize as either automation or non-automation based on their textual characteristics (Mann and Püttmann, 2023). To operationalize changes in labor supply, we measure the cumulative inflow of ethnic Germans during the allocation period and normalize it by the size of the pre-existing low-skilled workforce. We find that these inflows significantly affect regional labor market conditions in terms of low-skilled employment and unemployment growth, in line with much of the established literature on immigration (e.g., Borjas, 1994; Card, 1990; Dustmann et al., 2008, 2017; Peri and Sparber, 2009). Our identification strategy employs a spatial approach that captures the total effect of labor supply on regional automation innovation, similar to previous studies conducted by Boustan et al. (2010) and Dustmann et al. (2017).

Our results demonstrate that an increase in labor supply reduces regional automation innovation activities. We observe a transient, negative effect of low-skilled labor supply on the share of automation patents. This effect peaks in the fourth year following the introduction of the allocation policy and then gradually converges toward zero after that. Our estimates indicate that an increase in the low-skilled workforce by 10 percent reduces the share of automation patents by about 3.3 percentage points or about 2.5 automation patents annually for the average region. In contrast, the number of non-automation patents remains largely unchanged by the increase in labor supply. Overall, these findings suggest that treated regions undergo a substantial shift in their direction of technical change. We test the robustness of these results by varying our choice of estimators, measures, sample definitions, and additional control variables. All tests corroborate our causal interpretation.

Why does an increase in labor supply induce a decrease in automation innovation? Theoretically, this can be explained by adjustments in firms' production processes under specific labor market conditions. Firstly, when labor becomes more abundant or cheaper as a factor of production, firms have fewer incentives to invest in automation innovation. This, however, requires that labor and capital are substitutes. Therefore, the impact on automation innovation depends on the general susceptibility to automation, which should be higher for low-skilled labor performing routine tasks (Autor et al., 2003; Acemoglu and Restrepo, 2019). Secondly, the increase in labor supply needs to change the labor market equilibrium, either in the form of price adjustments (wages) (Acemoglu, 2010) or quantity adjustments (employment). Therefore, the impact of an increase in labor supply depends on the flexibility of wages and the scarcity of labor.

We conduct a series of heterogeneity analyses to provide evidence on how labor supply affects automation innovation. Indeed, we find that the effect of labor supply on automation innovation originates mainly from the manufacturing sector, which traditionally employs substantial numbers of low-skilled workers performing routine tasks. Moreover, we find that the effect in the manufacturing sector is concentrated among large firms and involves process- instead of product-related automation innovation. Finally, with respect to labor market conditions, we find that the effect on automation innovation is confined to regions with a tight labor market, i.e., with a higher labor scarcity. These findings underscore that susceptibility to automation, labor cost considerations *within* firms, and labor scarcity govern the effect of increased labor supply on automation innovation.

Our paper makes three contributions. First, we provide empirical evidence from a contemporary context to the predominantly theoretical literature on the relationship between relative factor supplies and technical change (e.g., Acemoglu, 2002, 2007; Hanlon, 2015; Kiley, 1999). The few existing empirical studies on the relationship between labor supply and innovation concentrate on historical contexts and remain inconclusive. For instance, San (2023) 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 (2020) explore the effect of mass immigration in the early 20th century in the US and find that the inflow of low-skilled workers increases the overall rate of innovation. In light of these conflicting findings, our study fills a crucial gap by demonstrating that innovation responses to labor supply primarily involve labor-saving technologies and are driven, at least within our context, by internal demand for automation.[1]

Second, we contribute to the literature on the role of factor endowments in technology adoption (e.g., Zeira, 1998). Previous research suggests that firms adjust to shifts in labor supply by transitioning to the most cost-efficient production technologies (e.g., Hanson and Slaughter, 2002; Dustmann and Glitz, 2015; Zator, 2019). Indeed, several studies demonstrate that low-skilled labor supply plays a significant role in explaining firms' adoption of production technologies (Lewis, 2011; Clemens et al., 2018; Imbert et al., 2019; Monras, 2019). Our study complements these findings by illustrating that firms not only *adopt* but also *develop* these technologies, as evidenced by their reduced activity in patenting automation innovations.

Third, a distinguishing feature of our work is the exploration of the channel through which low-skilled labor supply affects automation innovation. For one, we find that the effect of labor supply on automation innovation occurs through increased employment. The finding of a quantity (rather than wage) adjustment is consistent with Germany's robust labor market regulations and aligns with prior literature (Glitz, 2012). By elucidating the employment channel, we complement the work of Dechezleprêtre et al. (2023), who demonstrate that automation innovation is sensitive to wage increases, and Acemoglu and Restrepo (2022), who find higher automation innovation activities in countries experiencing rapid aging. Moreover, our research sheds light on the mechanism through a series of heterogeneity analyses concerning the susceptibility to automation (by studying different economic sectors, i.e., manufacturing vs. non-manufacturing), the internal demand for automation innovation (by investigating firm size and process innovation), and the responsiveness of regional labor markets (by differentiating between tight and slack labor markets). These findings yield important policy implications for labor market, migration, and innovation policies, particularly how such policies can be shaped to account for the interplay between labor supply, market conditions, and innovation dynamics.

The remainder of this paper is structured as follows: Section 2 describes the institutional background of the quasi-experimental allocation of ethnic Germans in the 1990s and 2000s. Section 3 introduces the data used in the empirical part of the paper. Section 4 describes the methodological framework and outlines the identification strategy. Section 5 presents the main results, while Section 6 sheds light on important margins of heterogeneity. Section 7 discusses policy implications and concludes.

[1] Relatedly, we contribute to the recent literature exploring the impact of immigration on the overall level of innovation (e.g., Hornung, 2014; Hunt and Gauthier-Loiselle, 2010; Kerr et al., 2015). While most previous studies have analyzed the effect of high-skilled immigration, our study takes a labor replacement perspective by focusing on the impact of low-skilled immigration. By doing so, we expand the understanding of the relationship between immigration and innovation dynamics.

2. Institutional background: Germany's migration allocation policy

In the following, we briefly outline the migration allocation policy, which we leverage in our empirical analysis. For a comprehensive institutional overview and an elaborate discussion with additional empirical evidence, see Online Appendix A.

After the fall of the Iron Curtain, Germany experienced a massive expansion of low-skilled labor supply through the 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).[2] Prospective ethnic German immigrants had to apply for visas at the German embassy in their home country and provide proof of German ancestry. Successful applicants were granted entry into Germany and naturalized in the national reception center, implying that they could immediately take up work (Dietz, 2006; Ohliger, 2008). During the early 1990s, ethnic German inflows varied considerably across regions, with newly arrived ethnic Germans constituting 20 percent or more of the population in certain municipalities (Klose, 1996).

To ensure a more balanced distribution of ethnic Germans across regions, the government enacted an allocation policy—the Assigned Place of Residence Act. Most West German federal states introduced the allocation policy in March 1996, with Lower Saxony following in April 1997 and Hesse in January 2002. The policy dispersed arriving ethnic Germans geographically according to exogenously set quotas, based primarily on tax revenues and population (across states) and on population and area (across counties within the states).

Following the introduction of the allocation policy, ethnic Germans lost the ability to choose their destination within Germany, and their placement ceased to be influenced by labor market considerations (see Glitz, 2012, for more details). Once allocated, ethnic Germans were bound to reside in their region for at least three years as noncompliance was heavily sanctioned with the loss of welfare benefits. Therefore, compliance with the rules was very high (Dietz, 2006), and the policy was considered successful (Federal Constitutional Court (1 BvR 1266/00, Rn. 1-56)).

The introduction of the allocation policy reduced the heterogeneity of inflows across regions relative to the pre-existing population (Fig. 1). In the pre-allocation period, the distribution of ethnic German inflows across regions was highly skewed, with certain regions systematically attracting a disproportionate number. Especially regions close to the national reception center (Friedland in Lower Saxony) and with employment opportunities in manufacturing experienced high inflows (Panagiotidis, 2021). The allocation policy substantially reduced the previous heterogeneity, leading to more balanced per-capita inflows across regions.

The inflow of ethnic Germans led to a *permanent increase* in the *regional supply of low-skilled labor*: Firstly, ethnic Germans had to stay in their region for multiple years as their social benefits were tied to residential compliance. As their inflow did not displace natives, the resident population increased almost proportionately (Glitz, 2012). Secondly, most incoming ethnic Germans were of working age, low-skilled, and had prior working experience in manual occupations, such as farmers, laborers, transport workers, operatives, and craft workers (Koller, 1993; Bundesverwaltungsamt, 2019).[3] As a result, they most often found employment in occupations with low skill requirements (Mika et al., 2010) and low incomes (Piopiunik and Ruhose, 2017).[4]

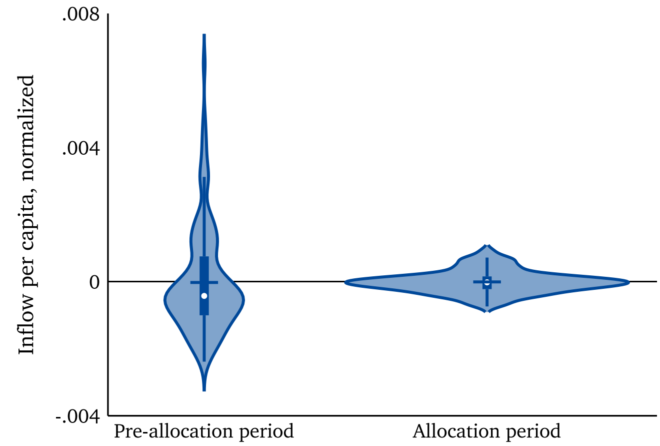

Fig. 1. Distribution of per-capita inflows across regions in the pre-allocation and allocation period

Notes: The figure illustrates the distribution of regional differences in mean per-capita inflows in the pre-allocation and the allocation period. Regional differences in the per-capita inflows are normalized. Horizontal ticks denote the mean, while white dots denote the median in the respective period. Observations are at the regional level.

The policy-induced allocation of ethnic Germans provides a quasi-experimental setting, contrasting with the earlier period when ethnic Germans had the freedom to choose their settlement region. We elaborate on the setting's advantages (and remaining challenges) for our identification strategy in Section 4.

3. Data

We construct a panel at the region-year level to examine the effect of regional labor supply on regional innovative activities over time. Following other studies (e.g., Dustmann and Glitz, 2015; Glitz, 2012; Pischke and Velling, 1997), we choose German labor market regions (*Arbeitsmarktregionen*) as our level of observation. This spatial approach captures the *total* effect of immigration-induced labor supply in a given region, taking into account skill downgrading and possible complementarities across regional skill groups (cf. Dustmann et al., 2016).

3.1. Sample

Our analysis leverages a balanced panel at the region-year level. The sample consists of 127 labor market regions with an average population of about 370,000 in 1995.[5] We thereby exclude labor markets in East Germany due to the extensive adjustment processes following German reunification. Additionally, we exclude labor markets in Bavaria and Rhineland-Palatinate. Both states did not implement the allocation policy and thus lack the disaggregated data necessary for our study.

[2] Immigration was subject to annual limits (from 1993: 225,000, from 1999: 100,000).

[3] The few formally high-skilled ethnic German migrants faced considerable barriers to the recognition of their qualifications and experienced significant skill downgrading (Bauer and Zimmermann, 1997; Eckstein and Weiss, 2004; Danzer and Dietz, 2014). Among the total of ethnic Germans, only up to 50% of their prior occupations were formally recognized (Haug and Sauer, 2007a). Moreover, ethnic Germans had a reputation for being motivated and industrious, making them attractive for low-skilled occupations in the labor-hungry manufacturing sector (Panagiotidis, 2021). Indeed, ethnic Germans were predominantly employed as low-skilled workers: 43% against 2% among natives (Kreyenfeld and Konietzka, 2002).

[4] From 1991 to 2002, the share of ethnic Germans migrants with working experience as well as their overall occupational distribution remained relatively stable, indicating a consistently low-skilled composition across cohorts (Appendix Figure B-1).

[5] For detailed information on the analysis sample, please refer to the Data Appendix D.1.

Our panel spans the period from 1991 to 2006, with 2032 observations at the region-year level. Considering the phased introduction of the allocation policy, with 76 regions starting in 1996, 34 regions in 1997, and 17 regions in 2002, this ensures a minimum pre-allocation period of five years for all regions. Appendix Table D-2 details the state-level implementation. While the policy was in place until 2009, regional data on ethnic German inflows are only available up to 2006. After this year, the numbers became negligible.

3.2. Variables

To investigate the impact of regional labor supply on automation innovation, we integrate data from multiple sources, including information on automation patents, ethnic German inflows, and regional economic conditions.

Automation patents

We measure automation innovation activities using patent data. Examining innovation and technical change through the lens of patents is well established in the literature (Comanor and Scherer, 1969; Griliches, 1998; Aghion et al., 2016). Nonetheless, this approach only provides insight into an intermediary stage of the innovation process—a point we revisit in our robustness checks. Moreover, the focus on patents as a measure of innovation restricts us from making direct assertions about the effect on actual labor-saving, firm productivity and, by extension, welfare outcomes.

We consider all patent applications filed at the European Patent Office (EP patents) with a priority date ranging from 1991 to 2006.[6] The reason to focus on EP patents is twofold. Firstly, they provide protection across Europe, indicating a higher economic value than German national patents. Secondly, EP patents include English descriptions, which are crucial for our approach to measuring automation innovation, as we elaborate below. We obtain text and bibliographic data on EP patents from the PATSTAT database (2022 Spring Edition). We use the inventors' geocoded address information to link patents to regions.

We classify patents as either automation or non-automation based on their textual features (see Online Appendix D.2 for technical details). We thereby draw on the method and the data by Mann and Püttmann (2023).[7] In particular, we train a predictive machine learning model that uses extracted "tokens" (i.e., stemmed words) from the patents' text to determine whether a patent protects an automation technology. As training data, we use the subset of EP patents with a US counterpart previously classified by Mann and Püttmann (2023).[8] The classification results based on our model closely mirror those of Mann and Püttmann (2023), enabling us to reliably classify all patents in our sample.[9]

Using the classification method introduced by Mann and Püttmann (2023) offers two key advantages. Firstly, their classification has been validated through positive correlations with conventional measures of automation, agreement with human assessments, and a strong prevalence of automation patents in industries characterized by routine occupations. Second, Mann and Püttmann (2023) define automation patents as those that refer to "a device that carries out a process independently." This encompasses a range of technologies in different manifestations, such as "a physical machine, a combination of machines, an algorithm, or a computer program", provided these technologies operate without the need for ongoing human intervention.[10] This broad definition of automation patents caters well to our analysis of the impact of labor supply on automation innovation activities without a predetermined emphasis on certain sectors or technologies.

The main focus of our analysis is the share of automation patents relative to all patents within each region and year, which we use as the dependent variable. A share variable is particularly suitable for examining changes in the direction of technical change (e.g., Calel and Dechezleprêtre, 2016). Specifically, a decreasing share would indicate that innovation is progressing away from automation within a given overall level of innovation. To supplement our analysis of the direction of technical change, we also examine the level of innovation by incorporating count data on the number of (non-)automation patents.

In our heterogeneity analysis, we further distinguish between product and process-related automation patents and between patentees of different firm sizes and industry activities. We classify our patents as either process- or product-related based on the patent's claim preamble (see Bena and Simintzi, 2022 and Ganglmair and Reimers, 2019 for similar approaches). Specifically, patents whose claims start with "A method", "A process" or "A procedure" are classified as process patents, and all others as product patents. To discern patentees based on firm size and industry activities, we integrate firm-level microdata (including the number of employees, annual turnover, and sector information) obtained from the Orbis Intellectual Property database (Orbis IP, April 2019).

Ethnic German inflows

We quantify changes to regional labor supply using the inflow of ethnic Germans into a region during the allocation period, as reported in official statistics of the federal reception center. Note that these numbers comprise *central allocation data*. No registry on actual residential take-up exists. In Online Appendix A, we explain why the compliance with the allocation scheme was very high.

Our preferred measure is the *cumulative inflow rate*, which we calculate as the cumulative inflow of ethnic Germans during the allocation period divided by the region's average stock of the "low-skilled" workforce during the pre-allocation period. This "low-skilled" workforce comprises the sum of *unskilled manual* workers and the *unemployed*, jointly accounting for approximately 21 percent of the total workforce. We select this subset of the total workforce as ethnic Germans were *de facto* low-skilled workers, therefore expanding labor supply primarily at the lower end of the skill distribution.[11] Moreover, low-skilled workers faced by far the greatest risk of unemployment in Germany (IAB, 2019),

[6] The priority date represents the filing date of the initial application submitted to the patent office and offers the most accurate approximation of the inventive activity's date (e.g., OECD, 2009).

[7] Mann and Püttmann (2023) train a machine learning model to classify all US patents between 1976 and 2014 based on 560 randomly drawn patents which were manually coded as automation or non-automation. Details on their manual coding guidelines can be found in their paper's Online Appendix.

[8] Note that while Mann and Püttmann (2023) classified US patents, our sample contains EP patents. However, a significant number of EP patents are part of a patent family with a US counterpart, describing identical inventions. Using the DOCDB patent family definition, we successfully match 41 percent of our patents to a US counterpart in their dataset.

[9] In the overlapping set, our classification differs from theirs in only about 11 percent of cases. To address concerns that differences between the two classifications could drive our results, we rerun our analysis using the subset of EP patents with the original Mann and Püttmann (2023) classification and find similar results. For illustrative purposes, Appendix Table D-3 provides two examples of classified automation patents along with their complete English abstracts. The distribution of automation innovation across technology fields aligns with the common perception of automatability.

[10] Note that the criterion of "independence" distinguishes automation from tools and numerous other manufacturing technologies. It further characterizes technologies capable of substituting human labor, rather than necessitating it.

[11] To determine the unskilled manual workforce, we rely on the occupation-based classification in the IAB data (Blossfeld, 1987). Non-manual unskilled occupations (such as services and administrative roles) also exist. However, we exclude these occupations from our workforce denominator as they were not highly relevant for or sought after by the ethnic Germans (Haug and Sauer, 2007a; Zimmermann, 2000). We prefer this classification over the education-based one due to known consistency issues (e.g., Dustmann et al., 2017). That said, using the education-based classification produces similar results.

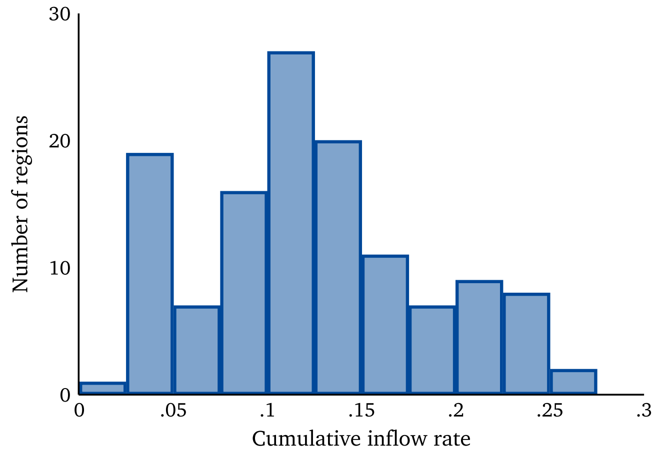

Fig. 2. Distribution of the region-specific cumulative inflow rate
Notes: The figure illustrates the distribution of the region-specific cumulative inflow rate. The cumulative inflow rate is defined as the cumulative inflow of ethnic Germans in the allocation period divided by the average stock of the low-skilled workforce during the pre-allocation period. Observations are at the level of the region. Appendix Figure B-2 illustrates the geographical distribution of the cumulative inflow rate.

implying numerous transitions between the two groups. In supplementary analyses and robustness checks, we adjust the inflow rate's denominator from the "low-skilled" workforce to either the overall workforce or the population in the region.

The cumulative inflow rate varies across regions (Fig. 2). While the median of the inflow rate lies between 10 and 15 percent, the variable ranges from 1 to 25 percent. Note that the cumulative inflow rate relates the number of ethnic Germans to the low-skilled workforce instead of being based on the distribution criteria of the allocation quota (population size and tax revenue across states, and different additional criteria within states).[12] Hence, differences in the pre-existing skill composition across regions provide an important source of variation in our treatment variable (cf. Glitz, 2012).

Regional characteristics

We supplement the panel data with regional characteristics to assess the validity of our identification strategy in several robustness tests. Information on the workforce and the share of unemployed workers are from the German Employment Office, whereas population size and gross domestic product (GDP) are from the Working Group Regional Accounts VGRdL. We complement the data with regional shares of skill and occupation groups using employment data from the Institute for Employment Research (IAB) Establishment History Panel. Appendix Table D-1 provides an overview of regional characteristics and their sources.

3.3. Descriptive statistics

Table 1 reports summary statistics for the region-year panel data set. The average regional share of automation patents is 26.9 percent. While the share of automation patents has risen in nearly all regions during our window of observation, the extent of this increase varies considerably between regions.[13] In our heterogeneity analyses, we examine additional automation share variables, which include subsets of automation patents, while maintaining the total set of patents as the denominator. For instance, the share of automation patents is higher in manufacturing firms as opposed to non-manufacturing ones and is considerably higher in *large* manufacturing firms compared to their smaller counterparts.[14] There is little difference in this share between process- and product-related automation patents. Each region sees, on average, 72.2 patent applications per year. Out of these, 23.7 are automation patents. The large standard deviations of these variables underline the considerable inter-regional variation in patenting activities.

The mean cumulative inflow of ethnic Germans during the allocation period is about 3,860 per region. This corresponds to a cumulative inflow rate of 0.124, or 12.4 percent, in relation to the average low-skilled workforce, comprising unskilled manual workers and the unemployed, during the pre-allocation period. Several regional characteristics from the pre-allocation period, such as population size, size of the workforce, GDP per capita (average 21,000 EUR), and the sector share of manufacturing (average 34 percent), suggest considerable heterogeneity across regions.

4. Methodological framework

We estimate the effect of low-skilled labor supply on automation innovation in a staggered difference-in-differences (DiD) framework. Our approach leverages the quasi-exogenous inflows of ethnic Germans during the allocation period in two ways. First, as the allocation policy followed a staggered roll-out, regions were treated at different times. Second, as the change in the low-skilled labor supply varies between regions, the treatment intensity differs cross-sectionally.

In the following, we discuss our identification strategy, describe the empirical models, and provide evidence for the impact of the inflow of ethnic Germans on regional labor markets.

4.1. Identification strategy

To clarify our identification strategy, we first outline the ideal experiment for examining the effect of low-skilled labor supply on regional automation innovation. In the ideal experiment, a homogeneous group of immobile and employable low-skilled workers would be randomly distributed across different regions populated by equally immobile workers. This would exogenously and permanently increase the labor supply in certain regions, presumably reducing the local firms' incentives to pursue labor-saving automation innovation.

This ideal experiment contrasts reality, where workers typically have the freedom to select their region of residence. This self-selection can introduce a correlation between variation in labor supply and regional characteristics, such as labor market conditions. If these characteristics also correlate with automation innovation activities, the resulting endogeneity complicates the estimation of the causal effect of labor supply on automation innovation.

[12] Additional spatial variation originates from "included" family members, different internal distribution schemes across states, delayed updating of population data for allocation purposes across states, or housing shortages, all of which are plausibly unrelated to regional labor market conditions (Brücker and Jahn, 2011; Piopiunik and Ruhose, 2017; Panagiotidis, 2021); see Appendix A for details.

[13] Appendix Figure B-7 displays the annual number of patent applications related to automation and non-automation between 1991 and 2006 in our sample. It reveals that automation patents have grown from approximately 1300 per year in 1991 to over 3600 in 2006. Appendix Figure B-8 shows that patents in the fields of electrical engineering, instruments, and mechanical engineering primarily drive the increase in the share of automation patents. Appendix Figure B-9 visualizes the regional distribution of automation patents across labor market regions during the pre-allocation and allocation periods.

[14] We classify firms according to major sector information in Orbis IP, labeling firms as manufacturing firms if they are active in machinery, equipment, furniture, and recycling, and classify them as large if they employ more than 249 employees and report an annual turnover of more than 50 million EUR (following the classification of the European Commission).

Table 1
Summary statistics.

Variable	Mean	Std. Dev.	Min	Max
Innovation (annual)				
Automation patents/patents	0.269	0.152	0.00	1.00
Automation patents/patents (manuf. firms)	0.135	0.120	0.00	0.76
Automation patents/patents (non-manuf. firms)	0.092	0.085	0.00	1.00
Automation patents/patents (small manuf. firms)	0.016	0.031	0.00	0.40
Automation patents/patents (large manuf. firms)	0.117	0.116	0.00	0.75
Automation patents/patents (process, manuf. firms)	0.064	0.074	0.00	0.56
Automation patents/patents (product, manuf. firms)	0.072	0.068	0.00	0.57
Automation patents	23.744	63.122	0.00	893.89
Non-automation patents	48.471	84.893	0.00	1059.10
Patents	72.215	144.501	0.00	1921.30
Citations of automation patents	1.123	1.076	0.00	10.45
Family size of automation patents	5.169	1.957	1.00	28.18
Ethnic German Inflows (in allocation period)				
Cumulative inflow rate	0.124	0.060	0.01	0.25
Cumulative inflow rate$_{\text{total workforce}}$	0.036	0.017	0.00	0.07
Cumulative inflow	3861.929	4263.494	74.00	32 868.00
Annual inflow	562.462	699.080	0.00	7342.00
Regional Characteristics (average in pre-allocation period)				
Low-skilled workforce (in '000s)	33.217	34.887	6.75	210.21
Unskilled manual workers (in '000s)	19.695	20.342	3.32	149.73
Unemployed (in '000s)	13.522	15.607	2.42	93.81
Total workforce (in '000s)	155.710	181.730	33.00	1138.54
Population (in '000s)	372.153	414.260	82.84	2611.19
Sector share of manufacturing	0.337	0.100	0.10	0.58
GDP per capita (in '000s, Euro)	20.872	3.953	12.95	36.11
Wage level (low-skilled workers, daily wage, Euro)	74.582	3.690	66.71	87.39

Notes: Summary statistics are derived from the region-year panel data set (2032 observations). Innovation variables are at the region-year level. All automation share variables have the entire set of patents as denominator. Cumulative inflow variables are at the regional level and the annual inflow at the region-year level. Regional characteristics are at the regional level. Monetary values in 1995 Euros. Innovation variables based on PATSTAT data. See Appendix Table D-1 for definitions and data sources of regional characteristics.

To address the issue of endogenous variation in labor supply, we leverage the introduction of the allocation policy. This policy aligns with the ideal experiment in so far as it exogenously allocated a homogeneous group of readily employable low-skilled individuals to different regions and restricted their movement by tying social benefits to residential compliance. While the allocation policy addresses endogenous sorting into regions, our setting poses two additional challenges for the analysis. First, many ethnic Germans had already been arriving in the years before the allocation period. These pre-allocation labor inflows may affect regions in a way that spills over to the allocation period. Second, while arriving workers were restricted in their freedom to move, the natives were not. It is possible that the arrival of additional workers led to outmigration among the existing population, reducing the net increase in labor supply.

We discuss all three elements – sorting into regions, prior labor inflows, and the mobility of native workers – and their relevance for our quasi-experimental setting in the following.

Sorting into regions

Before the introduction of the allocation policy, the self-selection of ethnic Germans can be explained by two main factors: (i) relevant labor market characteristics and (ii) distance from the port of entry in Germany. Given their generally low skill levels, ethnic Germans were more likely to choose regions abundant in job opportunities for manual labor. The manufacturing sector held the largest potential for accommodating low-skilled workers. Hence, regions with a high prevalence of manufacturing jobs were particularly attractive. Indeed, we find evidence for ethnic Germans systematically choosing regions with a high sector share of manufacturing during the pre-allocation period (Fig. 3(a)).[15] At the same time, ethnic Germans tended to choose regions near the national reception center (Panagiotidis, 2021). We provide evidence for the geographical bias in the ethnic Germans' self-selection in Appendix Figure B-3.

The self-selection of ethnic Germans into regions with a high sector share of manufacturing counteracts the presumed negative effect of increased labor supply on automation innovation. This is based on the reasonable assumption that jobs in the manufacturing sector are characterized by routine manual and routine cognitive tasks, which are more susceptible to automation (Autor et al., 2003; Acemoglu and Restrepo, 2019). From this follows that the effect of increased labor supply on automation innovation should be positively biased in the pre-allocation period.

The self-selection of ethnic Germans stops during the allocation period, equalizing inflows into regions with many vs. few manufacturing jobs (Fig. 3(b)).[16] This removes the described countervailing effect so that the negative average treatment effect on automation emerges. Note that even if the allocation policy did not fully eliminate the correlation between labor inflows and industry structure, we would obtain conservative estimates of the true effect. In sum, the quasi-experimental allocation of ethnic Germans provides regional variations in low-skilled labor supply, which are plausibly exogenous to confounding regional characteristics.

[15] These regions were characterized by subpar wages and GDP, yielding a correlation between pre-allocation inflows and wages or GDP (Appendix Figure B-4).

[16] Furthermore, we find no sorting of ethnic Germans with respect to innovation or the share of automation innovation after the introduction of the allocation policy (Appendix Figure B-5). These results are consistent with earlier studies documenting the exogeneity of regional inflows during the allocation period 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). Moreover, we find no evidence that the few *high-skilled* ethnic Germans sorted into certain regions that stand out by their wage level, GDP per capita, the share of automation patents, or the share of the pre-existing high-skilled workforce (Appendix Figure B-6 and Appendix Table B-1). This suggests that the allocation policy also led to a balanced skill composition of workers across regions.

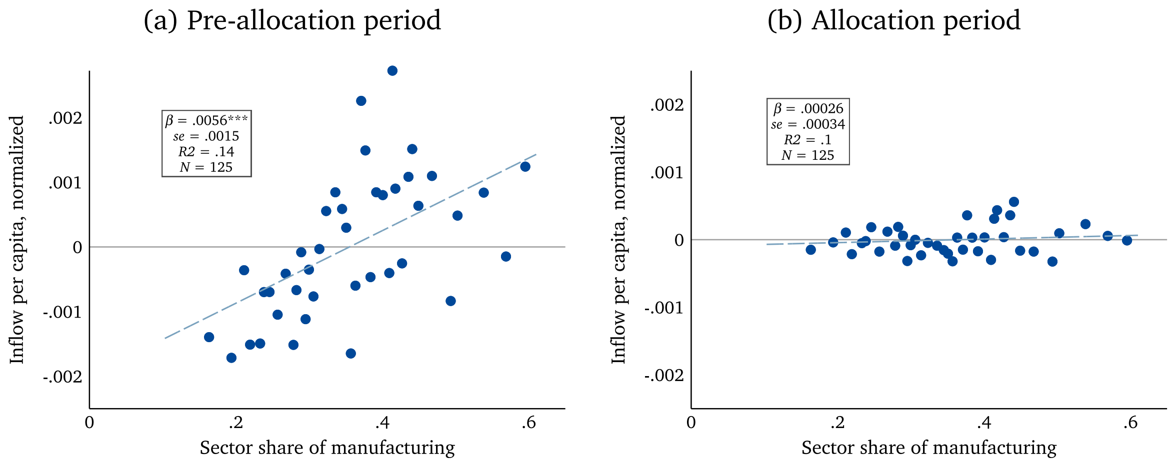

Fig. 3. Differences in per-capita inflows by the regional share of the manufacturing industry
Notes: The figure illustrates the relationship between the distribution of per-capita inflows and the sector share of manufacturing in the pre-allocation and the allocation periods. Regional differences in inflows are normalized. Sector share of manufacturing as of the year 1991. Observations are at the level of the region, aggregated into 40 bins representing 2.5 percentiles each.

Prior labor inflows

The fact that the allocation policy was enacted only after several years of high labor inflows might introduce spillovers within regions across time. The high prior inflows likely created an abundance of labor in some regions that persisted well into the allocation period. This abundance, in turn, may reduce firms' automation innovation activities even if the region experiences low labor inflows during the allocation period. Indeed, while the labor inflows before and during the allocation period are overall uncorrelated, several regions received exceptionally high labor inflows in the pre-allocation period and relatively low inflows during the allocation period.[17] Consequently, our setting approximates the ideal experiment when focusing on regions where the inflows prior to the allocation period are minimal or orthogonal to the inflows during the allocation period. In Section 5.3, we provide evidence consistent with such spillovers leading to an underestimation of the treatment effect.

Mobility of native workers

The allocation policy did not limit the mobility of the native regional workforce. If natives moved out of regions in response to high labor inflows, the net increase in labor supply would be smaller. Consequently, we would underestimate the labor supply effect on automation innovation, rendering our estimates conservative. That said, we do not find that the natives' mobility increases in response to the ethnic German inflows. Instead, the population grows proportionately with the inflows (Appendix Table B-2).[18]

4.2. Empirical models

We examine automation innovation activities in regions before and after the staggered introduction of the allocation policy. In our main specification, the treatment variable is the *cumulative inflow rate* (CIR_r), which captures the extent to which a region, r, experiences a relative increase in labor supply during the allocation period. We operationalize this treatment variable as the total inflow of ethnic Germans during the allocation period relative to the average stock of the low-skilled workforce in the pre-allocation period. As an alternative to this continuous treatment variable, we use a dummy that indicates regions with an above-average cumulative inflow rate.

The most flexible specification we implement is a dynamic DiD – event study – model. This model is particularly suitable for studying effect dynamics and evaluating the common trend assumption, thereby validating our research design. To this end, we include interactions of the cumulative inflow rate, CIR_r, with leads and lags from −5 to +10 years around the introduction of the allocation policy for a given region. We further include region fixed effects, α, and calendar year fixed effects, γ, to capture time-invariant differences between regions and common time trends. The specification is as follows:

$$y_{rt} = \sum_{k=-5}^{10} \beta_k \mathbf{1}_{\{l_{rt}=k\}} CIR_r + \sum_{m=1991}^{2006} \gamma_m \mathbf{1}_{\{t=m\}} + \alpha_r + \epsilon_{rt}. \quad (1)$$

We normalize the coefficient $\beta_{k=-1}$ to zero and, hence, express the dynamic treatment effects relative to the last calendar year, t, before the introduction of the allocation policy. The coefficients on the leads and lags capture the causal effect of the labor inflow relative to this year.

We discuss magnitudes and summarize additional results based on a modified specification. Here, we replace the leads and lags with a binary variable that takes the value of one in the allocation period and zero otherwise, representing the static DiD model. The coefficient β_{post} reports the average effect of labor inflows in the allocation period. This modified specification is as follows:

$$y_{rt} = \beta_{post} \mathbf{1}_{\{l_{rt}\geq 0\}} CIR_r + \sum_{m=1991}^{2006} \gamma_m \mathbf{1}_{\{t=m\}} + \alpha_r + \epsilon_{rt}. \quad (2)$$

For the major part of our empirical analysis, the dependent variable y_{rt} is the annual share of automation patents relative to all patents in the region.[19] As this variable is continuous, we run linear (OLS) regressions. We further examine changes in the level of (non-)automation patents. As these are count data with a skewed distribution, we estimate Poisson pseudo-maximum-likelihood regressions. We cluster errors, ϵ, at the region level to account for correlations within regions over time. Region-year observations are weighted with pre-determined regional population sizes as of 1991.

[17] This applies to regions near the port of entry and those having signed the so-called *Gifhorn declaration*, demanding a more balanced distribution of ethnic Germans. See Appendix Table A-1 for a list of the ten regions with the highest inflows during the pre-allocation period.

[18] This result aligns well with prior studies (Glitz, 2012; Pischke and Velling, 1997), attributing the lack of displacement to Germany's relatively generous social security system and unemployment benefits.

[19] The dependent variable deserves two clarifications: First, the denominator remains largely unaffected by the labor supply expansion, as we will show in Section 5.2. Second, 92 percent of all observations have at least 5 patent applications, so the dependent variable is not very sensitive to small regions.

Table 2
Effect of labor inflows on employment and unemployment growth during the allocation period.

	(1)	(2)	(3)	(4)
Dep. Var.:	Employment growth rate			Unempl. growth rate
	Total	Low-skilled	High-skilled	
Inflow rate$_{\text{total workforce}}$	0.883**	1.880***	0.175	8.634***
	(0.409)	(0.677)	(0.331)	(1.478)
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	1256	1256	1256	1256
R-squared	0.925	0.934	0.885	0.741
Within R-squared	0.002	0.003	0.000	0.029

Notes: The table presents the results of linear regression analyses. The dependent variable is the annual percentage change in total employment (column 1), low-skilled employment (column 2), high-skilled employment (column 3), and unemployment. Low-skilled employment encompasses the following occupation classes: unskilled manual workers, unskilled service workers, and unskilled commercial and administrative workers. High-skilled employment encompasses all other occupation classes. The continuous treatment variable measures the annual inflow of ethnic Germans relative to the regional workforce in the prior year. The regressions are estimated at the region-year level and weighted by the regional population in 1991. Standard errors, clustered at the regional level, are in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Given the staggered implementation of treatment in our setting, the comparison between high- and low-inflow regions can be confused with that between earlier and later-treated regions. In other words, effects from other periods may contaminate the estimated treatment coefficients. We therefore compare the dynamic treatment effects of our baseline model to those of several alternative estimation techniques that take the timing of treatment into account.

4.3. Labor market mechanism

Before turning to our main analysis, we explore how ethnic German inflows affect regional labor market conditions.

For this purpose, we regress the annual growth rates in regional employment and unemployment on the regional inflow of ethnic Germans during the allocation period. In contrast to our main specifications, we take the *annual inflows* divided by the lagged *total workforce* as our treatment variable. This way, we can measure the immediate absorption of readily employable ethnic Germans in the labor market across all skill groups in the allocation period. We distinguish between total employment, employment in low-skilled occupations, and employment in high-skilled (i.e., not low-skilled) occupations.[20]

We find a substantial effect of ethnic inflows on regional employment and unemployment (Table 2). The inflow rate has a positive and nearly proportional effect on the total employment growth rate (column 1). A closer look at skill-specific groups shows that this effect is exclusively driven by growth in low-skilled employment (column 2). In contrast, high-skilled employment seems largely unaffected by these immigrant inflows (column 3). This discrepancy in employment growth across different skill levels aligns with the fact that the majority of ethnic Germans are low-skilled workers. The inflow rate also positively affects the unemployment growth rate (column 4). In other words, ethnic Germans increase the pool of job-seeking workers from which firms can hire. These findings support a direct effect of ethnic German inflows on regional labor market conditions. They further justify our decision to express the inflow rate as the ratio of ethnic Germans to the low-skilled workforce, including the unemployed.

Notably, we find no evidence of any systematic effect of ethnic inflows on wages (Appendix Table B-3). This result aligns with the prior literature (Glitz, 2012) and the comparatively inflexible German labor market characterized by strict regulation and powerful unions.[21] These particular dynamics of the German labor market imply that our study does not directly test Acemoglu's (2010) theory, where increased labor supply affects automation innovation by reducing wages.

5. Main results

In the following, we present our findings related to the effect of labor supply on automation innovation. We begin by examining the effect on the share of automation patents (Section 5.1), then move to the effect on the number of automation and non-automation patents (Section 5.2). In addition, we summarize various robustness checks (Section 5.3).

5.1. Effect on the share of automation patents

We find a negative effect of low-skilled labor supply on the regional share of automation patents. Fig. 4(a) presents the estimated lead and lag effects in a model with continuous treatment. The inflow rate exerts a significant negative effect in the years following the introduction of the allocation policy. These effects are not immediate but materialize over time, peaking in the fourth treatment year.[22] Moreover, the estimates converge towards zero from the fifth year of the allocation period onward, suggesting that the negative effect on the share of automation innovation may be only transient.[23] The coefficients in the pre-allocation period are insignificant and fluctuate around zero, supporting the common trend assumption and underlining the exogeneity of the ethnic German inflows. Consistent results are observed in Fig. 4(b), which presents the corresponding lead and lag effects in a model with binary treatment.

Table 3 presents the static DiD effects during the allocation period, featuring continuous and binary treatment as well as specifications without and with region fixed effects. We interact the treatment variables with a dummy for the allocation period. We find significant negative effects on the share of automation patents across all four specifications. The magnitude of the estimated coefficient in our preferred specification, featuring continuous treatment along with region and calendar year fixed effects (column 2), equals −0.325. This suggests that

[20] The low-skilled occupation classes are labeled in the IAB data as follows: unskilled manual workers, unskilled service workers, and unskilled commercial and administrative workers.

[21] For example, the coverage of collective bargaining in Germany exceeded 80 percent in 1990 and 68 percent in 2000 (OECD, 2004). The level of unionization is substantially higher in Germany compared to the US, where collective bargaining coverage was only 14 percent in 2000. Accordingly, D'Amuri et al. (2010) and Dustmann and Glitz (2015) find little to no effect of immigration on wages in Germany in the 1990s.

[22] Given the typical duration between R&D investments and patent filing, a delay in the automation innovation response is plausible. A large-scale inventor survey indicates that approximately 80 percent of R&D projects last two years, from project start to patent filing (Walsh and Nagaoka, 2009).

[23] It is worth noting that the annual inflows were continuously decreasing during the allocation period.

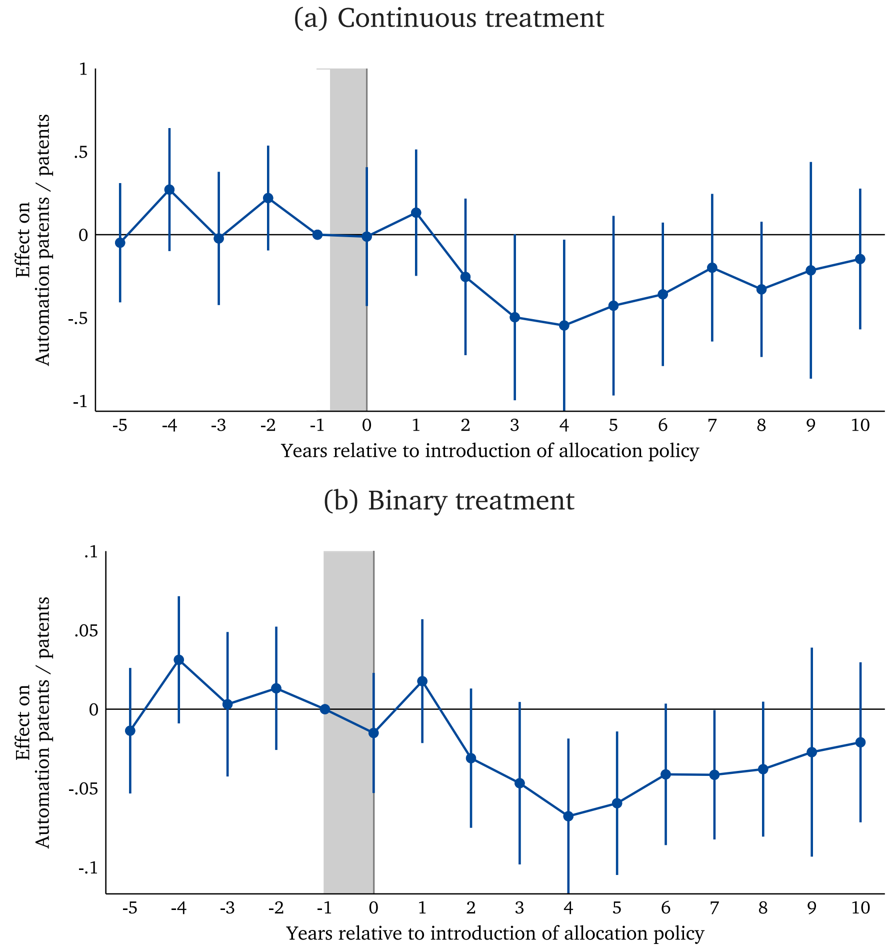

Fig. 4. Effect of labor inflows on the share of automation patents – event study with continuous and binary treatment
Notes: The figure displays event study estimates and the 95 percent confidence intervals based on linear regressions as specified in Eq. (1). In both panels, the dependent variable is the share of automation patents. In panel (a), the treatment variable is continuous: the cumulative inflow rate during the allocation period, interacted with leads and lags. In panel (b), the treatment variable is binary: a dummy indicating regions with above-average cumulative inflows of ethnic Germans during the allocation period, interacted with leads and lags. The time dummies indicate that the allocation policy is introduced l years away, with $l \in \{-5; +10\}$. The coefficient for $l = -1$ is normalized to zero. Region and time fixed effects included. Standard errors clustered at the regional level. The coefficients correspond to those reported in Appendix Tables B-4 and B-5.

increasing the low-skilled workforce by 10 percent lowers the share of automation patents by about 3.3 percentage points, corresponding to an economically sizable reduction of about 2.5 automation patents for the average region.[24]

Overall, these results suggest that an exogenous increase in low-skilled labor supply significantly shifts the direction of technical change away from automation innovation.

5.2. Effect on the number of (non-)automation patents

We complement our analysis of the share of automation patents by examining the number of (non)-automation patents. In doing so, we adhere to our preferred event study specification with continuous treatment but substitute the share of automation patents with two alternative outcomes: the number of automation patents and the number of non-automation patents, each per region and year. Given the count nature of these two variables, we utilize Poisson pseudo-maximum-likelihood instead of OLS regressions.

We find a substantial and statistically significant negative effect of labor supply on the number of automation patents (Fig. 5(a)). The peak effect occurs in the fourth year of the allocation period, mirroring the dynamics we observe regarding the share of automation patents. Conversely, we do not detect any negative effect of labor supply on the number of non-automation patents (Fig. 5(b)). This suggests that non-automation innovation did not adapt to regional labor supply changes. For both outcomes, the estimates in the pre-allocation period are statistically insignificant and hover near zero, reinforcing the validity of our research design.[25]

These results corroborate the idea that regional labor supply affects the direction of technical change. They align with theoretical predictions suggesting that labor scarcity stimulates labor-saving innovation while labor abundance discourages it. Conversely, the lack of an effect of labor supply on non-automation innovation counters alternative explanations. Most importantly, it speaks against the notion that the

[24] San (2023) documents that a 10% decrease in labor supply in the 1960s US farming industry leads to 1.3 more patents related to affected crops. Given Germany's high patent and innovation intensity in manufacturing in the late 1990s and early 2000s, it is not surprising that our effect size is larger. Comparisons to other (contemporary) studies are not straightforward, as these studies use variation in wages as treatment.

[25] We find highly consistent results when applying the model with binary treatment (Appendix Figure B-10). For completeness, we also investigate the effect of labor supply on the total number of patents per region and year and find a small negative effect statistically indistinguishable from zero (Appendix Figure B-11).

Table 3
Effect of labor inflows on the share of automation patents – DiD with continuous and binary treatment.

	(1)	(2)	(3)	(4)
Dep. Var.:	Automation patents/patents			
Cum. inflow rate × $\text{Allocation}_{t\geq 0}$	−0.381**	−0.325**		
	(0.156)	(0.150)		
1(Cum. inflow rate>p50) × $\text{Allocation}_{t\geq 0}$			−0.044**	−0.042**
			(0.018)	(0.018)
Region fixed effects	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2029	2029	2029	2029
R-squared	0.110	0.681	0.110	0.682
Within R-squared	0.008	0.012	0.008	0.015
Dep. Var. mean	0.269	0.269	0.269	0.269

Notes: The table presents the results of linear regression analyses as defined in Eq. (2). The dependent variable is the share of automation patents. In columns (1) and (2), the treatment variable is continuous: the cumulative inflow rate during the allocation period, interacted with a dummy ($\text{Allocation}_{t\geq 0}$) that indicates whether the allocation policy was introduced in that year or earlier. In columns (3) and (4), the treatment variable is binary: a dummy indicating regions with above-average cumulative inflows of ethnic Germans during the allocation period, interacted with a dummy ($\text{Allocation}_{t\geq 0}$) that indicates whether the allocation policy was introduced in that year or earlier. The regressions are estimated at the region-year level and weighted by the regional population in 1991. Standard errors, clustered at the regional level, are in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

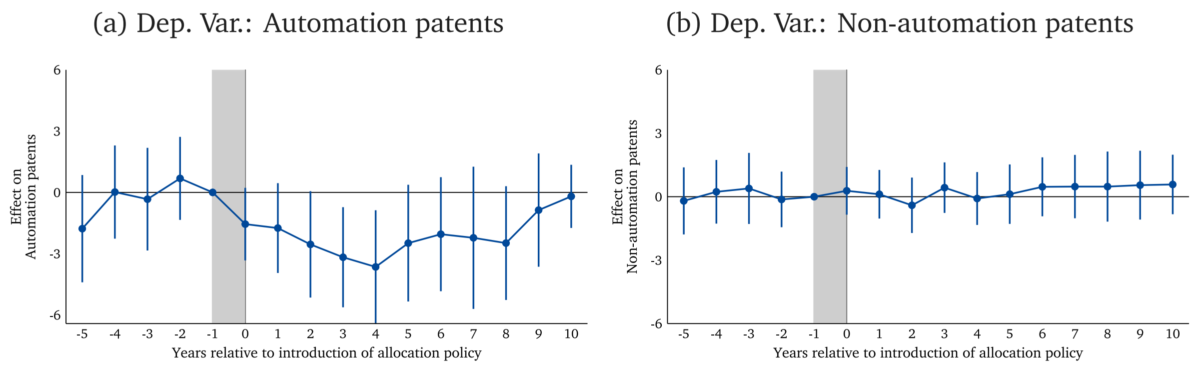

Fig. 5. Effect of labor inflows on (non-)automation patents – event study with continuous treatment
Notes: The figure displays event study estimates and the 95 percent confidence intervals based on Poisson pseudo-maximum-likelihood regressions as specified in Eq. (1). The dependent variable in panel (a) is the count of automation patents. The dependent variable in panel (b) is the count of non-automation patents. In both panels, the treatment variable is continuous: the cumulative inflow rate during the allocation period, interacted with leads and lags. The time dummies indicate that the allocation policy is introduced l years away, with $l \in \{-5; +10\}$. The coefficient for $l = -1$ is normalized to zero. The coefficients can be interpreted as semi-elasticities. Region and time fixed effects included. Standard errors clustered at the regional level. The coefficients correspond to those reported in Appendix Table B-6.

innovation response is driven by increased product demand due to expanded market size (cf. Peters, 2022). Lastly, these results mitigate concerns about the potential sensitivity of results when the outcome variable is the *share* of automation patents.

5.3. Robustness

We evaluate the robustness of our results by varying the choice of estimation techniques, measures, sample definitions, and control variables. Additionally, we explore whether our findings can alternatively be explained by a shift in patenting behavior rather than automation. Finally, we run our analysis based on the endogenous labor inflows from the pre-allocation period. We summarize the results in the following and present the corresponding Figures and Tables in Appendix C.

Alternative measures of automation innovation (Appendix C.1)
We replicate our main results with different classifications of automation and non-automation patents. First, we use the original classification by Mann and Püttmann (2023). Despite missing information for almost half of the EP patents in our data, we find a similar effect of labor supply on the share of automation patents. Second, we use a keyword-based classification as a transparent and hands-on alternative to approaches using machine learning. For this classification, we label a patent as automation if its text contains keywords that likely indicate automation (e.g., 'automat', 'execut', or 'detect'). The results from using automation patents classified with different sets of automation-related keywords align closely with our main results.

Alternative operationalizations of the cumulative inflow rate (Appendix C.2)
We find consistent results when operationalizing the cumulative inflow rate differently. In particular, we can exclude high-skilled ethnic Germans from the inflow rate's numerator, use an education-based definition of the low-skilled workforce, and substitute the mean low-skilled workforce with that in 1991 or the last year of the pre-allocation period. Likewise, by normalizing the inflows with the regional population instead of the low-skilled workforce, we obtain similar labor supply effects on automation innovation. Lastly, our results are robust to winsorizing the cumulative inflow rate at the 5th (95th) percentile.

Accounting for pre-allocation labor inflows (Appendix C.3)
During the pre-allocation period, several regions received high labor inflows, whose effect on the labor market and firms' automation innovation activities may spill over to the allocation period. Through several robustness checks, we seek to isolate the actual treatment effect of the exogenous labor inflows in the allocation period on automation innovation. First, we include an interaction between the pre-allocation cumulative inflow rate and the policy dummy as additional controls. Our results on the effect of labor supply on automation innovation

remain unchanged. Second, we run three sets of subsample analyses excluding either regions with high *pre-allocation* cumulative inflow rates, regions near the Friedland reception center, or regions that previously signed the *Gifhorn declaration* demanding a more even distribution of ethnic Germans across regions. Indeed, we obtain significantly larger effects on automation innovation when focusing on subsamples of regions with presumably low spillovers from the pre-allocation period. This confirms our presumption that pre-allocation inflows render our results conservative.

Accounting for relative change in labor inflows (Appendix C.4)

For many regions, the introduction of the allocation policy led to a relative change in the region-specific cumulative inflow rate from the pre-allocation to the allocation period. Almost half of all regions experienced a positive change, reflecting a higher inflow rate in the allocation period than before. At the same time, several regions experienced a substantial reduction in the inflow rate relative to the pre-allocation period. We find stronger effects of labor supply on automation when focusing on regions for which the introduction of the allocation policy increased the inflow rate.

Accounting for other concurrent labor inflows (Appendix C.5)

In addition to the inflow of ethnic Germans, there was substantial internal migration from the Former GDR (i.e., East Germany) to West German regions (Glitz, 2006), along with other native and foreign inflows (Amior and Stuhler, 2022). We add these concurrent labor inflows as control variables to our main specification and find our results unchanged.

Accounting for differences in industry and skill composition (Appendix C.6)

Our results on the labor supply effect on automation innovation are robust to controlling for the pre-existing regional industry structure and skill composition. We introduce industry composition – divided into six categories – either by extrapolating trends in industry shares from the pre-allocation period or by interacting averaged pre-allocation industry shares with year dummies. Similarly, using the same approach, we account for skill composition—broken down into high, medium, and low skill levels. Including these variables does not change our findings regarding the effect of labor supply on automation patents.

Alternative estimation techniques (Appendix C.7)

The staggered implementation of the allocation policy could potentially bias our estimates as regions that introduced the policy in later years serve as controls for regions that introduced the policy early on. We employ several recently developed estimation techniques that are immune to such biases. More specifically, we show robustness to the methods introduced by Borusyak et al. (2021), Callaway and Sant'Anna (2021), De Chaisemartin and d'Haultfoeuille (2020), and Sun and Abraham (2021). The direction, magnitude, and transitory nature of the labor supply effect on the share of automation patents are consistently observed across all methods.

Alternative sample definitions and subsample analysis (Appendix C.8)

The regions in our sample exhibit substantial variation in their innovative activities, prompting us to test whether extreme cases drive our results. Our findings remain consistent after excluding regions with a patent count below the 10th or beyond the 90th percentile in 1991. Moreover, German states employed slightly different criteria for allocating ethnic Germans across regions (for instance, based on population versus a combination of population and area) and introduced the policy at different times. To assess whether our findings hinge on the allocation practices of a particular state, we examine subsamples with the regions of a given state excluded. The effect of labor supply on automation patents persists in all subsamples. Finally, we find our results robust to alternative sample weights, using GDP instead of population.

Examining changes in patent quality (Appendix C.9)

The observed decline in automation patents might be attributed to firms either reducing R&D investments in automation innovation or decreasing their tendency to file patents on a given set of automation innovations. Both responses lead to a decrease in the number of patents but are likely to have distinct impacts on patent quality. A cutback on R&D likely results in fewer innovations across all quality levels without affecting average patent quality. In contrast, a change in *patenting behavior* likely increases average patent quality as cost-saving considerations will disproportionately reduce the patenting of low-quality inventions. We proxy patent quality with two established bibliographic indicators: the number of citations and the patent family size (Harhoff et al., 2003). We find no consistently positive effect on these two proxies, suggesting that the reduction in automation patents more likely reflects firm responses at the innovation margin rather than a change in patenting behavior.

Analysis based on pre-allocation labor inflows (Appendix C.10)

The implementation of the allocation policy transitioned the expansion of labor supply from being *endogenous* to *exogenous*. As argued above, the endogenous self-selection of ethnic Germans likely biases the negative effect on automation innovation upwards, effectively diminishing the true effect towards zero. A direct implication is that the effect on automation patents should be weaker without the exogenous treatment. To test this, we extrapolate the endogenous (pre-allocation) inflows into the allocation period. We find a substantial decrease in the effect of labor supply on the share of automation patents, with the effect's magnitude reduced by around 60 percent.

6. Heterogeneity results

In this section, we investigate the extent to which the labor supply effect varies between sectors, firms and labor market conditions. We thereby provide evidence on how changes in labor supply affect automation innovation within our study's context. First, we test the automation susceptibility with respect to manufacturing vs. non-manufacturing industries, as Acemoglu (2010) suggests that automatability depends on the marginal product of labor; second, we test whether labor supply specifically affects large firms and process innovations, which would be indicative of the source of demand for innovation; third, we test the effect responsiveness with respect to labor market tightness.

6.1. Susceptibility to automation innovation

The effect of labor supply on automation innovation hinges on an industry's susceptibility to automation, which reflects labor substitutability and technical feasibility (Acemoglu, 2010). Manufacturing industries, such as Germany's automotive sector, involve scalable processes primarily consisting of routine manual tasks, which were already automatable in the 1990s and 2000s (Autor et al., 2003; de Vries et al., 2020). Such industries are thus more prone to automation innovation than others (Acemoglu and Restrepo, 2019).

We assess the automation innovation response to labor supply by firms in manufacturing vs. non-manufacturing industries by running separate regressions with the share of automation patents from each subgroup as the dependent variable. That is, the average share of automation patents by manufacturing firms corresponds to the regional number of automation patents by manufacturing firms divided by the total number of patents.

The overall reduction in the share of automation patents is primarily driven by the negative response of manufacturing firms (Table 4). Conversely, the negative response from non-manufacturing firms is considerably weaker and statistically insignificant. Notably, manufacturing firms have an almost 50 percent larger share of automation patents than non-manufacturing ones, which supports the view that they are more prone to and active in automation innovation. Yet, even when accounting for these differences in the share of automation patents, the response from non-manufacturing firms remains noticeably weaker.

Table 4
Effect of labor inflows on the share of automation patents by (non-)manufacturing firms – DiD with continuous treatment.

	(1)	(2)	(3)	(4)
Dep. Var.:	Automation patents/patents			
	Non-manufacturing firms		Manufacturing firms	
Cum. inflow rate × $\text{Allocation}_{t\geq 0}$	0.012	−0.051	−0.423***	−0.310**
	(0.136)	(0.130)	(0.151)	(0.130)
Region fixed effects	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2029	2029	2029	2029
R-squared	0.031	0.394	0.199	0.722
Within R-squared	0.009	0.001	0.023	0.019
Dep. Var. mean	0.092	0.092	0.135	0.135

Notes: The table presents the results of linear regression analyses as defined in Eq. (2). The dependent variable is the share of automation patents held by non-manufacturing firms in columns (1) and (2), and the share of automation patents held by manufacturing firms in columns (3) and (4). The classification in (non-)manufacturing is based on the respective firm's major sector code, as reported in ORBIS IP. In all columns, the treatment variable is continuous: the cumulative inflow rate during the allocation period, interacted with a dummy ($\text{Allocation}_{t\geq 0}$) that indicates whether the allocation policy was introduced in that year or earlier. The regressions are estimated at the region-year level and weighted by the regional population in 1991. Standard errors, clustered at the regional level, are in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

6.2. Demand for automation innovation

Conceptually, the decrease in the share of automation innovation could be a response to reduced *internal demand* (originating within the innovating firm) or *external demand* (from other firms). Previous studies indicate that low-skilled labor supply influences firms' decisions to adopt new production technologies from external providers (Clemens et al., 2018; Monras, 2019). However, product markets are seldom regional, weakening the link between regional changes in labor supply and external demand for automation innovation. Hence, we consider internal demand as the more plausible channel in our context.

Since we lack data on the demand for automation technologies, we seek indirect evidence to investigate this relation. First, we exploit that firms of different sizes likely vary in their internal vs. external demand orientations. Second, we leverage that process-related automation patents (e.g., a new automated process) should be more pertinent for internal use than product-related automation patents (e.g., a new industrial robot).

Small vs. large firms

We investigate the responsiveness of innovators of various sizes to the labor supply increase. More specifically, if the decline in automation innovation is driven by internal demand, we anticipate that large manufacturing firms would be more responsive to changes in regional labor supply. These large firms tend to be more vertically integrated (doing both R&D and production), employ more low-skilled workers, and have a greater potential for incorporating automation into their production processes. Conversely, smaller firms are thought to be more attuned to external demand for automation inventions, often developing technologies for commercialization.

We assess the automation innovation response to labor supply by small and large manufacturing firms by running separate regressions with the share of automation patents held by either small (and medium-sized) manufacturing firms or large manufacturing firms.

We find that the effect of labor supply on automation innovation is driven by the response of large manufacturing firms (Table 5, columns 1 and 2). The strong negative effect among large firms likely reflects cost incentives for vertically integrated innovators with a large stock of low-skilled workers. The response of small manufacturing firms is close to zero and statistically insignificant. We conclude that – at least in our context – internal demand for automation technologies plays an important role in firms' decisions to invest in automation innovation.

Process vs. product innovations

To support the argument that the response in automation innovation is driven by internal vs. external demand, we further investigate whether the reduction in automation patents relates to process or product innovations. Whereas process innovations mostly reflect internal use, product innovations predominantly reflect market activities (Klepper, 1996).

We test this empirically by distinguishing between process-related and product-related automation patents. The effects of ethnic German inflows on both types of automation patents are presented in Table 5, columns 3 and 4. The share of process-related automation patents reacts more strongly to the increase in labor supply than the share of product-related automation patents. As before, this heterogeneity result suggests that internal demand drives the automation innovation responses of firms.[26]

6.3. Responsiveness of automation innovation to labor market tightness

The effect of labor supply on automation innovation can occur through price adjustments (wages) or quantity adjustments (employment). Our findings in Section 4.3 indicate that the predominant adjustment in the German labor market did not occur at the wage margin. We therefore explore whether the effect on automation innovation depends on the labor markets' responsiveness along the quantity dimension. In particular, we expect that the effect of an increase in labor supply is stronger in regions where firms invest in automation innovation due to a scarcity of workers available (or willing) to undertake manual jobs.[27]

We examine whether the effect on the share of automation patents is stronger in regions with a high labor scarcity. To this end, we distinguish in our analysis between regions with tight and slack labor

[26] Note that firms may refrain from patenting process-related automation innovations intended for internal use and instead decide to avoid misappropriation through secrecy (cf. Hall et al., 2014; Ganglmair and Reimers, 2019). Consequently, selection into patenting may lead to an underestimation of the true effect on process-related automation innovations.

[27] The historical evidence suggests that labor scarcity in the regional labor market played a crucial role in the integration of ethnic Germans into the labor market (Haug and Sauer, 2007b). Indeed, ethnic Germans were industrious and willing to take up low-skilled jobs that native Germans were reluctant to perform (Haug and Sauer, 2007b). The co-existence of unemployment and labor scarcity was a characteristic feature of the German labor market during that period, where market frictions such as low inter-regional mobility or job transition rates contributed to its 'sclerotic' nature (Blanchard and Summers, 1986; Gartner et al., 2012).

Table 5
Effect of labor inflows on the share of automation patents by firm and patent characteristics – DiD with continuous treatment.

	(1)	(2)	(3)	(4)
Dep. Var.:	Automation patents/patents (manuf. firms)			
	Small firms	Large firms	Non-process pat.	Process pat.
Cum. inflow rate × $\text{Allocation}_{t\geq 0}$	−0.026	−0.263*	−0.144	−0.166**
	(0.027)	(0.135)	(0.092)	(0.065)
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2029	2029	2029	2029
R-squared	0.196	0.743	0.555	0.649
Within R-squared	0.001	0.016	0.008	0.016
Dep. Var. mean	0.016	0.117	0.072	0.064

Notes: The table presents the results of linear regression analyses as defined in Eq. (2). The dependent variable is the share of automation patents held by small manufacturing firms in column (1), the share of automation patents held by large manufacturing firms in column (2), the share of product-related automation patents held by manufacturing firms in column (3), and the share of process-related automation patents held by manufacturing firms in column (4). Firm size follows the classification of the European Commission for small and medium-sized enterprises (max. 249 employees and max. 50 million EUR annual turnover). The distinction between process and product patents is text-based and follows Ganglmair and Reimers (2019). In all columns, the treatment variable is continuous: the cumulative inflow rate during the allocation period, interacted with a dummy ($\text{Allocation}_{t\geq 0}$) that indicates whether the allocation policy was introduced in that year or earlier. The regressions are estimated at the region-year level and weighted by the regional population in 1991. Standard errors, clustered at the regional level, are in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

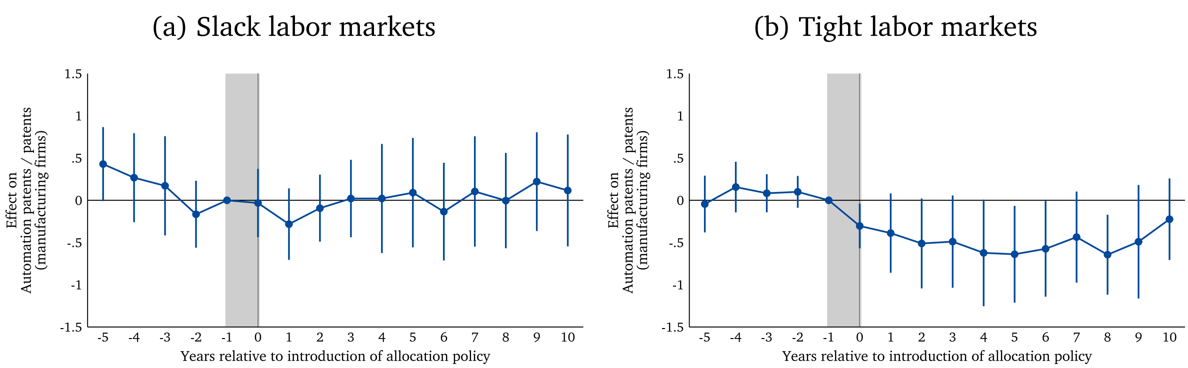

Fig. 6. Effect of labor inflows on the share of automation patents in slack and tight labor market regions – event study with continuous treatment
Notes: The figure displays event study estimates and the 95 percent confidence intervals based on a linear regression as specified in Eq. (1). In both panels, the dependent variable is the share of automation patents held by manufacturing firms, and the treatment variable is continuous: the cumulative inflow rate during the allocation period, interacted with leads and lags. We introduce further interactions with a binary variable that indicates regions with a tight labor market: an unemployment rate in the last pre-allocation year higher than the median rate. The estimates in panel (a) present the baseline coefficients (with the additional interaction being zero). The estimates in panel (b) present the sum of the baseline and interaction coefficients indicating regions with a tight labor market. The time dummies indicate that the allocation policy is introduced l years away, with $l \in \{-5; +10\}$. The coefficient for $l = -1$ is normalized to zero. Region and time fixed effects included. Standard errors clustered at the regional level. The coefficients correspond to those reported in Appendix Table B-12.

markets defined by the region's unemployment rate. More specifically, we split the sample at the median unemployment rate in the last pre-allocation year. For each subsample, we then separately estimate the dynamic effects of labor supply on the share of automation patents held by manufacturing firms. We repeat this split-sample approach with the static DiD model and further conduct an analysis using the full sample, introducing an interaction term between the treatment variable and a dummy indicating regions with tight labor markets.

The event study estimates reveal a strong negative labor supply effect on the share of automation patents in tight labor market regions (Fig. 6(b)). In contrast, we observe no discernible effect in slack labor market regions (Fig. 6(a)). This heterogeneity is confirmed by the coefficients from static DiD models with continuous treatment (Table 6). Similarly, we find that high-wage regions are more responsive to labor supply inflows than low-wage regions (Appendix Table B-14). This suggests that labor inflows have a greater marginal effect on automation innovation in regions where they alleviate labor scarcity constraints.

In conclusion, our findings suggest that the effect of labor supply on automation innovation depends on several factors. In our context, these include the economic sector's susceptibility to automation, firms' capacity to implement automation internally, and the regional labor market tightness.

7. Discussion and concluding remarks

By exploiting the allocation of ethnic German immigrants across German regions, we analyze the effect of a plausibly exogenous expansion of low-skilled labor supply on automation innovation. We find that an increase in the low-skilled workforce reduces the number of automation patents in relative and absolute terms. While labor inflows raise employment *immediately*, their discouraging effect on automation patents peaks only in the fourth year after treatment. The average treatment effect conceals substantial heterogeneity: the effect is stronger for automation patents in the manufacturing sector, for automation patents held by large manufacturing firms, and for automation patents that relate to processes and not products. Lastly, the effect is confined to regions with tight labor markets, where additional labor supply relaxes production constraints. These findings suggest that the effect of labor supply on automation innovation is governed by firms' susceptibility to automation, their internal labor cost considerations, and labor scarcity.

Our study's quasi-experimental setting supports the causal interpretation and, hence, the internal validity of our estimates. However, the unique circumstances of Germany's allocation policy for ethnic Germans may limit the extent to which our findings generalize to other settings. Several elements of the German context – the permanent

Table 6
Effect of labor inflows on the share of automation patents in slack and tight labor market regions – DiD with continuous treatment.

	(1)	(2)	(3)
Dep. Var.:	Automation patents/patents (manuf. firms)		
Labor markets:	Slack	Tight	All
Cum. inflow rate × Allocation$_{t\geq0}$	−0.082	−0.438**	−0.098
	(0.162)	(0.189)	(0.156)
Cum. inflow rate × Allocation$_{t\geq0}$ × Tight labor market			−0.326
			(0.227)
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	1021	1008	2029
R-squared	0.688	0.755	0.724
Within R-squared	0.001	0.051	0.024
Dep. Var. mean	0.135	0.135	0.135

Notes: The table presents the results of linear regression analyses as defined in Eq. (2). In all columns, the dependent variable is the share of automation patents held by manufacturing firms, and the treatment variable is continuous: the cumulative inflow rate during the allocation period, interacted with a dummy (Allocation$_{t\geq0}$) that indicates whether the allocation policy was introduced in that year or earlier. The sample in column (1) consists of "slack labor market" regions with an unemployment rate in the last pre-allocation year that is lower or equal to the median rate. The sample in column (2) consists of "tight labor market" regions with an unemployment rate in the last pre-allocation year that is above the median rate. In column (3), we use the full sample but introduce a further interaction of the treatment variable with a dummy that indicates "tight labor market" regions. The regressions are estimated at the region-year level and weighted by the regional population in 1991. Standard errors, clustered at the regional level, are in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

settlement of ethnic Germans who were close substitutes to native workers, a large and productive manufacturing sector susceptible to automation, and internationally competitive labor unit costs in manufacturing (Dustmann et al., 2014) – may not be directly transferable to other settings. Bearing this caveat in mind, our findings imply that governments can influence (regional) innovation activities by steering labor supply, for example, through specific migration policies. This insight is pertinent, as many countries face serious demographic challenges like population aging and immigration.

More broadly, our findings have valuable implications for policymaking across three key domains: labor markets, migration, and innovation. Firstly, our results address labor market policies by revealing the spillover effects of low-skilled labor supply on regional innovation activities. Adjustments in automation innovation can influence the demand for and relative remuneration of input factors in an economy, with consequences for social inequality. A reduction in automation innovation shifts the available technologies towards more labor-intensive production, leading firms to hire more workers for automatable jobs. This results in a feedback loop where a greater low-skilled labor supply can shield low-skilled workers from being replaced by machines. On the one hand, this finding bears relevance for the design of labor market institutions. Countries with strict labor market regulations may wish to shield workers from technology-induced disruptions. Our findings from Germany suggest that such regulation does not disable the effect of labor supply on automation innovation even when wages are strongly regulated. On the other hand, this finding is also informative in the domain of immigration policies. The labor-preserving impact of reduced automation innovation originating from large-scale immigration can partially offset the elevated direct labor market competition experienced by native workers. This dynamic can dampen the effects of immigration on wages and employment in the medium and long term. This indirect labor market consequence of immigration has so far received little attention in the literature (cf. Borjas, 1994; Edo, 2019).

Secondly, we provide a direct evaluation of the innovation impact of a migrant allocation policy. Many countries express concerns about the residential concentration of migrants, as it can lead to segregation and the formation of ethnic enclaves. Research has demonstrated that such enclaves hinder language acquisition (Danzer and Yaman, 2016; Danzer et al., 2022) and may foster distinct welfare cultures (Bertrand et al., 2000). In response, some governments have implemented allocation policies, such as residential dispersal (e.g., Sweden, Denmark) or school busing dispersal (e.g., the US). As the empirical evidence regarding these policies' direct labor market effects remains mixed (Damm, 2009; Glitz, 2012), it is worth considering an evaluation of such policies also in terms of their effects on innovation and productivity. Indeed, our research informs policymakers grappling with the delicate balance between immigration and labor market policies (Facchini and Steinhardt, 2011) by shedding light on such secondary effects of placement policies: increasing the supply of low-skilled labor, the allocation policy had the – presumably unintended – effect of eroding firms' incentives to automate production. However, predicting the direct and indirect effects of placement policies is complex, especially when counterfactual scenarios are poorly understood. For instance, endogenous sorting of migrants may actually enhance productivity through agglomeration effects (Peters, 2022), depending on the specific pattern of self-selection.

Thirdly, our research also contributes to the realm of innovation policy. The interplay between technological progress and the labor market has garnered significant public and political attention, particularly in light of the recent advancements in artificial intelligence and robotization. Our study reveals that an abundance of low-skilled labor curtails innovation activities in the manufacturing sector, thereby underscoring the labor market's critical role in guiding technological progress. As the impacted innovations were predominantly labor-saving automation technologies, the increase in regional labor supply led to a shift in the direction of technical change. Such a shift can set firms on distinct technological paths, with potential long-term implications for their productivity and social welfare. For instance, firms that automate less may become less efficiency-seeking and ultimately less competitive in the product market (Aghion et al., 2022). At the same time, having firms move their resources from automation to more consumer-oriented innovation may increase product diversity and the value added in an economy in the long run (Hémous and Olsen, 2022). In general, our research informs the debate on the optimal policy environment for fostering innovation; that is, whether, for example, cutthroat competition (Acemoglu et al., 2012), risk insurance through social policy (Stiglitz, 2015), or an incentivizing tax system (Griffith et al., 2014; Haufler et al., 2014; Widmann, 2023) is conducive to innovation. Our findings suggest a trade-off between employment opportunities and firms' incentives to innovate. Against this backdrop, policies that promote innovation could be combined with suitable (active) labor market policies, exemplified by the Nordic model (Stiglitz, 2015), for overall welfare improvement. This could also be an effective tool against income inequality resulting from automation if benefits accrue mostly to high-skilled workers or capital owners.

This paper concentrates on the automation of low-skilled manual labor during the 1990s and 2000s. Since then, the scope of automation, including artificial intelligence, has broadened, affecting an ever-growing range of manual and cognitive tasks. Consequently, policymakers are asked to address the present and future challenges of automatization. As such, our findings provide a foundation for further research that informs policy on balancing labor market dynamics and technological progress.

Declaration of competing interest

The authors declare that they have no relevant or material financial interests that relate to the research described in this paper ('Labor Supply and Automation Innovation: Evidence from an Allocation Policy'; Authors: Alexander M. Danzer, Carsten Feuerbaum and Fabian Gaessler).

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jpubeco.2024.105136.

References

Acemoglu, D., 2002. Directed Technical Change. Rev. Econ. Stud. 69 (4), 781–809.

Acemoglu, D., 2007. Equilibrium Bias of Technology. Econometrica 75 (5), 1371–1409.

Acemoglu, D., 2010. When does Labor Scarcity Encourage Innovation? J. Polit. Econ. 118 (6), 1037–1078.

Acemoglu, D., Restrepo, P., 2019. Automation and New Tasks: How Technology Displaces and Reinstates Labor. J. Econ. Perspect. 33 (2), 3–30.

Acemoglu, D., Restrepo, P., 2022. Demographics and Automation. Rev. Econ. Stud. 89 (1), 1–44.

Acemoglu, D., Robinson, J.A., Verdier, T., 2012. Can't We All Be More Like Scandinavians? Asymmetric Growth and Institutions in an Interdependent World. NBER Working Paper No. 18441.

Aghion, P., Antonin, C., Bunel, S., Jaravel, X., 2022. The Effects of Automation on Labor Demand: A Survey of the Recent Literature. CEPR Discussion Paper No. DP16868.

Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R., Van Reenen, J., 2016. Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry. J. Polit. Econ. 124 (1), 1–51.

Amior, M., Stuhler, J., 2022. Immigration and Monopsony: Evidence Across the Distribution of Firms.

Autor, D.H., Levy, F., Murnane, R.J., 2003. The Skill Content of Recent Technological Change: An Empirical Exploration. Q. J. Econ. 118 (4), 1279–1333.

Bauer, T., Zimmermann, K.F., 1997. Unemployment and Wages of Ethnic Germans. Q. Rev. Econ. Finance 37, 361–377.

Bena, J., Simintzi, E., 2022. Machines Could Not Compete with Chinese Labor: Evidence from US Firms' Innovation. Available at SSRN 2613248.

Bertrand, M., Luttmer, E.F.P., Mullainathan, S., 2000. Network Effects and Welfare Cultures. Q. J. Econ. 115, 1019–1055.

Blanchard, O.J., Summers, L.H., 1986. Hysteresis and the European Unemployment Problem. NBER Macroeconomics Annual 1, 15–78.

Blossfeld, H.-P., 1987. Labor-market Entry and the Sexual Segregation of Careers in the Federal Republic of Germany. Am. J. Sociol. 93 (1), 89–118.

Borjas, G.J., 1994. The Economics of Immigration. J. Econ. Lit. 32 (4), 1667–1717.

Borusyak, K., Jaravel, X., Spiess, J., 2021. Revisiting Event Study Designs: Robust and Efficient Estimation. arXiv preprint arXiv:2108.12419.

Boustan, L.P., Fishback, P.V., Kantor, S., 2010. The Effect of Internal Migration on Local Labor Markets: American Cities during the Great Depression. J. Labor Econ. 28 (4), 719–746.

Brücker, H., Jahn, E.J., 2011. Migration and wage-setting: Reassessing the labor market effects of migration. Scand. J. Econ. 113 (2), 286–317.

Bundesverwaltungsamt, 2019. (Spät-)Aussiedler und ihre Angehörigen Zeitreihe 1950 - 2019.

Calel, R., Dechezleprêtre, A., 2016. Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market. Rev. Econ. Stat. 98 (1), 173–191.

Callaway, B., Sant'Anna, P.H., 2021. Difference-in-Differences with Multiple Time Periods. J. Econometrics 225 (2), 200–230.

Card, D., 1990. The Impact of the Mariel Boatlift on the Miami Labor Market. ILR Rev. 43 (2), 245–257.

Clemens, M.A., Lewis, E.G., Postel, H.M., 2018. Immigration Restrictions as Active Labor Market Policy: Evidence from the Mexican Bracero Exclusion. Amer. Econ. Rev. 108 (6), 1468–1487.

Comanor, W.S., Scherer, F.M., 1969. Patent Statistics as a Measure of Technical Change. J. Polit. Econ. 77 (3), 392–398.

Damm, A.P., 2009. Ethnic Enclaves and Immigrant Labor Market Outcomes: Quasi-Experimental Evidence. J. Labor Econ. 27 (2), 281–314.

D'Amuri, F., Ottaviano, G.I., Peri, G., 2010. The Labor Market Impact of Immigration in Western Germany in the 1990s. Eur. Econ. Rev. 54 (4), 550–570.

Danzer, A.M., Dietz, B., 2014. Labour Migration from Eastern Europe and the EU's Quest for Talents. JCMS: J. Common Mark. Stud. 52 (2), 183–199.

Danzer, A.M., Feuerbaum, C., Piopiunik, M., Woessmann, L., 2022. Growing up in Ethnic Enclaves: Language Proficiency and Educational Attainment of Immigrant Children. J. Popul. Econ. 35 (3), 1432–1475.

Danzer, A.M., Yaman, F., 2016. Ethnic Concentration and Language Fluency of Immigrants: Evidence from the Guest-worker Placement in Germany. J. Econ. Behav. Organ. 131, 151–165.

De Chaisemartin, C., d'Haultfoeuille, X., 2020. Two-way Fixed Effects Estimators with Heterogeneous Treatment Effects. Amer. Econ. Rev. 110 (9), 2964–2996.

de Vries, G.J., Gentile, E., Miroudot, S., Wacker, K.M., 2020. The Rise of Robots and the Fall of Routine Jobs. Labour Econ. 66, 101885.

Dechezleprêtre, A., Hémous, D., Olsen, M., Zanella, C., 2023. Induced Automation Innovation: Evidence from Firm-level Patent Data. Working Paper.

Dietz, B., 2006. Aussiedler in Germany: From Smooth Adaptation to Tough Integration. In: Lucassen, L., Feldmann, D., Oltmer, J. (Eds.), Paths of Integration. Migrants in Western Europe (1880-2004). Amsterdam University Press, Amsterdam, pp. 116–136.

Doran, K., Yoon, C., 2020. Immigration and Invention: Evidence from the Quota Acts. Working Paper.

Dustmann, C., Fitzenberger, B., Schönberg, U., Spitz-Oener, A., 2014. From Sick Man of Europe to Economic Superstar: Germany's Resurgent Economy. J. Econ. Perspect. 28 (1), 167–188.

Dustmann, C., Glitz, A., 2015. How Do Industries and Firms Respond to Changes in Local Labor Supply? J. Labor Econ. 33 (3), 711–750.

Dustmann, C., Glitz, A., Frattini, T., 2008. The Labour Market Impact of Immigration. Oxf. Rev. Econ. Policy 24 (3), 477–494.

Dustmann, C., Schönberg, U., Stuhler, J., 2016. The Impact of Immigration: Why do Studies Reach such Different Results? J. Econ. Perspect. 30 (4), 31–56.

Dustmann, C., Schönberg, U., Stuhler, J., 2017. Labor Supply Shocks, Native Wages, and the Adjustment of Local Employment. Q. J. Econ. 132 (1), 435–483.

Eckstein, Z., Weiss, Y., 2004. On the Wage Growth of Immigrants: Israel, 1990–2000. J. Eur. Econom. Assoc. 2 (4), 665–695.

Edo, A., 2019. The Impact of Immigration on the Labor Market. J. Econ. Surv. 33 (3), 922–948.

Facchini, G., Steinhardt, M.F., 2011. What Drives U.S. Immigration Policy? Evidence from Congressional Roll Call Votes. J. Public Econ. 95 (7), 734–743.

Ganglmair, B., Reimers, I., 2019. Visibility of Technology and Cumulative Innovation: Evidence from Trade Secrets Laws. ZEW-Centre for European Economic Research Discussion Paper 19-035.

Gartner, H., Merkl, C., Rothe, T., 2012. Sclerosis and Large Volatilities: Two Sides of the Same Coin. Econom. Lett. 117 (1), 106–109.

Glitz, A., 2006. The Labour Market Impact of Immigration: Quasi-experimental Evidence. Centre for Research and Analysis of Migration, Working Paper.

Glitz, A., 2012. The Labor Market Impact of Immigration: A Quasi-experiment Exploiting Immigrant Location Rules in Germany. J. Labor Econ. 30 (1), 175–213.

Griffith, R., Miller, H., O'Connell, M., 2014. Ownership of Intellectual Property and Corporate Taxation. J. Public Econ. 112, 12–23.

Griliches, Z., 1998. Patent Statistics as Economic Indicators: A Survey. In: R&D and Productivity: The Econometric Evidence. University of Chicago Press, pp. 287–343.

Habakkuk, H.J., 1962. American and British Technology in the Nineteenth Century: The Search for Labour Saving Inventions. Cambridge University Press.

Hall, B., Helmers, C., Rogers, M., Sena, V., 2014. The Choice between Formal and Informal Intellectual Property: A Review. J. Econ. Lit. 52 (2), 375–423.

Hanlon, W.W., 2015. Necessity is the Mother of Invention: Input Supplies and Directed Technical Change. Econometrica 83 (1), 67–100.

Hanson, G.H., Slaughter, M.J., 2002. Labor-market Adjustment in Open Economies: Evidence from US States. J. Int. Econ. 57 (1), 3–29.

Harhoff, D., Scherer, F.M., Vopel, K., 2003. Citations, Family Size, Opposition and the Value of Patent Rights. Res. Policy 32 (8), 1343–1363.

Haufler, A., Norbäck, P.-J., Persson, L., 2014. Entrepreneurial Innovations and Taxation. J. Public Econ. 113, 13–31.

Haug, S., Sauer, L., 2007a. Aussiedler, Spätaussiedler, Russlanddeutsche: Berufliche, sprachliche und soziale Integration. Osteuropa 57 (11), 252–266.

Haug, S., Sauer, L., 2007b. Zuwanderung und Integration von (Spät-) Aussiedlern: Ermittlung und Bewertung der Auswirkungen des Wohnortzuweisungsgesetzes. Forschungsbericht 3. Bundesamt für Migration und Flüchtlinge. Nürnberg.

Hémous, D., Olsen, M., 2022. The Rise of the Machines: Automation, Horizontal Innovation, and Income Inequality. Am. Econ. J.: Macroecon. 14, 179–223.
Hicks, J., 1932. The Theory of Wages. Macmillan, London.
Hornung, E., 2014. Immigration and the Diffusion of Technology: The Huguenot Diaspora in Prussia. Amer. Econ. Rev. 104 (1), 84–122.
Hunt, J., Gauthier-Loiselle, M., 2010. How Much Does Immigration Boost Innovation? Am. Econ. J.: Macroecon. 2 (2), 31–56.
IAB, 2019. Qualifikationsspezifische Arbeitslosenquoten 1975–2018. Available at: http://doku.iab.de/arbeitsmarktdaten/qualo_2019.xlsx.
Imbert, C., Seror, M., Zhang, Y., Zylberberg, Y., 2019. Migrants and Firms: Evidence from China. CESifo Working Paper No. 7440.
Jahn, V., Steinhardt, M.F., 2016. Innovation and Immigration – Insights from a Placement Policy. Econom. Lett. 146, 116–119.
Kerr, S.P., Kerr, W.R., Lincoln, W.F., 2015. Skilled Immigration and the Employment Structures of US Firms. J. Labor Econ. 33 (S1), S147–S186.
Kiley, M.T., 1999. The Supply of Skilled Labour and Skill-biased Technological Progress. Econ. J. 109 (458), 708–724.
Klepper, S., 1996. Entry, Exit, Growth, and Innovation Over the Product Life Cycle. Amer. Econ. Rev. 86 (3), 562–583.
Klose, H.-U., 1996. Bevölkerungsentwicklung und Einwanderungspolitik. In: Integration Und Konflikt: Kommunale Handlungsfelder Der Zuwanderungspolitik. Friedrich-Ebert-Stiftung, Bonn.
Koller, B., 1993. Aussiedler nach dem Deutschkurs: Welche Gruppen kommen rasch in Arbeit. Mitteilungen aus der Arbeitsmarkt-und Berufsforschung 26 (2), 207–221.
Kreyenfeld, M., Konietzka, D., 2002. The Performance of Migrants in Occupational Labour mMrkets. Eur. Soc. 4 (1), 53–78.
Lewis, E., 2011. Immigration, Skill Mix, and Capital Skill Complementarity. Q. J. Econ. 126 (2), 1029–1069.
Mann, K., Püttmann, L., 2023. Benign Effects of Automation: New Evidence from Patent Texts. Rev. Econ. Stat. 105 (3), 562–579.
Mika, T., Hering, L., Hochfellner, D., 2010. Welche berufliche Qualifikation und Erfahrung brachten Aussiedler und Spätaussiedler bei der Zuwanderung mit. Gesundheit, Migration und Einkommensungleichheit (Ed.) Forschungsdatenzentrum der Rentenversicherung, DRV Bund, Berlin, DRV-Schriften 55, 131.
Monras, J., 2019. Immigration, Internal Migration, and Technology Adoption. CEPR Discussion Paper No. DP13998.
OECD, 2004. OECD Employment Outlook: 2004. Organisation for Economic Co-operation and Development.
OECD, 2009. OECD Patent Statistics Manual 2009. Organisation for Economic Co-operation and Development.
Ohliger, R., 2008. Country Report on Ethnic Relations: Germany. EDUMIGROM Background Papers.
Panagiotidis, J., 2021. Postsowjetische Migration in Deutschland. Bundeszentrale für politische Bildung.
Peri, G., Sparber, C., 2009. Task Specialization, Immigration, and Wages. Am. Econ. J.: Appl. Econ. 1 (3), 135–169.
Peters, M., 2022. Market Size and Spatial Growth-Evidence from Germany's Post-War Population Expulsions. Econometrica 90 (5), 2357–2396.
Piopiunik, M., Ruhose, J., 2017. Immigration, Regional Conditions, and Crime: Evidence from an Allocation Policy in Germany. Eur. Econ. Rev. 92, 258–282.
Pischke, J.-S., Velling, J., 1997. Employment Effects of Immigration to Germany: An Analysis Based on Local Labor Markets. Rev. Econ. Stat. 79 (4), 594–604.
San, S., 2023. Labor Supply and Directed Technical Change: Evidence from the Termination of the Bracero Program in 1964. Am. Econ. J.: Appl. Econ. 15 (1), 136–163.
Stiglitz, J.E., 2015. Leaders and Followers: Perspectives on the Nordic Model and the Economics of Innovation. J. Public Econ. 127, 3–16.
Sun, L., Abraham, S., 2021. Estimating Dynamic Treatment effects in Event Studies with Heterogeneous Treatment Effects. J. Econometrics 225 (2), 175–199.
Walsh, J.P., Nagaoka, S., 2009. Who Invents? Evidence from the Japan-US Inventor Survey. RIETI Discussion Paper Series 09-E-034.
Widmann, R., 2023. Immigrant Inventors and Local Income Taxes: Evidence from Swiss Municipalities. J. Public Econ. 219, 104822.
Zator, M., 2019. Digitization and Automation: Firm Investment and Labor Outcomes. Working Paper.
Zeira, J., 1998. Workers, Machines, and Economic growth. Q. J. Econ. 113 (4), 1091–1117.
Zimmermann, K.F., 2000. Aussiedler seit 1989 - Bilanz und Perspektiven. Jahrbuch für Wirtschaftsgeschichte / Econ. Hist. Yearbook 41 (1), 225–238.