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The Effect of Recent Technological Change on US Immigration Policy *

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Abstract

Did recent technological change shape immigration policy in the United States? I argue that as automation shifted employment from routine to manual occupations, it increased competition between natives and immigrants. In turn, this lead to a more restrictive US immigration policy. I provide empirical evidence for this by analyzing voting on low-skill immigration bills in the House of Representatives. Policy makers representing congressional districts with a higher share of manual employment and those exposed to manual-biased technological change are more likely to support restricting low-skill immigration. Additional results on the effect of (i) immigration on wages, (ii) voter's attitudes on low-skill immigration, and (iii) political polarization complete the analysis. I do not find a corresponding effect of technological change on trade policy consistent with the highlighted mechanism.

JEL Classifications: F22; J61; K37; O30
Keywords: Political Economy, Voting, Immigration Policy, Technological Change

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1 Introduction

Immigration has long been a key area of policy debate in the United States (Hatton & Williamson 2005). However, recently the issue has become even more polarized with the discourse being increasingly influenced by populist and radical-right opinions.[1] The most observable part of this is the polarization of Republicans and Democrats on immigration policy as well as the election of Donald Trump on an anti-immigration and -trade platform.

Technological change, in the form of industrial robots, has been highlighted as one factor leading to increased support for populists in the US and Western Europe (Frey et al. 2018; Anelli et al. 2021).[2] However, others have found that winners outweighed the losers and technological change increased support for some moderate parties (Gallego et al. 2022; Schöll & Kurer 2021). The underlying mechanism why technological change should increase support for politicians and parties with anti-immigration policies and not ones that agitate against technology or those that support welfare spending also remains mostly undocumented. The usual explanations are that (i) politicians are unable to solve the economic hardship caused by recent technological change or attribute it falsely to immigration (Kurer 2020), or (ii) support for populists more broadly represents status concerns and a show of discontent with the current system (Kurer & van Staalduinen 2020; Häusermann et al. 2021). In both cases, anti-immigration policies would not provide any actual economic gains to voters. Further, whether technological change shapes the actual implementation of policies remains undocumented as the focus has been exclusively on individual attitudes and voting outcomes.

This paper fills these gaps by studying the link between technological change and immigration policy making. I find that technological change which was complementary to manual employment increased support for restricting low-skill immigration policy in the US house of representatives. I provide empirical evidence that this anti-immigration response is motivated by the increased labor market competition between natives and immigrants.[3] This occurred, because employment polarization expanded the share of natives in direct competition with low-skill immigrants as routine jobs in the middle of

[1]The rise of populist parties have been a broad phenomenon in Western Democracies with Guriev & Papaioannou (2020) providing a summary of the cultural and economic explanation presented in the literature.

[2]Another important economic factor for the rise in populism has been Chinese import competition (Feigenbaum & Hall 2015; Che et al. 2016; Colantone & Stanig 2017; Colantone & Stanig 2019; Autor et al. 2020). Caselli et al. (2021) and Milner (2021) document that the impact of robotization and trade both favor populist, but are distinct in their impact.

[3]The overall impact of immigration on local wages has been a vividly debated issue. Most of the literature is reviewed in Dustmann et al. (2016). Recent evidence, however, seems to clearly support that while immigration might have an overall positive effect on wages it clearly depressed wages at the lower end of the skill distribution and in non-traded sectors with limited labor protection (see Dustmann et al. 2013; Mandelman & Zlate Forthcoming; Allen et al. 2018; Burstein et al. 2020; Bächli & Tsankova 2021). The later factors apply in particularly to the manual intensive service occupations that has expanded due to automation (Autor & Dorn 2013).

the skill distribution —which attract few immigrants (Card 2009)— disappeared and the relative demand for manual occupations increased.[4] Accordingly, the share of voters gaining from anti-immigration policies increased.

The key swing-state of Ohio, which switched from supporting Obama in 2006/10 to Trump in 2016/20, illustrates this argument. Figure 1 shows the manual employment share in 2000 and 2010 and voting on low-skill immigration bills in 2005 and 2014 across Ohio congressional districts. First, the maps highlight that there is a correlation between the manual employment share in a congressional district and representatives being in favor of restricting low-skill immigration. Second, as manual employment expanded in Ohio between 2000 and 2010 the voting behavior of representatives turned more averse to low-skill immigration.

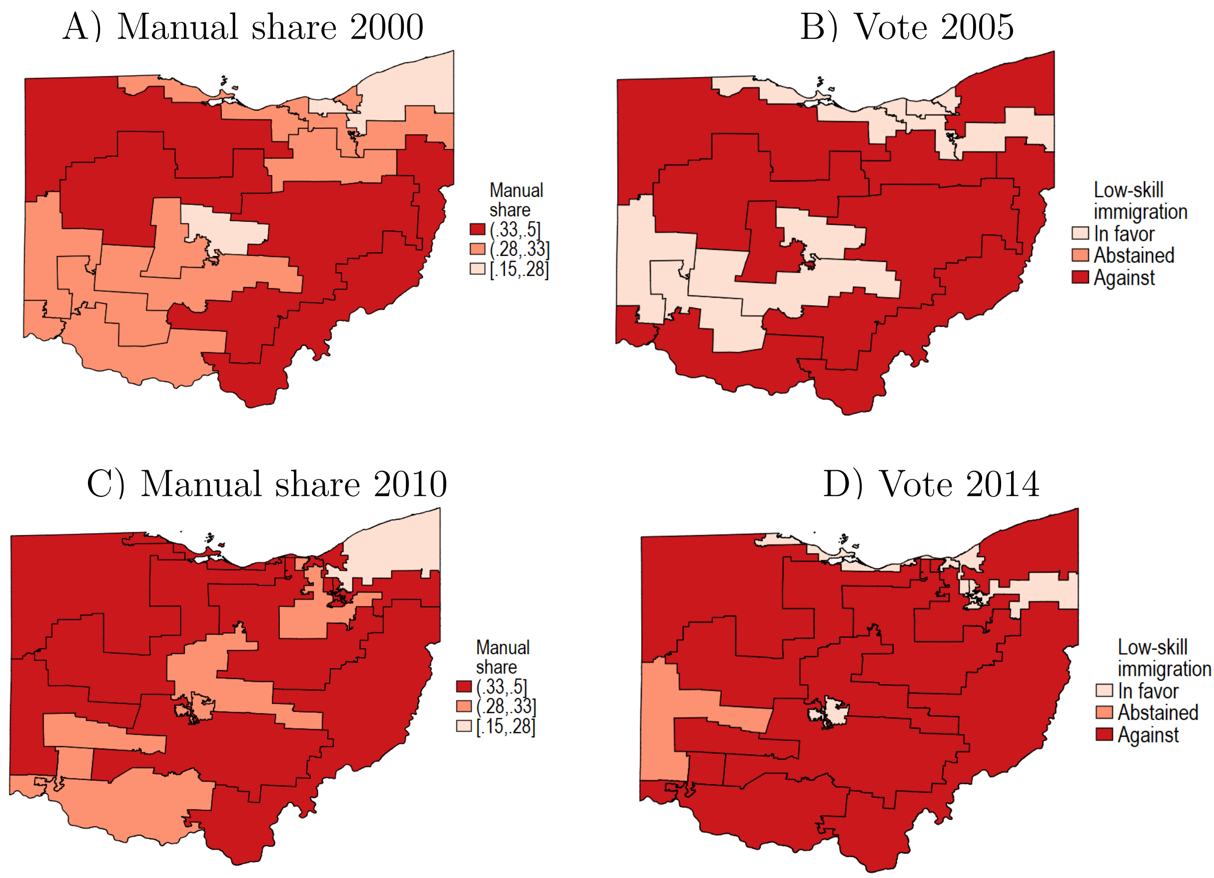
My findings challenge the hypothesis that the link between technological change and increased support for populist parties is due to immigrants being scapegoated or due to voters having increased status concerns. Instead it highlights the increase in the proportion of voters that economically gain from restricting low-skill immigration. This suggests that when moderate policy makers adapt to changing demands on immigration policy, technological change might not more broadly increase support for populist politicians. I find no evidence that recent technological change led to a corresponding shift in trade policy. This is consistent with the proposed labor market mechanism.

The presented argument builds on research that has highlighted how public views on immigration differ based on labor market competition. Low-skilled native workers, usually measured by having below college education, are considerably more likely to prefer limiting immigrant inflows than their highly educated counterparts (e.g. Scheve & Slaughter 2001; Mayda 2006; O'Rourke & Sinnott 2006). This, in turn, translates into changes in representatives' voting behavior on immigration policy (Facchini & Steinhardt 2011; Conconi et al. 2020). The latter is not surprising as for political incumbents casting roll-call votes is one of the most visible activities to take clear policy positions and communicate them to their constituents (Mayhew 1974).

More formally this paper documents empirically the effect of (i) the manual employment share and (ii) manual-biased technological change across congressional districts on voting on low-skill immigration bills in the House of Representatives from 1973 to 2014. First, my findings underlines that indeed the task composition of local employment plays a key role in voting decisions of representatives on low-skill immigration policy. A one percentage point higher manual employment share in a congressional district makes it

[4] The disappearance of routine occupations and subsequent employment polarization has been the key characteristics of changes in the labor market of the US and other advanced countries since the 1980s (Autor et al. 2003; Acemoglu & Autor 2011; Autor & Dorn 2013; Goos et al. 2014). Notably, immigrants to the US have already beforehand been clustered at the extremes of the skill distribution due to the communication skills required for most routine occupations, like clerical and retail occupations, being difficult to transfer across language barrier (Card 2009; Lewis & Peri 2015).

Figure 1: Manual employment share and support low-skill immigration



Notes: The map depicts the manual share in 2000 and 2010 and voting on immigration bills in 2005 ("H.R. 4437") and 2014 ("H.R. 5759") across Ohio congressional districts. Both bills were aimed at restricting low-skill immigration so "in favor" in the map was a Nay-vote and "against" was a Yay-vote on the respective bill. Both bills have been similarly contested nationwide with 240 (219) in favor and 182 (198) against low-skill immigration. Figure A.1 provides maps depicting the manual share and low-skill immigration voting for the whole continental US.

3.4% less likely that a representative votes in favor of liberalizing low-skill immigration. Second, it shows that when technological change was complementary to manual employment —e.g. in the form of automation of routine tasks— this led to increased support for restricting immigration policy. A one standard deviation increase in manual-biased technological change increases the likelihood of a representative voting in favor of restricting low-skill immigration by 8.8% percentage points. Notably, I document that technological change not just altered policy through replacing representatives that are favorable to immigration with those opposing it, but even changed the voting behavior of representatives that remained in office.

My main measure of interest captures how new technologies change the demand for manual tasks relative to other tasks. This is done by creating a shift-share variable combining industry level changes in manual to median wages with the initial industry structure by 1950. This differs from previous studies that have focused mainly on the impact of industrial robots on support for populists (e.g. Frey et al. 2018; Anelli et al. 2021). Rather than focusing on one individual technology my measure is closer in spirit to work by Autor et al. (2003) and Autor & Dorn (2013) that focused on the task content of occupations and their complementarity and substitutability with technology. Using manual-biased technological change has several advantages in the setting of my analysis compared to focusing on a specific technology.[5] First, my period of interest covers a relatively long period of time from 1973-2014. This is necessary to study a reasonably large number of votes on immigration bills, however data on most specific technologies is limited by the time-horizon for which data is available. Second, as I will show my measure is based on a large number of industries (in manufacturing and services) and quasi-random shocks to them over time. This is crucial for the use of a shift-share empirical design as highlighted by Borusyak et al. (2022). Also, my measure of manual-biased technological change, shifts the focus towards the political implications of the automation of routine tasks that has been the main driver of US labor market polarization (Autor et al. 2003; Acemoglu & Autor 2011; Autor & Dorn 2013; Goos et al. 2014). This is important as most of the literature on the political consequences of technology adoption so far has focused on the rather recent and manufacturing centered adoption of industrial robots (Frey et al. 2018; Anelli et al. 2021; Caselli et al. 2021; Milner 2021).

To narrow down that the effect of technological change on immigration policy is due to changes in labor market competition between natives and immigrants, I provide additional evidence along a number of lines. First, I highlight that low-skill immigration is indeed associated with depressed natives' wages in manual occupation across congressional districts. Second, using individual level data I document that employment in manual occupations is associated with negative attitudes on immigration, while employment in routine and abstract jobs is associated with favorable attitudes on immigration. Third, I rule out that the anti-immigration response simply reflects status concerns and broader dissatisfaction with globalization. I do this by studying the impact of technological change on trade policy, finding no comparable effect.[6] Interestingly, while technological change increased the election chances of Republican representatives, the newly elected representatives were relatively moderate for their party till the 2000s. Only from the 2010s technological change increased the election chances of Republicans with more right-leaning position outside of

[5]The commonly used data of the International Federation of Robotics provides a suitable example for more precisely outlying the shortcomings if used in my setting. First, the adoption of industrial robots is only recorded starting in the 1990s for some European countries and even latter for the US. Second, it is only available at an extremely aggregated industry level with a maximum of 19 categories with 16 of these being in manufacturing, a sector of the economy generally in decline. Third, most of the recorded adoption occurs in automotive industries making shock exposure centered in small geographic areas of the US in which other trends might also be driving anti-immigration sentiment and political outcomes.

[6]Autor et al. (2013*b*) note that exposure to automation and Chinese import competition are largely uncorrelated and affect different local labor markets. Further, automation mainly led to a rise in low-skill services at the bottom end of the skill distribution (see e.g. Autor & Dorn 2013), which are largely non-tradable and should not be exposed to foreign competition.

immigration policy. One reason for this might be the increasing polarization of US politics along party lines (Poole & Rosenthal 1984) with populist and nativist candidates being the only politicians that take sufficiently anti-immigration stances to appeal to voters affected by technological change.

My analysis is most closely related to the literature studying whether labor market competition influences support for immigration (Scheve & Slaughter 2001; Mayda 2006; O'Rourke & Sinnott 2006; Facchini & Steinhardt 2011; Conconi et al. 2020) and the literature that studies the impact of new technologies on support for populist and nativist politicians (Frey et al. 2018; Anelli et al. 2021; Gallego et al. 2022; Schöll & Kurer 2021; Caselli et al. 2021; Milner 2021). In addition to corroborating the role of labor market competition in support for immigration, the contribution of my paper is to document that occupational tasks and not just education plays a key role in determining this labor market competition. Further, the main contribution of my paper is to highlight how technological change altered labor market competition and led to the making of more restrictive immigration policy in the US. Importantly, my findings also suggest that the relationship between technological change and the election of more broadly right-leaning politicians might have only emerged over recent decades. Before this, while becoming more restrictive on immigration policy due to technological change, the position of representatives on other policy issues remained more centrist.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 provides descriptive evidence with Appendix B providing a theoretical framework consistent with these. Section 4 outlines the main empirical strategy and results on voting on immigration policy. Section 5 evaluates the sensitivity of these results. Section 6 discusses the broader political implications on trade policy and election outcomes. Finally, Section 7 concludes the paper.

2 Data

2.1 Main sources

To measure the making of US immigration policy, I use US house of representatives roll call data from Poole & Rosenthal (2000). This provides information on the voting behavior of legislators on 17 bills focusing on immigration policy between 1973 and 2014. Reflecting an expanded list of immigration bills as identified in Facchini & Steinhardt (2011). Following their methodology, I use bills that focus on legal and illegal immigration, which are linked to the inflow of foreign labor. I restrict the analysis to the final passage vote of bills to reduce the amount of strategic voting in the data and obtain a better reflection of the underlying interests of the legislator's constituency.[7] A full list of bills is presented in Table A.1 of the Appendix.

The bills are coded into primarily focusing on low-skill immigration or high-skill immigration legislation. High-skill immigration bills are clearly aimed at a specific subset of immigrants that have educational or occupational qualifications required to apply under specific visa schemes ("Temporary access for skilled workers and H1-B", "Fairness for high-skilled immigrants act", "STEM jobs act"). In contrast, low-skill immigration bills are usually broader and include provisions on multiple issues, for example illegal immigration enforcement, border protection, employer provisions on hiring, legal immigration quotas (in particular family based visas). I exclude bills coded as relating to high-skill immigration from the main analysis as, in contrast to low-skill immigration bills, they should be unaffected. Finally, bills are distinguished by their direction either aimed at liberalizing or restricting immigration. "Yay" ("Nay") are coded as 1 for a pro-immigration vote and "Nay" ("Yay") are coded as 0 for an anti-immigration vote if the bill would liberalize (restrict) immigration.

I combine this with individual level information from the Census Integrated Public Use Micro Samples [IPUMS-USA; Ruggles et al. 2019] that can be used to measure task composition and technological change in the US economy. Appendix D describes the varying geographic levels for which the data is available and provides more information on the conversion of data across geographical areas using population-area weights. I augment this information with NHGIS census data [Manson et al. 2019] that is more geographically detail, but only provides aggregated information. Using data on individual occupations, industry and wages, I am able to construct the manual employment share and manual-biased technological change variable as will be described in the following section.

Appendix Table A.4 presents the data sources for the remaining variables used in the main empirical analysis. Appendix Table A.5 presents summary statistics. The NAES (2004) opinion survey of the US electorate during the 2004 election is used to obtain individual level information on voters attitudes on immigration and trade policy for a separate analysis.

2.2 Measurement of tasks and technological change

The first step in constructing these variables is to classify occupations into different task groups using information on manual, routine and abstract task intensity in 1980 from Autor & Dorn (2013). Details on the tasks can be found in Appendix D. These reported task intensities are difficult to compare across groups. To circumvent this, I use the hourly

[7] Milner & Tingley (2011) study the difference in voting behavior on immigration across different types of votes. In general, the voting behavior for final passage votes is similar to the general voting behavior, however they also document that a certain part of the votes excluded from my analysis are clearly less relevant for evaluating the relationship between labor markets and voting behavior on immigration.

wage across occupations in 1980 to estimate the wage rate for each task type giving a weight to the different tasks.[8] These calculated wages are unlikely to provide a precise economic interpretation in terms of the value of a task for a specific occupation as highlighted by Autor & Handel (2013), however they should be sufficient for a relative ranking as needed in my case.[9] Next, I divide the estimated wage paid for a specific task by the total wage. This provides the ranking for how task intensive an occupation is relative to others. For manual tasks this wage share is denoted $MW_{O,80}$. The reason for doing these additional steps compared the ranking of Autor & Dorn (2013) in Equation 16, which performs well in classifying routine intensive occupations (their focus of interest), is that their unweighted formula does less well in ranking manual or abstract intensive occupations due to the way the task intensity is recorded (see details in the footnote).[10] Using the improved ranking occupations are ordered along their relative task intensities and defined as intensive in the respective task based on being in the top 33% at the national level in 1980 (from here on the steps are again analogous to Autor & Dorn 2013). Table A.2 provides information on the top-10 manual, routine and abstract intensive occupations by employment in 1980, which suggests a reasonable classification of occupations by task intensity.

Following this, I construct the manual employment share ($MSH_{d,t}$) across congressional district (d) and years (t) based on the share of occupations that were classified as manual task intensive:

$$MSH_{d,t} = \frac{\sum_{i=1}^{I} O_{d,t,i} * 1[MW_{O,80} > MW_{O,80}^{P66}]}{\sum_{i=1}^{I} O_{d,t,i}} \tag{1}$$

[8] The estimated weights are: $Wage_{i,o,80} = 2.04^{***}\ MTI_{i,o,80} + 1.14^{***}\ RTI_{i,o,80} + 2.04^{***}\ ATI_{i,o,80}$. Hourly wages are constructed from the available data for wage income, hours worked and weeks worked. I account for top-coded wages (varying by state and year) by excluding the highest 5% of incomes in each state in each year. In addition, I restrict the sample to individuals that reported to having worked close to full-time over the last year and account for outliers in reported hours (for last week) not being representative of weekly hours over the whole year.

[9] To obtain the actual value of tasks relevant for a specific occupation and not just an occupational ranking, one requires information on worker-level task inputs (Autor & Handel 2013, Eq. 10), which is not available in the census data.

[10] The issue likely arises as occupations differ in the reported overall number of tasks performed (from 2.32 to 18.99 total tasks reported). The log-function of Equation 16 $[RTI = ln(T^R_{1980} - ln(T^M_{1980}) - ln(T^A_{1980})]$ in Autor & Dorn (2013) penalizes the occupations with more tasks in total when classifying them as task intensive. Further, this is complicated by the occurrence of manual, routine and abstract tasks not directly being comparable and the values not corresponding to their relevance in an occupation as the mean number differs from 1.31 for manual to 2.89 for abstract and 4.62 for routine. Making the distinction between manual and routine intensity more pronounced than manual and abstract. For this reason, many occupations would be falsely classified as manual and abstract intensive at the same time, while others would be intensive in no task. Using task specific wages as a weight to give meaning to the number of tasks performed and using the share instead of a log-function rectifies these two issues when classifying manual and abstract intensive occupations. The classification of occupations I obtain in Table A.2 indeed seems to make intuitive sense for all three tasks with relatively few occupations coded as manual and abstract intensive at the same time.

where i denotes the individual and O the occupation. This provides the first variable of interest as it measures directly labor market competition between natives and immigrants based on the task content across congressional districts. The considerable variation in the manual employment share across the US is illustrated in Figure A.1 in the Appendix.

To investigate whether technological change has altered the voting behavior of representatives I need to measure technological change over a relatively long time-horizon and also capture it's complementarity/substitutability with manual tasks. An example of this is automation, which substituted routine tasks and for this reason was in relative terms complementary to manual tasks (see e.g. the theoretical setup in Autor & Dorn (2013) as long as goods and services are at least weakly complementary). I proxy for manual-biased technological change by exploiting changes in the manual wage premium. The manual wage premium is the wage of manual intensive occupations relative to other occupations. The wage of an occupation represents the demand for the bundle of tasks it is comprised of and in turn workers select to be employed in the occupation that has the highest reward to the tasks they can provide (Autor & Handel 2013). Accordingly, if technological change is complementary to manual tasks, this will raise the wage paid for manual intensive occupations relative to other occupation. In turn, this increase in wages will incentivize workers to relocate from less manual intensive to more manual intensive occupations.

A main issue is that supply shocks to the bundle of tasks provided locally, for example through the inflow of low-skill immigrants, can affect the local manual wage premium as well as political attitudes. For changes in the manual wage premium to be a measure of factor-biased technological change my measure needs to reflect changes in demand for manual tasks, but be unrelated to local supply shocks. For this, I exploit the fact that the possibility of implementing new technologies plausibly varies by industries at the national level rather than the local level. Based on this I construct a shift-share variable ($MBTC_{d,t}$) that measures manual-biased technological change through combining industry-level changes in the manual wage premium at the national level interacted with the pre-existing distribution of industries by 1950 across congressional districts:

$$MBTC_{d,t} = \sum_{j=1}^{J} EmpSH_{j,d,1950} \times \left(\frac{\bar{w}_{M,j,t}}{\bar{w}_{j,t}} \right) \tag{2}$$

$EmpSH_{j,d,1950}$ describes the employment share of industry $j \in j, ..., J$ in 1950 for a congressional district. This is interacted with the industry-level manual wage premium for native workers in decade t, which is constructed by dividing the median wage in manual occupations ($\bar{w}_{M,j,t}$) by the median industry wage ($\bar{w}_{j,t}$).[11]

[11] I consider the overall median wage in the industry rather than the median routine wage to avoid capturing compositional changes to routine employment. Otherwise for example a demand driven change

The baseline specification will not allow including the most detailed geography (congressional district) fixed effects due to changes in boundaries over time. For this reason, the shift-share variable might capture time-fixed differences in the manual wage premium across industries unrelated to technological change, but correlated with political attitudes. To deal with this I absorb the unobserved heterogeneity across industries in the manual premium at point t by subtracting the manual premium in 1950.

The discussion on the price of tasks in Autor & Handel (2013) points to two important things to consider when using wages as a proxy for task demand. A first consideration is whether the measure might reflect changes in the relationship between job tasks and human capital required for them. An example of this would be the introduction of compulsory tertiary education requirements exclusively for some manual intensive occupations at some point during the analysis, i.e. minimum 2-year degree requirement for nurses. First, in my setting this would go against finding any impact of $MBTC_{d,t}$ as at least in 1980 (when ranked) manual tasks were at the bottom end of the education distribution. Accordingly, a potential increase in the manual premium due to a relative increase in educational requirements should a priori lead to more favorable attitudes towards immigration (see Mayda 2006; Facchini & Steinhardt 2011). The opposite direction of the expected labor market competition effect. Second, and more importantly, this issue seems of little concern for the broad occupational task groups I use. In the data I find little evidence of changes in the pattern of education required for manual occupations relative to other occupations. Changes in education levels for task groups rather reflect the general trend of rising education levels in the US.[12] To even further rule out that this drives results, the individual level Census data allows me to directly account for changes in the educational composition of manual, routine and abstract occupations.

A second consideration is whether the bundle of tasks in an occupation changes over time. My measure assumes that occupations classified in 1980 as manual intensive remain so over time. The same assumption equally applies for the construction of the commonly used routine employment share. Importantly, there is no reason to suspect that the bundle of task of occupations classified as manual occupations changed more drastically than those of routine occupations.[13] The way $MBTC_{d,t}$ is constructed helps to further lessen these concerns. First, as the median wage of manual occupations is used, drastic changes in the task composition (and corresponding wages) of some manual occupations

in employment from high-paying routine to abstract occupations would lead to an increase in the manual-biased technological change variable $MBTC_{d,t}$ that is only driven by changes at the upper end of the skill distribution.

[12]The share of natives in manual occupations with a college degree rose from 2% in 1970 to 12% in 1990 and 18% in 2010. Similarly, the share in routine and abstract occupations rose from 6% in 1970 to 24% in 1990 and 36% in 2010.

[13]The opposite seems more likely when considering the top-3 occupations in TableA.2. For example, the tasks performed by Truck drivers, primary school teachers, and Janitors (manual) plausibly have changed less compared to secretaries, cashiers and bookkeepers (routine).

should have little impact. Second, using the overall median wage rather than the median routine wage in the denominator should reduce the impact of the more plausible changes in the task composition of routine occupations. It also avoids the issue that some industry-decade cells have only a very small share of routine employment.

Having addressed potential concerns, my outlined manual-biased technological change measure has a number of important advantages —in my settings— over using the adoption of a specific technology. First, it captures both the substitutability and complementarity of tasks and technology, while studies focusing on particular technologies are likely to only pick up the displacement effects (substitutability) of technology adoption. Second, data on specific technologies is generally not available for the full time period of interest, which is necessary to have an adequate number of votes on immigration bills across congressional districts. Third, data on technology adoption is in general only available at very aggregate industry levels (and mainly for manufacturing). This not only restricts the focus on an increasingly narrow sector of US employment, but even more concerning is that a small number of industries categories has recently been highlighted as a major issue when using shift-share variables (see e.g. Borusyak et al. 2022). In contrast, my measure appears to exploit a large number of plausibly quasi-random shocks as documented in Figure C.1. Table C.1 further presents that there is little correlation between the $MBTC_{d,t}$ variable and initial 1950 congressional district characteristics.

Another advantage of the focus on intra-industry changes in relative wages between occupations is that these are unaffected by non-heterogeneous industry-level shocks that affect all occupations within an industry in a similar way. These can be changes in domestic demand or foreign competition that lead to broad booms or declines in an industry. One particular relevant example here is the China trade shock, where Autor et al. (2013*a*) finds a similar negative wage impact across different skill groups (even as there are differential employment effects), which accordingly should not confound my measure of manual-biased technological change.

Table A.3 in the Appendix provides a descriptive idea of what industry drive the variation in manual-biased technological change showing the 5 industries with the highest employment share in 1950 as well as depicting the 5 industries with the highest and lowest increase in the manual wage premium between 1950 and 2010. It appears that industries in the retail, personal services and accounting sectors have seen the highest relative rise in the manual wages premium, while industries in the manufacturing, business and professional services sectors have experienced the strongest decline in the manual wage premium.[14]

[14]Interestingly, Autor & Dorn (2013) make the puzzling observation that there is no wage decline for routine-intensive retail and clerical occupations overall, however when looking at wage changes inside the related industries a strong rise in the manual wage premium is observable in line with the high routine task content in these sectors. This appears to suggest that the relatively stable wages for retail and clerical occupations might be explained by industry specific factors (e.g. little exposure to foreign competition) and that wage growth would have been even higher without automation in these occupations.

The increase in the manual wage premium for the respective industries appears to be in line with the high share of routine-intensive clerical and retail occupations. While the strong decline of the manual wage premium in manufacturing industries seems to be in line with studies suggesting that manual task replacing technological change still dominates there (see e.g. Beaudry & Green 2005; Beaudry et al. 2010; Lewis 2011). This suggests that the manual wage premium provides a suitable proxy for manual-biased technological change across congressional districts.

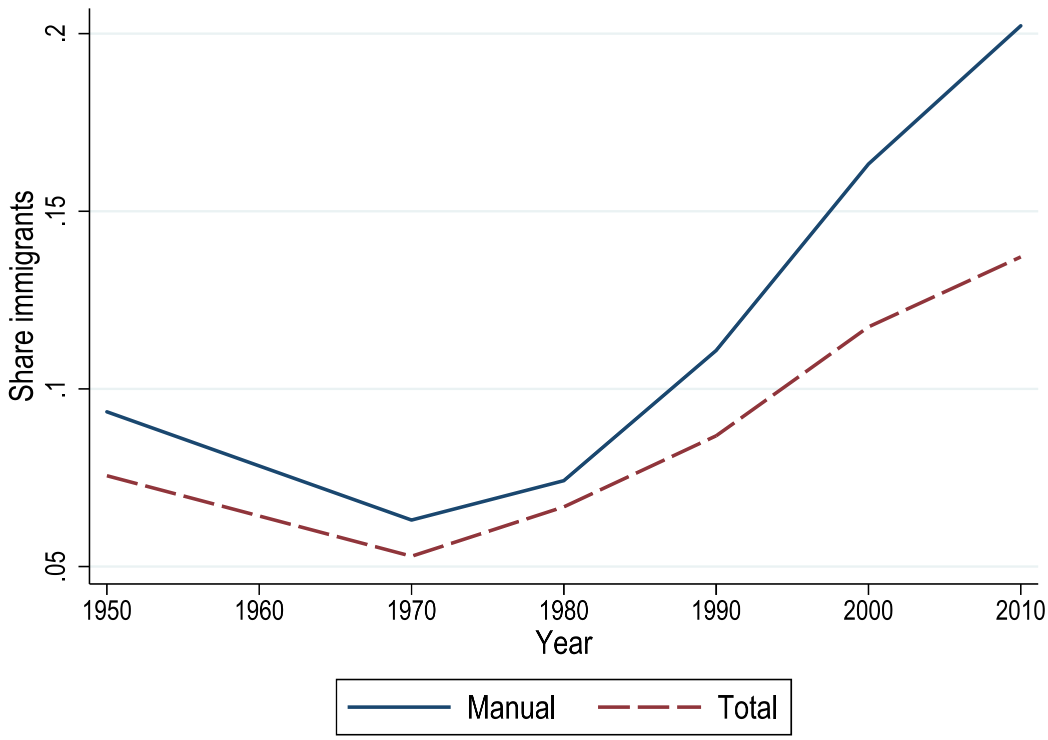
3 Stylized evidence

This section discusses in more detail how recent technological change, for example in the form of automation, plausibly increased labor market competition between natives and immigrants in the US. In turn, this altered representatives voting decision on low-skill immigration policy. For this, three pieces of descriptive evidence are provided. First, the section shows that immigrants over-proportionally are employed in manual occupations and that there is a negative impact of immigration on wages of natives in these occupations. Second, the section highlights that occupational tasks and the resulting labor market competition play a key role in views on immigration of individuals and that the employment composition of congressional districts shapes representatives voting on low-skill immigration policy. Third, it discusses how technological change in the US has shifted from being skill-biased till the 1990s (substituting manual employment) towards employment polarization due to automation (complementary to manual employment) and the implications for immigration policy. Section B presents a theoretical framework based on these stylized facts.

3.1 Impact of immigration on manual workers

A first key point is that the extremes of the skill distribution in the US consistently record a higher share of immigrants than the middle of the skill distribution (Card 2009). This means a concentration of immigrants in manual and abstract employment due to disadvantages of immigrants in routine employment, like clerical and retail occupations, that require better communication skills which are difficult to transfer across language barriers (Lewis & Peri 2015). Figure 2 shows the persistent over-representation of foreign-born individuals in manual occupations. The figure also highlights the considerable rise in immigration to the US since the 1980s with manual employment over-proportionally impacted by this (also highlighted in Mandelman & Zlate Forthcoming). Consequently, while natives in manual employment appear to be in strong competition with low-skill immigrants, natives in routine and abstract employment are experiencing little competition from low-skill immigrants. This is also reflected by evidence that to a certain extent

Figure 2: Share of immigrants in manual employment 1950-2010



Notes: The figure illustrates the share of immigrants (defined as foreign-born) in manual employment and total US population from 1950 to 2010.

natives change occupations to ones more intensive in communication-language tasks to avoid the labor market pressure from immigration (Peri & Sparber 2009).

Despite this, the actual impact of immigration on local wages has been a vividly debated issue. Most of the literature is reviewed in Dustmann et al. (2016) with the impact of immigration on overall wages having been difficult to clearly pin down. The reason for the positive wage impact of immigration is that there is imperfect-substitution between natives and immigrants and some studies have found that for this reason most of the negative wage impact is on other immigrants (Manacorda et al. 2012; Ottaviano & Peri 2012). However, the most recent empirical evidence seems to suggest that immigration did depress wages of natives at the lower end of the skill distribution as well, in particular in non-traded sectors with limited labor protection (see e.g. Dustmann et al. 2013; Mandelman & Zlate Forthcoming; Allen et al. 2018; Burstein et al. 2020; Bächli & Tsankova 2021).

Table 1 provides direct support that low-skill immigration decreased the wages of natives in manual occupations across congressional districts in the period 1970-2010. Column 1 shows that overall immigration is not associated with lower wages in manual employment for natives. However, when distinguishing immigration into high-skilled and low-skilled immigration in column 2 and 3 there is a clear negative correlation between low-skill im-

Table 1: Relationship immigration and natives' wages

Dependent variable: Natives' manual wage, median wage and manual premium

	Manual (1)	Manual (2)	Manual (3)	Manual (4)	Median (5)	Premium (5)
Immigrant share	0.026					
	(0.387)					
Immigrant share no-college		-1.683***				
		(0.547)				
Immigrant share college		6.767***				
		(1.591)				
Immigrant share manual			-5.690***	-11.02***	3.381	-0.771***
			(1.688)	(3.220)	(3.121)	(0.123)
Immigrant share other			3.950***			
			(1.144)			
Manual share (native)	-14.52***	-13.52***	-13.29***	-14.86***	-20.13***	0.256***
	(0.492)	(0.557)	(0.596)	(0.494)	(0.425)	(0.0188)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (1st stage)				25.1	25.1	25.1
Observations	2157	2157	2157	2157	2157	2157
R^2	0.667	0.768	0.767	0.746	0.821	0.529

Notes: The table displays the relationship between (manual) immigration and wages across congressional districts. The dependent variable is the manual wage in columns 1-3, median wage in column 4, and manual premium (manual to median wage) in column 5. In columns 3-5 the share of manual immigrants in a congressional district is instrumented by state bordering Mexico times decade fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

migration and natives' manual wages. Both, when low-skill immigration is defined based on education in column 2 and occupation in column 3. Of course, location choices of immigrants are endogenous and immigrants are more likely to settle in areas with higher wages. To account for this I use whether a US state borders Mexico interacted with time fixed effects as an instrumental variable strategy. This exploits that a large share of low-skilled immigration to the US enters over the land route through Mexico and are more likely to settle closer to the entry point. The negative effect of low-skill immigration on manual wages increases in magnitude in column 4. This is in line with the concern in the OLS specification that immigrants select into areas where they can earn higher wages. Columns 5 and 6 highlight that labor market competition between low-skill immigrants and natives occurs predominantly in manual occupations as there is no corresponding negative effect on the median wage and the local manual wage premium declines across congressional districts, in line with what one would expect from a labor supply shock to an employment task.

3.2 Labor market competition and preferences on immigration

The second key point is if this labor market competition between natives and low-skill immigrants in manual employment affects policy preferences. First, a difference should be observable between attitudes on immigration policy between natives in manual occupations and those in routine and abstract ones. Table 2 highlights the relationship between manual, routine and abstract employment and individual attitudes on immigration policy using opinion survey data from NAES (2004) during the 2004 election cycle. Column 1 shows that individuals in manual employment are more likely to report that immigration/illegal aliens is one of the most important problems facing the US. This holds when controlling for state and interview date fixed effects as well as restricting the sample to US born individuals in employment in column 2. Column 3 shows that, in contrast, routine and abstract employees are nearly identically less concerned with immigration compared to manual employees. This is inline with neither of these two occupational groups facing labor market competition from low-skill immigrants. Columns 4-6 show that manual employment is also associated with less support for the government liberalizing or keeping immigration policy the same, while associated with increased support for restricting it.

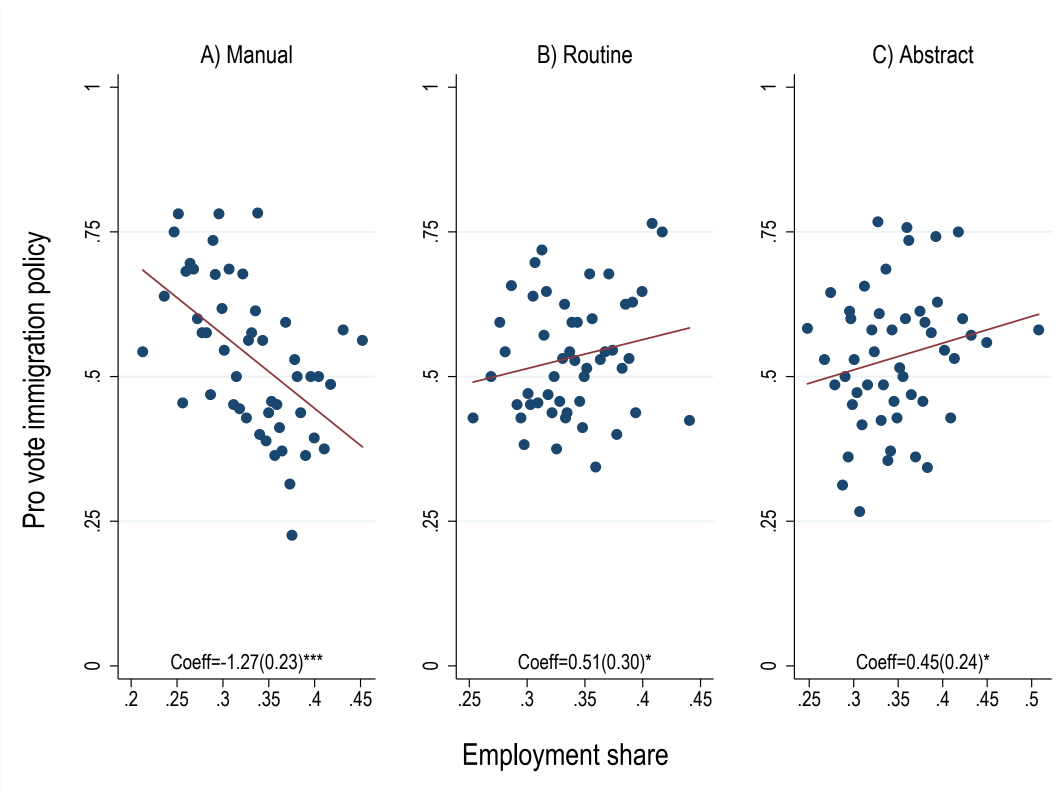
Table 2: Employment tasks and voters attitudes on immigration policy

Dependent variable: Individual-level attitudes on immigration during 2004 election						
	Most important problem immigration/illegal aliens			Government immigration policy		
				Liberalize	Same	Restrict
	(1)	(2)	(3)	(4)	(5)	(6)
Manual employment	0.007***	0.007***		-0.023***	-0.061***	0.085***
	(0.001)	(0.001)		(0.006)	(0.009)	(0.010)
Routine employment			-0.006***			
			(0.001)			
Abstract employment			-0.007***			
			(0.001)			
State FE	No	Yes	Yes	Yes	Yes	Yes
Interview FE	No	Yes	Yes	Yes	Yes	Yes
US born	No	Yes	Yes	Yes	Yes	Yes
Employed	No	Yes	Yes	Yes	Yes	Yes
Observations	79217	35000	35000	12160	12160	12160
Pseudo R^2	0.006	0.062	0.061	0.042	0.030	0.033

Notes: The table presents the individual-level relationship between voters' manual, routine, and abstract employment and their attitudes on immigration policy. The table reports marginal effects at means of Probit regressions (similar results using OLS). Columns 1-3 report whether individuals reported "immigration/illegal aliens" as one of the most important problems facing the country. Column 4-6 report attitudes whether the federal government should liberalize, keep the same or restrict immigration. NAES (2004) occupational classifications used for constructing manual (trades-person, service worker, laborer, and semi-skilled worker), routine (clerical or office worker, and salesperson) and abstract (professional, manager, and business owner) employment. Individuals in manual, routine and abstract employment sum to all individuals included in columns 2-5. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second, representatives from districts with a higher share of manual employment should be observed to vote against liberalizing low-skill immigration, while representatives from districts with a higher share of routine and abstract employment should vote in favor of liberalizing low-skill immigration. This follows directly from individual attitudes as representatives use votes on bills to signal their policy positions to their constituents (Mayhew 1974). Figure 3 shows that a higher manual employment share in 1980 is negatively correlated with support for liberalizing low-skill immigration in the bills voted on between 1983 and 1992, while the opposite is the case for representatives from districts with a high routine or abstract employment share. Figure A.1 provides corresponding maps visualizing the variation across the continental US. This extends on previous work by Mayda (2006) and Facchini & Steinhardt (2011) and highlights that occupational tasks play a key role in attitudes on immigration and not just educational differences.

Figure 3: Employment tasks and voting on immigration policy



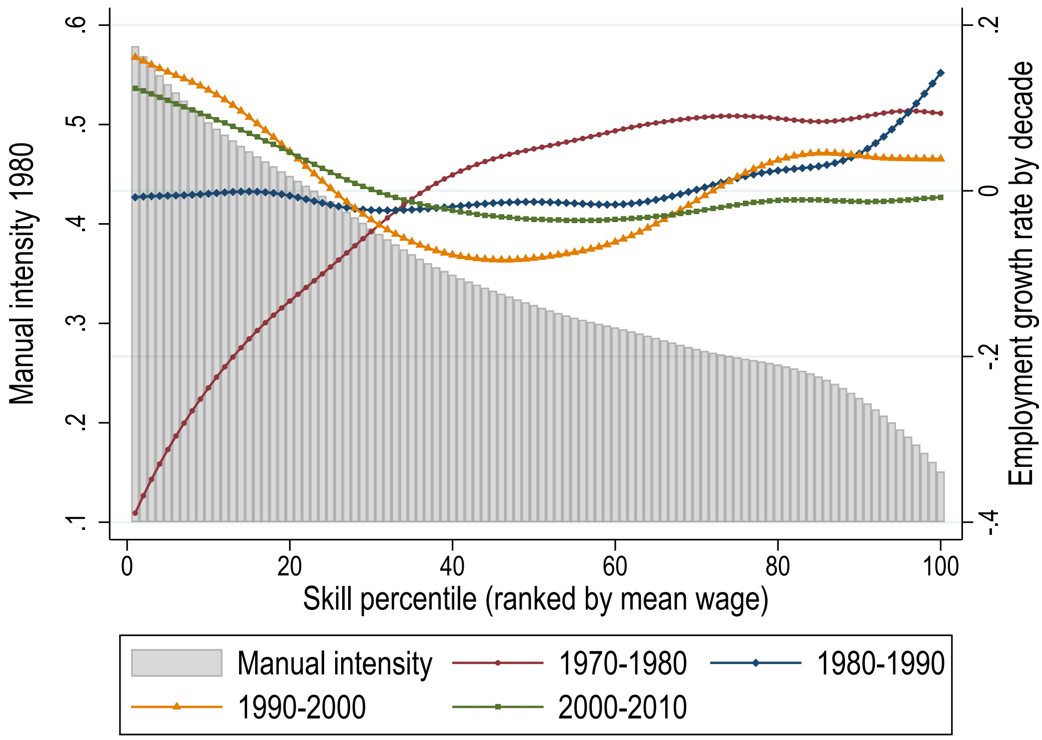
Notes: Employment share of natives across tasks in 1980 and voting on liberalizing low-skill immigration between 1983 and 1992 across corresponding congressional districts. Classification based on occupations being in the top 33% of task intensity at the national level. Figure A.1 provides corresponding maps to Panel A. Robust standard errors. N=1673 in 50 bins.

3.3 Automation and the expansion of manual employment

The third key point is that technological change impacts the demand for tasks and can alter through this the political support for low-skill immigration. In particular automation

(Autor et al. 2003; Acemoglu & Autor 2011; Autor & Dorn 2013; Goos et al. 2014) led to considerable labor market polarization in which employment declined in routine occupations, but expanded in manual ones.[15] Figure 4 illustrates the recent change in US employment growth along the skill distribution. The figure highlights that until 1990 employment growth mostly occurred at the upper end of the skill distribution, while since 1990 employment growth increased at the bottom end. The later being due to automation and the increased demand for low-skill service occupations (Autor & Dorn 2013). The figure also highlights that this employment growth since 1990 was in occupations that are mostly manual intensive.

Figure 4: Manual intensity and employment growth by skill percentile

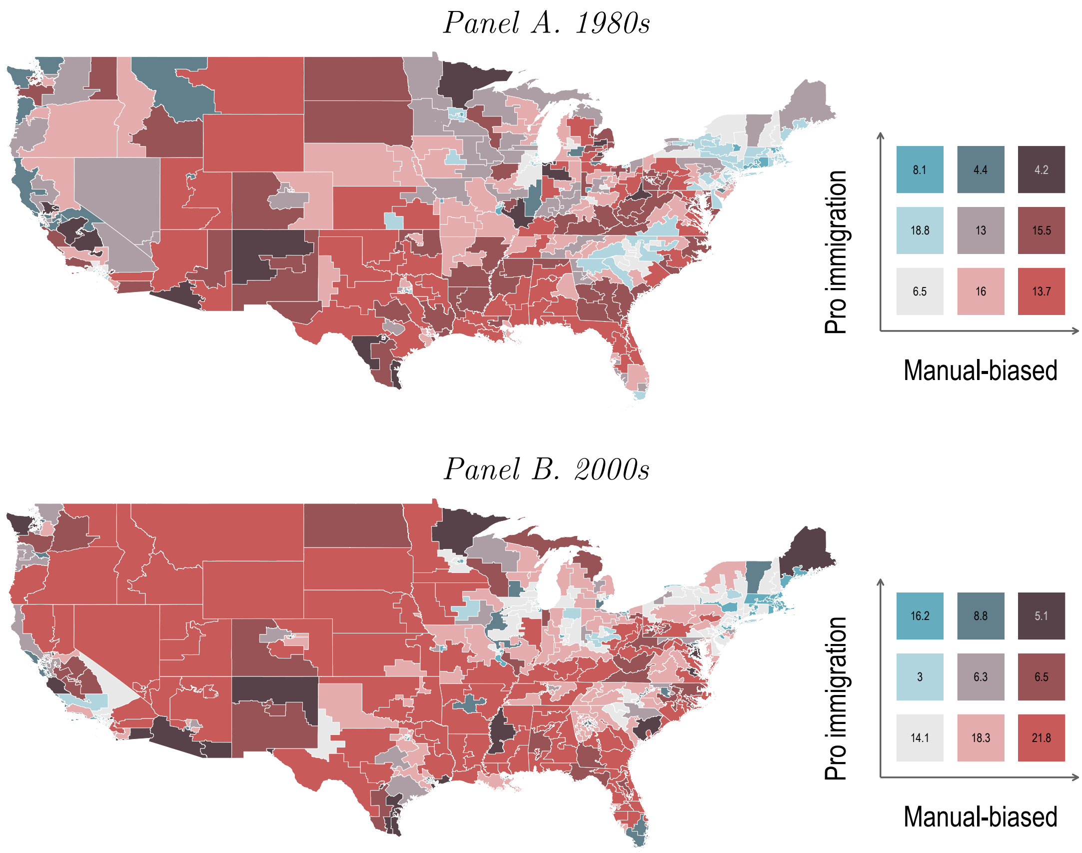


Notes: The figure displays the smoothed US employment growth rates by decade for 1970-2010 and manual intensity of occupations in 1980 ranked by skill percentile. The dotted lines corresponding to the right y-axis depict employment growth by decade. The gray bars corresponding to the left y-axis depicts share of manual intensity by skill percentile. The skill percentile of occupations is constructed based on the mean hourly wage in 1980.

[15] Mandelman & Zlate (Forthcoming) also find automation to negatively affect routine occupations, but argue that a considerable part of the employment growth at the bottom-end of the skill distribution reflects low-skill immigrants, while natives upgraded their skills. To account for this I focus exclusively on changes within the US born population in the empirical analysis. Figure A.2 shows that the rise in manual employment was indeed less pronounced than highlighted in Autor & Dorn (2013) or Figure 4. There is, however, still an increase in manual employment observable for native born workers in the period 2000-10, even if no longer for 1990-2000. The relatively stable manual share also masks a reallocation of native workers from manual-routine operator jobs mainly in manufacturing towards exclusively manual low-skill services since 1990.

This changing pattern of technological change implies that until 1990 the share of natives in competition with low-skill immigrants was decreasing, while afterwards the share of natives facing labor market competition from immigrants started to rise. This in turn can be expected to affect representatives votes on immigration policy. This corresponds well to the overall developments in the making of US immigration policy presented in Table A.1. All bills enacted up to 1984 exclusively restricted low-skill immigration. However, as competition with immigrants had declined in the period 1970-90, this coincided with a period of bills enacted that were favorable to low-skill immigration. Following this favorable window towards immigration and as automation gathered pace and labor market competition between natives and immigrants plausibly started to increase again all enacted bills after 1995 restricted low-skill immigration.

Figure 5: Manual-biased technological change and immigration policy



Notes: The figure depicts bi-variate maps between manual-biased technological change and voting on immigration policy across US congressional districts for the 1980s in Panel A and for the 2000s in Panel B. The high resolution maps allows zooming into specific areas. The bi-variate map depicts (i) **red**: high manual-biased technological change and anti-immigration stance, (ii) **blue**: low manual-biased technological change and pro-immigration stance, (iii) **white**: low manual-biased technological change and anti-immigration stance, and (iv) **black**: high manual-biased technological change and pro-immigration stance. The bivariate maps are constructed using the code by Naqvi (2022).

Figure 5 illustrates manual-biased technological change and voting on low-skill immigration bills across US congressional districts in the 1980s (Panel A) and the 2000s

(Panel B). The color-scheme in the bi-variate maps depict (i) high manual-biased technological change and anti-immigration stance in red, (ii) low manual-biased technological change and pro-immigration stance in blue, (iii) low manual-biased technological change and anti-immigration stance in white, and (iv) high manual-biased technological change and pro-immigration stance in black.

Panel A depicts that most congressional districts are relatively centrist on immigration policy with most reporting both votes in favor and against liberalizing low-skill immigration policy.[16] By 1980 there appears to be if at all only a relatively weak relationship between manual-biased technological change and immigration policy. The change between Panel A and B depicts a clear increase in the number of congressional districts exposed to manual-biased technological change from 1980 to 2000 where representatives voted in favor of restricting low-skill immigration. This is observable by the second map being considerably more bright red (the bottom right of the legend). The share of congressional districts falling into this category rose from 12% in 1980 to 18.5% in 2000 (see values in map legend). Less visible on the map —as it occur mostly in densely populated areas— is that there is also a considerable number of congressional districts experiencing negative manual-biased technological change by the 2000s, where the number of representatives favorable to low-skill immigration increased. These are represented in bright blue (the upper left of the legend). Here, technological change had a stronger complementarity with routine/abstract than manual tasks, or the latter were directly substituted. The share of these congressional districts rises from 4.6% in 1980 to 13.4% in 2000. This polarization occur mostly due to a decline in the number of congressional districts that are little exposed to manual-biased technological change and representatives which are ambivalent on immigration policy (gray in the middle of the legend). The share of these congressional districts declines from 14.8% in 1980 to 4.4% in 2000. The geographically polarized pattern of manual-biased technological change plausibly reflects distinct geographic effects of the automation of routine tasks. In certain areas it led to employment growth at the bottom end of the skill distribution (manual occupations), while in others it occurred at the top (abstract occupations). The maps highlight that manual-biased technological change had a considerable impact across congressional districts and played a key role in shaping the voting behavior of representatives on low-skill immigration policy. The remainder of the paper will provide more formal empirical evidence that indeed in areas which experienced manual-biased technological change representatives voted to restrict low-skill immigration.

[16] Any purely cross-sectional interpretation of the manual-biased technological change variable should be subject to considerable caution. But it appears worth pointing out that consistent with skill-biased technological change till the 1980s (see Figure 4) areas that experienced negative/low manual-biased technological change in Panel A are areas that report a high routine employment share by 1990 (see Autor et al. (2013*b*) Figure 1).

4 Main Empirical Analysis

This section presents the main empirical analysis. Section 4.1 provides more systematic evidence on the effect of occupational tasks on the voting behavior of representatives on immigration policy. Section 4.2 shows the key result that manual-biased technological change led to a more restrictive US immigration policy.

4.1 Tasks and voting on immigration

I start the empirical analysis by more rigorously evaluating whether differences in the manual employment share influence representatives voting behavior on low-skill immigration policy. This expands on the preliminary evidence presented in Figure 3. For this I estimate the following Probit equations:[17]

$$prob(Vote_{d,t} = 1|Z_{d,t}) = \Phi(\alpha MSH_{d,t} + X'_{d,t}\beta + \gamma_s + \gamma_t)$$

where $Vote_{d,t} = 1$ is a dichotomous variable taking a value of one if the representative of district d votes for a bill liberalizing unskilled immigration at time t, $\Phi(.)$ represents the cumulative distribution function of a standard normal, $MSH_{d,t}$ is the manual employment share. $X'_{d,t}$ is a vector of controls including congressional district and representative characteristics. Finally, γ_s and γ_t denote state and vote fixed effects, respectively.[18] To simplify interpretation the estimation tables report marginal effects (at means) which represent the change in probability of a representative voting in favor of liberalizing low-skill immigration due to a change in the independent variable. Table 3 Panel A presents the Probit estimates for the effect of the manual employment share of a representative's congressional district on the representatives voting on immigration policy.

Column 1 in Table 3 shows that the effect of the manual employment share has the expected negative sign, however the effect is insignificant. A first issue might be that the estimation captures the welfare state channel —wealthier constituencies are opposed towards immigration due to carrying the fiscal burden— as well as labor market competition (Hanson et al. 2007; Dustmann & Preston 2007; Facchini & Mayda 2009). Column 2 controls for average income and poverty share. Accounting for the welfare state channel, I find that the estimated effect of the manual employment share increases considerably in magnitude and is now clearly significant. A second issue is that previous rounds of migration affect the manual employment share as well as representatives' support for liberalizing immigration policy (Gimpel & Edwards 1999; Fetzer 2006). Column 4 controls for the share of immigrants (foreign-born), Hispanics and African-Americans. A third

[17]Results are robust to using OLS as the estimator.

[18]The state level is the smallest geographical unit that remains consistent in its borders across the whole time period as the borders of congressional districts are redrawn up to every 10 years.

Table 3: Effect manual task share on immigration policy

Dependent variable: Vote low-skill immigration policy (1=Pro; 0=Against)

	(1)	(2)	(3)	(4)	(5)
Panel A. Probit					
Manual Share	-0.223	-3.435***	-1.103**	-1.381***	-1.457***
	(0.166)	(0.433)	(0.450)	(0.453)	(0.444)
Poverty		3.465***	0.835*	0.741*	0.787*
		(0.498)	(0.458)	(0.435)	(0.435)
log(Family Income)		-0.316*	-0.311**	-0.193	-0.145
		(0.174)	(0.150)	(0.139)	(0.143)
Immigration			1.827***	1.839***	1.767***
			(0.310)	(0.313)	(0.317)
Hispanic			0.408**	0.222	0.298
			(0.187)	(0.187)	(0.197)
African-American			1.284***	1.101***	1.133***
			(0.131)	(0.138)	(0.142)
Unemployment Rate				3.164***	3.237***
				(0.788)	(0.782)
Age 65+					0.696*
					(0.400)
State fixed effects	Yes	Yes	Yes	Yes	Yes
Vote fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	5755	5755	5755	5755	5755
Pseudo R^2	0.167	0.258	0.437	0.439	0.439
Panel B. IV-Probit					
Manual share	-2.697***	-3.883***	-2.199**	-3.313***	-3.368***
	(0.368)	(0.385)	(0.859)	(0.965)	(1.000)
	[0.537]	[0.427]	[0.841]	[0.939]	[0.971]
F-stat (1st stage)	296.6	135.1	115.1	125.0	123.6
Observations	5719	5719	5719	5719	5719

Notes: The table presents the effect of the manual employment share on voting on low-skill immigration policy. Vote in favor of more immigration coded as 1 and 0 otherwise. Probit results presented in Panel A and IV-Probit results in Panel B. The table reports marginal effects at means. Robust standard errors clustered on state-vote in parentheses. Clustered on representatives in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

issue is that tighter labor markets might influence support for liberalizing immigration policy. Column 5 controls for the unemployment rate.[19] A fourth issue is that demographic characteristics might affect demand for manual employment in the form of care services and also shapes attitudes towards immigration (Espenshade & Hempstead 1996; Chandler & Tsai 2001; Haubert & Fussell 2006). Column 6 controls for the share of the population over 65 years. The estimated effect is notably very similar to the correlation presented in Figure 3 without any controls. A sizable negative and significant relation-

[19]The positive relationship between the unemployment rate and support for liberalizing immigration policy might appear counter-intuitive. However, this has been frequently observed in the empirical literature (Gimpel & Edwards 1999; Facchini & Steinhardt 2011). The positive effect appears driven by the 1970s and 80s, while in later periods the effect turns negative.

ship is observable in columns 2-5 between the size of the manual employment share and representatives support for liberalizing immigration policy.

The estimates so far explore the relationship between the manual employment share in a congressional district at the beginning of a decade and subsequent voting on low-skill immigration policy. However, this raises the question of what variation in the manual employment share is exploited here. This could be persistent differences in the industrial structure, technological change or other economic shocks not related to technology. The empirical analysis has so far been agnostic on this, focusing on what the variation is not (e.g. income, immigration, demographics). The latter potentially leading to biased results.[20] Another issue is that individuals might respond to (anticipated) immigration pressures by selective out-migration or occupational changes potentially leading to measurement error.

Analogous to Autor & Dorn (2013) I address potential biases by exploiting historical differences in industry specialization to isolate the long-run, quasi-fixed component of the manual share. The historical component of the manual share is constructed by interacting 1950 industry shares of congressional districts with the nationwide manual employment share for industries in 1950 (see Autor & Dorn 2013, equation 22). This measure is a logical instrumental variable for measuring the manual employment share as it is determined two decades prior to 1970. I expect it to be correlated with the long-run difference in labor market competition between natives and low-skill immigrants due to specialization in specific tasks but uncorrelated with contemporaneous confounding factors. This variable interacted with decade dummies is than used in the first-stage to estimate the manual employment share.

Table 3 Panel B presents the corresponding IV-Probit results. The IV-estimates for the effect of the manual employment share on the voting behavior of representatives increase in magnitude compared to the OLS-estimates and are now similar in size across all specifications. The IV-Probit marginal effect in column 6 of Table 3 is -3.37, which suggests that a one percentage point increase in the manual employment share, from the average of 31% to 32%, makes it 3.37 percent more likely that a representative of a congressional district votes in favor of restricting low-skilled immigration. This more formally underlines the crucial role of the occupational task composition of constituencies in the way representatives vote on US immigration policy. From this it follows clearly that any technological change that alters the task composition in constituencies will also

[20] For example, unobserved local shocks could be cyclical variation in demand for local products leading to temporary changes in the task composition as described in Autor & Dorn (2013), p.1581. Notably, if this changes financial anxiety this can have a direct effect on individual attitudes towards immigration (Goldstein & Peters 2014). This can lead to downward (upward) biased OLS estimates depending on whether the demand shock is mainly for manual (routine/abstract) tasks. Notably, this might be an alternative reason for the importance of poverty share and log family income as controls in the OLS specification that captures this issue to some extent.

impact voting on immigration policy. Results are similar when using 1950 controls and time-trends or fixed effects in Table A.6.

4.2 The effect of technological change

So far, estimates focused on the relationship between relatively fixed differences in labor market competition of natives and low-skill immigrants across congressional districts and its effect on the voting behavior on immigration policy of representatives. I now turn to the main question: The role of recent technological in changing the voting behavior of representatives.

The main empirical analysis focuses on whether manual-biased technological change made representatives more likely to vote in favor of restricting immigration policy. To analyze this, I estimate Probit specifications of the following form:

$$prob(Vote_{d,t} = 1|Z_{d,t}) = \Phi(\gamma MBTC_{d,t} + X'_{d,t}\beta + \gamma_s + \gamma_t)$$

where γ measures the effect of manual-biased technological change variable $MBTC_{d,t}$ on the voting outcome $Vote_{d,t}$ of a representative. As described in Section 2, $MBTC_{d,t}$ proxies for manual-biased technological change by capturing the demand driven variation in the manual wage premium across congressional districts d and decades t.

Table 4 Panel A presents the corresponding Probit estimates. In line with expectations the coefficient for MBTC is negative. This implies that representatives for congressional districts where technological change was complementary to manual tasks became more averse to low-skill immigration. The estimated coefficient is similar in size and significance across column 1-6, when including controls for the welfare channel, immigration, labor market conditions and demographic factors. The baseline specification in column 5 suggests that a one percentage point increase in manual-biased technological change makes it 4.2 percent less likely that a representative votes for liberalizing low-skill immigration.[21] Accordingly, moving a congressional district to experience a standard deviation higher manual-biased technological change (2.1 percentage points) leads the corresponding representative to be 8.8% less likely to be in favor of liberalizing low-skill immigration policy. Results are similar when using 1950 controls interacted with time-trends or time fixed effects in Table A.6.

I take the figures for wage growth from Autor & Dorn (2013) Figure 1 to calculate a counterfactual without automation on how representatives might have voted on low-skill

[21] Further analysis highlights that the effect of MBTC is largest in contested districts as suggested by the marginal Probit coefficient as well as when interacting MBTC with the manual employment share. Whether changes in MBTC are due to increases in the manual wage or reductions in the wage for other tasks seems to both increase support for restricting low-skill immigration policy. However, the effect might be (insignificantly) stronger for declines in other wages suggesting there might be some room for the role of status concerns.

immigration policy. The 1st quartile compared to the median suggests that automation is associated with a potential growth of the manual premium as large as 4.4% from 1980 to 2005. Taking the coefficient of -4.2 in the baseline specification this would suggest that representatives became -18.5% less likely to vote in favor of liberalizing low-skill immigration policy (95% confidence interval: -6.3% to -30.4%). The 2005 vote on HR 4437 "Border Protection, Anti-terrorism, Illegal Immigration" aimed at restricting low-skill immigration passed by 240 Yay to 182 Nay votes. Without automation 44 of 240 representatives would plausibly have voted Nay instead of Yay. Accordingly, the bill would not have passed the house with 196 Yay and 226 Nay votes. Of course, this exercise relies heavily on partial equilibrium assumptions, for example, that the final passage bill would have the same content and that the observed wage polarization is exclusively due to automation. This means the numbers should likely be taken as an upper-bound. It does however highlight that automation likely had a relevant impact on immigration policy making in the US.

Table 4: Effect of technological change on immigration policy

Dependent variable:	Vote on low-skill immigration policy (1=Pro; 0=Against)				
	(1)	(2)	(3)	(4)	(5)
A. Effect manual-biased technological change					
MBTC	-5.282***	-4.936***	-3.353**	-4.179***	-4.184***
	(1.155)	(1.307)	(1.335)	(1.392)	(1.388)
Controls	See notes				
Observations	5719	5719	5719	5719	5719
Pseudo R-sq	0.169	0.236	0.326	0.329	0.329
B. Change in representatives voting behavior					
MBTC	-4.889***	-5.191***	-4.995***	-4.996***	-5.122***
	(1.678)	(1.655)	(1.670)	(1.683)	(1.680)
Representative FE	Yes	Yes	Yes	Yes	Yes
Observations	5458	5458	5458	5458	5458

Notes: Panel A presents the effect of manual-biased technological change (MBTC) on voting on low-skill immigration policy. Votes in favor of more immigration coded as 1 and 0 otherwise. The table reports marginal effects at means from Probit regressions in Panel A. Controls in each column equivalent to Table 3. Column 1 includes state FE and vote FE. Column 2 adds poverty share and log family income. Column 3 adds immigration share, Hispanic share, and African-American share. Column 4 adds unemployment rate. Column 5 adds share age 65+. Panel B includes additionally representative fixed effects estimated using OLS. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B presents corresponding results when accounting for representative fixed effects using OLS due to the large number of fixed effects. This does two things. First, the specification shows whether individual representatives changed their support for immigration policy due to technological change while they remained in office. Alternatively, the effect might have been solely due to electoral turnover with representatives being in favor of liberalizing immigration policy being replaced by those more averse to it. Second, this reflects a more demanding panel-specification circumventing to a considerable extent the issue that redistricting makes it impossible to account for congressional district fixed effects. Panel B columns 1-5 document that individual representatives change their support for low-skill immigration with the magnitude of the coefficients being similar to Panel A.

5 Robustness analysis

This section highlights the robustness of the main finding. First, Section 5.1 presents a falsification exercise showing that manual-biased technological change occurring after votes is unrelated to representatives voting behavior beforehand. Second, Section 5.2 addresses constraints related to the available data. Third, Section 5.3 provides more insights into the measurement of technological change. Appendix C completes the robustness analysis discussing i) recent concerns with shift-share variables in Section C.1, ii) other economic factors in Section C.2, iii) the impact of trade competition from China and NAFTA in Section C.3 and iv) immigration composition in Section C.4.

5.1 Falsification exercise

A concern might be that unobserved trends cause manual-biased technological change and increased anti-immigration sentiment. To verify that my results capture the period-specific effect of exposure to manual-biased technological change, and not some long-run common causal factor behind both the representatives support for restricting immigration and increased manual-biased technological change, I conduct a falsification exercise by regressing past voting outcomes on future MBTC.

For this, I construct measures of MBTC for congressional districts that will occur over the next 10, 20 and 30 years. Table 5 shows the correlation between voting outcomes and the change in future MBTC. Column 1 looks at future MBTC over the next 10 years, column 2 at the next 20 years, and column 3 at the next 30 years. The presented correlations provide little evidence that would suggest reverse causality. All columns depict a close to zero and insignificant relationship between voting in favor of liberalizing low-skill immigration policy and future MBTC. This exercise demonstrates that representatives of congressional districts that will experience more MBTC in the future were not already turning against low-skill immigration beforehand. This supports that MBTC indeed captures plausibly exogenous industry level shocks.

5.2 Data concerns

Data constraints lead to two further concerns with the empirical evidence that require addressing. First, the redistricting of congressional districts makes it difficult to account

Table 5: Falsification exercise

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)
MBTC (t+10)	-0.069		
	(2.959)		
MBTC (t+20)		-1.455	
		(1.865)	
MBTC (t+30)			-0.830
			(1.804)
Controls	Yes	Yes	Yes
Observations	2798	2384	474

Notes: The table presents a falsification exercise, where the manual-biased technological change that occurs over the next 10, 20 or 30 years in the future is regressed on votes that occurred beforehand. For example, the future manual-biased technological change that occurred during the 2000s (t+1) is regressed on votes on low-skill immigration policy during the 1990s (t). The sample declines in size as no data is available on manual-biased technological change after 2010. Controls are state FE, vote FE, poverty share, log family income, immigration share, Hispanic share, African-American share, unemployment rate, share age 65+. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

for some unobserved factors even as accounting for specific representatives should have already lessened these concerns. Second, as my baseline measure of technological change requires that several decisions are taken in the construction with the reasons for them discussed in Section 2, it appears sensible to evaluate whether results are robust to alternative choices in the variable construction.

The main evaluation of these issues is done in Table 6, which employs an alternative empirical setup akin to the one recently used in Autor et al. (2020). The key difference is that the analysis is conducted based on county-congressional-district cells instead of using the complete congressional district. This allows to include county fixed effects. Column 1 shows that results for MBTC are nearly identical when using county fixed effects. Completely ruling out that results are driven by the absence of detailed geography fixed effects. An alternative way to account for geographic heterogeneity is collapsing the data at the state-level, which also confirms baseline results (see Table A.7). Column 2 replicates the results on the changing in voting behavior for individual representatives including cell-pop weights reflecting how important a county-congressional-district cell is for a representatives voting decision.

Column 3-6 focus on the way the MBTC variable is constructed. Column 3 shows that using changes in the manual share to construct the shift-share variable leads to similar results. This variable should represent an intermediate step for the effect of MBTC, i.e. employment in a specific task adjust to changes in relative wages of this task, in turn the employment composition influences representatives voting behavior.[22] Accordingly, while providing a less direct proxy for technological change its interpretation is more straightforward and that similar results are obtained is reassuring.

In column 4 MBTC is constructed based on the manual-routine wage premium (instead of the manual-median wage premium). This seems a more intuitive proxy for capturing automation of routine tasks, however automation itself makes this variable less reliable. Routine occupations likely undergo drastic change in the way these occupations are performed due to automation, e.g. the introduction of computers might replace workers but also require new skills in clerical occupations. This issue seems less prevalent for manual occupations (cleaners, truck drivers, etc), which have changed little over time. Accordingly, the measure in column 4 is likely more prone to measurement error. This measure also by default does not take into account other forms of technological change, e.g. skill-biased technological change, that might still be more prevalent in certain industries and in the period pre-1990 that also affect voting on immigration policy. This second potential measurement error likely further contributes to the estimate being smaller and less precise. To account for this I add the manual-abstract and abstract-routine wage-premium as controls in Column 5.[23] The coefficient for manual-routine wage premium is now similar in size and significance to my preferred measure for MBTC. Column 6 includes both, MBTC and the manual-routine wage premium, with the latter being no longer having any effect in this case.

Columns 7 uses the ranking strategy of Autor & Dorn (2013) instead of wage-shares to classify manual intensive occupations. Results in columns 3-6 are similar without representative fixed effects and weights.[24] A similar exercise confirms these results also for the congressional district level (Table A.8). There MBTC is additionally constructed without subtracting pre-existing 1950 differences in the manual wage premium (no impact in the county-congressional-district setup), using tasks shares to define thresholds, and varying the threshold for manual intensity from 33% to 25% and 40%. For the 25%-threshold results are nearly identical, while for the 40% coefficient size and precision drops, which seems reasonable, as a wider definition of MBTC is likely doing worse in capturing manual-biased technological change.

There are important trade-offs required due to data availability with regards to the construction of the shift-share variables that make the congressional district specification

[22]The coefficient between the two variables is $0.513(0.014)^{***}$ suggesting that a one percent increase in the manual premium is associated with a 0.51 percentage point increase in the manual share.

[23]The coefficient of the manual-abstract wage-premium is negative as the manual-routine wage-premium suggesting some direct occupational transition between manual and abstract occupations is occurring as well. The coefficient of the abstract-routine wage-premium is positive this plausibly reflects either the (small) overlap between manual and routine occupations as documented in A.2 or alternatively status concerns of routine workers whose wages deteriorate relative to abstract workers.

[24]The corresponding coefficients for columns 3-6 being: (iii) $-3.656^{***}(0.431)$; (iv) $-3.949^{***}(0.473)$; (v) $-7.295^{***}(0.904)$; (vi) MBTC:$-5.548^{***}(0.609)$, MBTC (m-r):$-0.200(0.741)$; (vii) $-5.699^{***}(0.480)$

the preferred specification.[25] First, in the county-congressional district specification the shares for the shift-share variables are based on less detailed industry categories in the 1970 NHGIS census data. The 1950 IPUMS classification has 148 industry categories compared to 41 in the 1970 NHGIS classification. Recent insights on shift-share variables by Borusyak et al. (2022) suggest that a large number of industry categories and independent shocks is the crucial condition for causal identification. This is the case in the congressional district level specification as Figure C.1 illustrates with an effective N=540 for the industry level shocks. Further, Table C.1 shows that the shocks exploited in the MBTC shift-share variable —in contrast to the manual share (MSH) shift share variable— are uncorrelated with 1950 characteristics providing plausibly quasi-random shocks. Table C.2 shows that results are robust to including industry fixed effect, clustering following Adao et al. (2019) and excluding industry outliers. More details are provided in Appendix Section C.1. Accordingly, crucial for identification are a large number of quasi-random shocks, which is best satisfied in the baseline congressional district specification using the manual premium as the shocks. Still it is very reassuring that Table 6 confirms that missing detailed geography fixed effects do not influence results.

5.3 Measurement of technological change

The evidence so far highlighted that results are robust to the way manual-biased technological change is measured. This section will provide more insights that my MBTC variable indeed captures the automation of routine tasks and the corresponding rise in manual employment. It also will highlight the effect of the closely related adoption of information technology (IT) capital and industrial robots on the making of immigration policy.

I start by highlighting that MBTC indeed reflects automation in the form of rising manual employment and corresponding job losses in routine occupations. I do this by using MBTC as an instrument for the manual employment share as well as for increased job losses in routine occupations. The manual share variable has already been discussed in detail with the only difference now being instrumented by MBTC rather than historical differences in manual employment. The Routine Task (35-55) variable aims at measuring automation related job losses in routine tasks. As individuals can not be linked over time in the Census it is of course difficult to do this directly. The closest proxy for this is whether routine employment has declined for a cohort of individuals that already were in the labor market in the previous census round. Accordingly, I calculate the change in routine employment for the same group of individuals when aged 35-55 years compared to

[25] The specification presented in Table 3 is completely impossible to replicate at the congressional district-county cell level as the manual employment share variable can not be constructed using the NHGIS data. In contrast to the individual-level IPUMS data, the NHGIS data only reports a very limited number of occupation categories that are inconsistent over census decades.

Table 6: Alternative county-CD-cell specification

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MBTC	-5.654***	-3.010***				-3.535***	
	(0.485)	(0.710)				(0.807)	
MSH shift-share			-1.394**				
			(0.583)				
MBTC (M-R only)				-1.334*	-4.377***	1.070	
				(0.758)	(1.158)	(0.844)	
MBTC (AD)							-2.422***
							(0.649)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vote FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Representative FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Cell-pop-weight	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20541	20530	20530	20530	20530	20530	20530

Notes: The table presents results at the congressional district-county level akin to Autor et al. (2020). The table also analyses whether the estimated effect is robust to using different measures for MBTC. Due to data limitations in the county-level NHGIS data only 41 industry categories are available and shares are from 1970. Column 1 presents results including county fixed effects. Column 2 adds representative fixed effects and weights the results by cell population. Column 3 uses the manual share at the industry level as shifter instead of the manual premium. Column 4 calculates MBTC based exclusively on manual and routine occupations (manual-routine wage premium). Column 5 adds the manual-abstract and routine-abstract premiums as controls. Column 6 includes MBTC and manual-routine wage premium. Column 7 uses a manual task intensity threshold identical to Equation 16 of Autor & Dorn (2013). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

when 25-45 years old in the previous census round. This more plausibly captures job losses in routine tasks due to automation as it avoids being confounded by younger generations obtaining more education and entering the labor market in abstract occupations which would be measured when studying directly the routine employment share (for the latter the first stage is relatively weak).

Table A.9 presents these IV-Probit results. First, columns 1 and 2 show that MBTC in the first stage is associated with a higher manual employment share and that the instrumented manual employment share as in previous results has a negative effect on support for low-skill immigration policy. Second, columns 3 and 4 highlight that the rise in manual employment is at least in part due to job losses in routine occupations as the share of a cohorts routine employment declines due to MBTC in the first stage. This clearly underlines that the MBTC variable reflects the effect of automation as described by Autor & Dorn (2013). In the second stage the Routine Task (35-55) variable has a positive relationship with support for low-skill immigration policy. Accordingly, the transition out of routine employment —due to automation— increased voting to restrict low-skill immigration. This provides further support that individuals changing from routine to manual occupations and the corresponding increase in natives competition with low-skill immigrants led to local representative becoming more likely to vote in favor of restricting low-skill immigration.

This exercise should only be seen as illustrative given the varied nature and effects of technological change. It is not possible to fully rule out that the underlying estimated effect of MBTC reflect partly other channels than automation. Nevertheless, the IV-Probit and corresponding first stage estimates clearly support that automation has been one important type of technological change captured by the MBTC variable. So while one can not narrow down the effect to automation exclusively, the presented evidence supports that the automation of routine tasks played an important role in the setting of stricter immigration policy in the US.

To further support the credibility of my results on manual-biased technological change, I now turn to the adoption of specific technologies. For this I use data from Acemoglu & Restrepo (2020) on the adoption of IT capital and industrial robots. The adoption of IT capital should be one of the main factors in automation of routine tasks (see e.g. Autor & Dorn (2013) Table 3), while the impact of industrial robots is more ambiguous as they mainly appear to automate routine-manual occupations without there being positive employment effects in other occupations (see Acemoglu & Restrepo (2020), Figure 8B). The variation in these measures is available only at the industry level so that I construct two shift-share variables. A main caveat is that there is only a very low number of industry-categories (19) available for this data. This means that there is no drawback to conducting this analysis solely at the congressional district-county level as the categories match well into the 1970 NHGIS categories. Variation in robot adoption is also mainly observable for manufacturing which represents 16 of the 19 categories. To have more credible variation in the constructed shift-share variables I restrict the analysis to the variation in manufacturing and control for the impact of de-industrialization (see Borusyak et al. 2022, in particular Table 1). A further shortcoming is that the analysis needs to be restricted to votes after 1990 as no data is available beforehand. For the robot adoption measure the industry-level adoption in EU countries —the reduced form in Acemoglu & Restrepo (2020)— is used rather than US data as the latter is only available from an even later time point.

Table 7 columns 1-3 present the effect of IT capital and columns 4-6 present the effect of industrial robot adoption. Columns 2-3 and 5-6 control for the manufacturing share in 1970 interacted with time fixed effects to account for the general pattern of de-industrialization that would otherwise be highly correlated with the shift-share measure of IT capital and robot adoption. The results in columns 1-2 and 4-5 suggest that exposure to these new technologies led to increased support for more restrictive low-skill immigration policies. Notably, the magnitude of the coefficient for the two technologies are similar even if the coefficients for industrial robots are not insignificant. The later likely reflecting that the automation done by industrial robots of tasks is more ambiguous in increasing labor competition between natives and immigrants as both manual-routine intensive occupations are especially negatively impacted. Columns 3 and 6 additionally include representative fixed effects and weights by cell-population. Notably, the effect disappears suggesting that the impact of these technologies is plausibly only due to representatives being elected that have more anti-immigration stances, but in contrast to MBTC there is no evidence for the same representative adopting their positions on immigration policy.

Table 7: IT capital and robot adoption

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)	(4)	(5)	(6)
IT capital	-1.781***	-1.090**	0.954			
	(0.527)	(0.533)	(0.669)			
Robot adoption				-2.483	-1.046	2.333
				(2.622)	(2.639)	(2.502)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Vote FE	Yes	Yes	Yes	Yes	Yes	Yes
Manufacturing 1970 × Time FE	No	Yes	Yes	No	Yes	Yes
Representative FE	No	No	Yes	No	No	Yes
Cell-pop-weight	No	No	Yes	No	No	Yes
Observations (county-CD)	12157	12157	12153	12157	12157	12153

Notes: The table presents results at the congressional district-county-vote cell-level akin to Autor et al. (2020). IT capital and robot adoption for 1990, 2000, 2010 are constructed using industry level data for 19 industries (16 manufacturing, services, research and agriculture) from (Acemoglu & Restrepo 2020) merged to 1970 industry shares from NHGIS data (better match than IPUMS 1950 categories). Only the within variation in the 16 manufacturing industries is exploited. European industry-level robot adoption is used in columns 4-6 due to more extensive data availability (reduced form in Acemoglu & Restrepo 2020). Both variables adjusted to be in 1000s for readability. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

No observable effect on changes in the voting behavior of representatives might be due to a number of reasons: First, the industry-categories might simply not be detailed enough and there is not enough variation to find any effects in the more demanding representative fixed effects specification. Similarly, the narrow focus of the data on the manufacturing sector might make it harder to document the impact of these technologies, especially for industrial robot where the vast majority of adoption occurs in the automotive industry. Second, the political adjustment to technological change might have changed over time. Due to stronger political polarization in the decades post-1990 representatives voted increasingly along party lines on immigration. This might imply that changes on immigration policy were only possible through turnover of the elected representatives. This argument seems to be actually supported by findings in the next section which more broadly analyses the political consequences of manual-biased technological change.

6 Broader political implication

6.1 Trade policy

The politics of immigration and trade are often viewed as being shaped by similar forces (see e.g. Colantone & Stanig 2019; Conconi et al. 2020). A question, therefore is whether technological change might have led to a broader increase in anti-globalization policies, that is not just increasing immigration restrictions, but also leading to protectionist policies on trade. While technological change increased natives' competition with low skill immigrants, it did not necessarily increase exposure to foreign competition. This is because most of the jobs lost as well as created are in non-trade sectors (Autor & Dorn 2013). In contrast, trade liberalization has mainly affected specific industries within manufacturing and led to an overall employment decline in these industries (Autor et al. 2013*a*; Pierce & Schott 2016). Accordingly, an effect on the latter would suggest that manual-biased technological change led to broad discontent with globalization, even if there appears to be little economic gain from increased trade protection for individuals. In this case an observed effect on trade policy could either reflect a protest vote due to increased economic hardship or a misperception of the real causes of local labor market changes. In contrast, if there is no observable effect on trade policy, this would be in line with the voting of representatives being driven by underlying changes in competition between natives and low-skill immigrants in the labor market.

Table 8 presents the results of MBTC on the voting behavior of representatives on trade policy. For this I collected 17 bills voted on in the House of Representatives for the corresponding time period, which are reported in Appendix Table A.10. Conconi et al. (2020) show that in general factor endowments of congressional districts affect voting on immigration and trade policy in similar ways. So that, voting on trade policy provides insight on whether technological change affected voting on immigration policy due to increasing competition between natives and low-skill immigrants or rather due to more general factors like status concerns and a broad show of discontent with globalization that have been suggested as ways how technological change led to rising populism (Anelli et al. 2021; Kurer & van Staalduinen 2020; Häusermann et al. 2021). Column 1 shows that the effect of MBTC on trade policy also has a negative sign, but this effect is insignificant and less than a fifth in magnitude of the corresponding coefficient in Table 4. Columns 2-6 shows that when controlling for other factors the effect of MBTC on trade policy remains nearly always insignificant and even changes sign across specifications. This finding supports the argument that manual-biased technological change affects voting on immigration policy through mainly increasing competition in the labor market between natives and immigrants in the US as it does not appear to have fostered general discontent against globalization.

Table 8: Effect MBTC on trade policy

Dependent variable: Vote on liberalizing trade policy (1=Pro; 0=Against)					
	(1)	(2)	(3)	(4)	(5)
MBTC	-0.832	0.216	-1.716*	-1.197	-1.165
	(0.969)	(0.990)	(1.011)	(1.015)	(1.014)
Poverty		-1.219***	0.347*	0.581***	0.539**
		(0.160)	(0.206)	(0.214)	(0.213)
log(Family Income)		0.204***	0.477***	0.380***	0.292***
		(0.054)	(0.060)	(0.063)	(0.067)
Immigration			-0.794***	-0.868***	-0.789***
			(0.125)	(0.127)	(0.127)
Hispanic			0.065	0.223**	0.079
			(0.089)	(0.096)	(0.099)
African-American			-0.650***	-0.506***	-0.572***
			(0.056)	(0.064)	(0.065)
Unemployment Rate				-2.568***	-2.630***
				(0.554)	(0.556)
Age 65+					-1.183***
					(0.268)
State fixed effects	Yes	Yes	Yes	Yes	Yes
Vote fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	7153	7153	7153	7153	7153
Pseudo R-sq	0.149	0.184	0.208	0.210	0.212

Notes: The table presents the effect of MBTC on voting on trade policy. Vote in favor of freer trade coded as 1 and 0 otherwise. The table reports marginal effects at means from Probit regressions. The list of votes used is reported in Table A.10. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

That trade does not have the same implications for labor markets as immigration is further underlined by Table 9 that shows attitudes of voters on trade issues by manual, routine and abstract employment again using NAES (2004). The correlation suggest that manual employment is in general associated with support for restrictions to trade and the feeling that trade was more harmful to their own and the US economic situation. However, in contrast to attitudes on immigration there is no clear difference in attitudes between manual and routine workers. Indeed only abstract employment is associated with individuals' attitudes being more favorable to trade.

6.2 Political polarization

The observed effect of manual-biased technological change on immigration policy might have occurred not solely through elected representatives adjusting their voting behavior (the intensive margin), but also through the election of candidates that are more averse to immigration (the extensive margin). Table 10 looks at the effect of MBTC on the election outcomes of representatives. Columns 1 and 2 highlight that MBTC led to more repub-

Table 9: Employment tasks and voters attitudes on trade policy

Dependent variable: Individual-level attitudes on trade during 2004 election						
	Favor government restricting trade		Trade harmed economic situation person/household		United States	
	(1)	(2)	(3)	(4)	(5)	(6)
Manual employment	0.109***		0.072**		0.112***	
	(0.030)		(0.032)		(0.033)	
Routine employment		-0.028		0.019		-0.046
		(0.039)		(0.043)		(0.044)
Abstract employment		-0.124***		-0.098***		-0.108***
		(0.030)		(0.032)		(0.033)
State & Interview FE	Yes	Yes	Yes	Yes	Yes	Yes
US born & Employed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1105	1105	1165	1165	1141	1141
Pseudo R^2	0.057	0.060	0.039	0.044	0.043	0.042

Notes: The table presents the individual-level relationship between voters' manual, routine, and abstract employment and their attitudes on trade policy. The table reports marginal effects at means of Probit regressions. Columns 1-2 report whether individuals favor government restrictions on trade. Columns 3-6 report whether the individual feels trade has hurt his household financially or the US economy overall, respectively. NAES (2004) occupational classifications used for constructing manual (trades-person, service worker, laborer, and semi-skilled worker), routine (clerical or office worker, and salesperson) and abstract (professional, manager, and business owner) employment. Individuals in manual, routine and abstract employment sum to all individuals included. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

lican representatives being elected and an increase in their vote share as recorded by the Federal Election Commission 1970-2014. Republican representatives are in general more averse to liberalizing immigration suggesting that MBTC occurred additionally along the extensive margin. Interestingly, column 3 highlights that the increase in Republican candidates did not lead to a clear increase in how conservative representatives are. This is measured using the DW1 nominate score as constructed by Poole & Rosenthal (2000). Indeed when accounting for the endogenous party affiliation of elected representatives in column 4 the newly elected republican representatives seem to have been more liberal in their overall voting pattern compared to their party.[26]

This seems to be somewhat in contrast to the findings that the adoption of industrial robots was a contributing factor in the rising support for nativist and populist politicians in the 2010s (Frey et al. 2018; Anelli et al. 2021). Similarly, it seems to differ from findings in Table 7 that immigration policy is mainly through representative turnover. Columns 5 and 6 reconcile this. They show that in the 2010s, in comparison to previous decades, MBTC started to lead to a conservative shift in the broader policy agenda of

[26]The measure used for the DW1 nominate score reflects a static ideological position across the whole course of a representatives career (see Poole & Rosenthal 2000). This means that the captured effect reflects purely the different political position of newly elected representatives and does not reflect positional changes of representatives throughout their career.

representatives as well. A plausible explanation for this is the increasing polarization of US politics. Party affiliation increasingly defines voting behavior on immigration. This could induce voters to elect candidates with a more broad populist and nativist policy agenda, because incumbent candidates are no longer able to choose individually their stances on immigration policy. Until 2010, 58.2% (41.8%) of Democrats and 12.5% (87.5%) of Republicans voted in favor of (against) liberalizing low-skill immigration. However in the 2010s voting was nearly perfectly polarized by party lines with 98.2% (1.8%) of Democrats and 4.0% (96.0%) of Republicans voting in favor of (against) liberalizing low-skill immigration.

Table A.11 provides further insights that MBTC affects the election of representatives based on their stance on immigration policy. Table A.11 column 1 shows that MBTC decreases the vote share of representatives in favor of liberalizing immigration (proxied by first vote on the issue). Columns 2-3 restricts the analysis to re-elected candidates and elections after the first observed vote on immigration policy. This rules out that representatives are able to hide their stance on immigration to their constituency. The observed effect in columns 1-3 is inline with the casting of roll-call votes being one of the most visible activities to take clear policy positions and communicate them to their constituents (Mayhew 1974) and the subsequent electoral punishment of representatives for their stance on immigration policy. Column 4 highlights that the effect of MBTC does not differ by republican and democratic candidates (after accounting for their stance on immigration). Additional results on the interaction of MBTC and immigration in Table C.5 column 5 also highlight that MBTC has a larger impact when there has been a lot of immigration into a congressional district. This further highlights the link between MBTC and labor market competition between natives and immigrants and that status concerns if at all play only a secondary role.

These last findings on broader political implications point to some important nuances. My overall findings suggest that technological change contributed to anti-immigration policies, while there seems to have been little impact on increasing populism or other nativist policies, in the form of trade policy. Indeed elected representatives often themselves appear to have adjusted their stance on immigration policy. However, this appears to have changed in the last decade with more broadly conservative politicians being elected. This seems in line with broader political developments also in other Western democracies. The important question that arises from this is whether this is because of politicians diverting less from party lines in roll call votes in recent decades or alternatively that the supply of politicians has changed with party primaries selecting more conservative candidates. A final thought should also be give to the pattern of technological change depicted in Figure 4. Until the 1990s technological change plausibly decreased labor market competition between natives and immigrants and more generally seems to have been providing relatively better paid occupations. In contrast, from 1990 it not just increased competition in the labor market, but also job creation at the bottom end of the skill distribution potentially increasing status concerns of individuals that experience downward mobility. One can speculate that what really boosted populism is the mix of economic interests due to labor market competition with immigrants and more broad feelings of economic dissatisification and political resentments.

Table 10: Effect of technological change on political representation

Dependent variable: Characteristics of elected representative	Republican	Vote share		DW-1 nominate score		
	(1)	(2)	(3)	(4)	(5)	(6)
MBTC	2.325**	1.780***	0.529	-1.105**	-0.102	-1.507***
	(1.104)	(0.521)	(0.930)	(0.435)	(1.042)	(0.495)
x 2000s					-1.323	0.030
					(1.741)	(0.736)
x 2010s					3.400*	1.464*
					(1.987)	(0.863)
Republican				0.703***		0.702***
				(0.006)		(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4201	4085	4201	4201	4201	4201
R^2	0.272	0.355	0.422	0.873	0.423	0.873

Notes: The table presents the effect of MBTC on the representatives elected in a congressional district. The table reports OLS effects on Republican representatives being elected, the republican vote share and DW-1 nominate score (conservative-liberal) of the elected representative. Data at the congressional district and congressional session level. Included controls are state FE, congress FE, poverty share, log family income, immigration share, Hispanic share, African-American share, unemployment rate, share age 65+. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Conclusions

This paper represents a first attempt to systematically investigate the impact of technological change on the making of immigration policy. My analysis, first, provides stylized evidence highlighting the mechanism for how technological change complementary to manual tasks —e.g. the automation of routine tasks— increases labor market competition between natives and low-skill immigrants. In turn, leading to increased support for a more restrictive immigration policy. Second, exhaustive empirical evidence is provided documenting the impact of manual-biased technological change on voting on immigration bills in the US house of representatives. Third, additional evidence is presented on the broader implications on trade policy as well as the electoral consequences.

My findings document a considerable effect of technological change on the making of US immigration policy. The effect is due to representatives from congressional districts more exposed to manual-biased technological change becoming more restrictive on immigration policy as well as electoral turnover with an increase in the likelihood of Republican candidates being elected. Notably, there is no evidence for a corresponding impact on US trade policy suggesting that this does not reflect a more broad anti-globalization sentiment that goes beyond immigration policy. This also corresponds to the elected Republican candidates, in general, having supported more centrist policies relative to their party. This suggest that technological change over the whole period analyzed did not play a major role in the polarization of US politics outside of immigration policy.

However, that there is no impact of technological change on political polarization might have recently changed. The electoral consequences of technological change since 2010 appear to be associated with the election of Republican representatives voting similar to the remainder of their party on all bills. This implies that technological change in the 2010s, in contrast to before, increased support of representatives for more conservative/right-leaning bills across all policy areas. These supplemental results in the paper showing that the relationship between technological change and support for populism emerged only recently might help explain opposing findings in the recent literature on this topic (Frey et al. 2018; Anelli et al. 2021; Gallego et al. 2022; Schöll & Kurer 2021). Whether this change in the effect over time is due the economic consequences of technological change having become more negative and increased status concerns concerns of affected individuals, or it reflecting the more broad polarization of US politics and changing electoral options for voters certainly remain important questions that have not yet been satisfactorily answered. These supplemental findings on US political polarization should, however, not overshadow the key effect that technological change had on creating a vehement policy response on immigration legislation.

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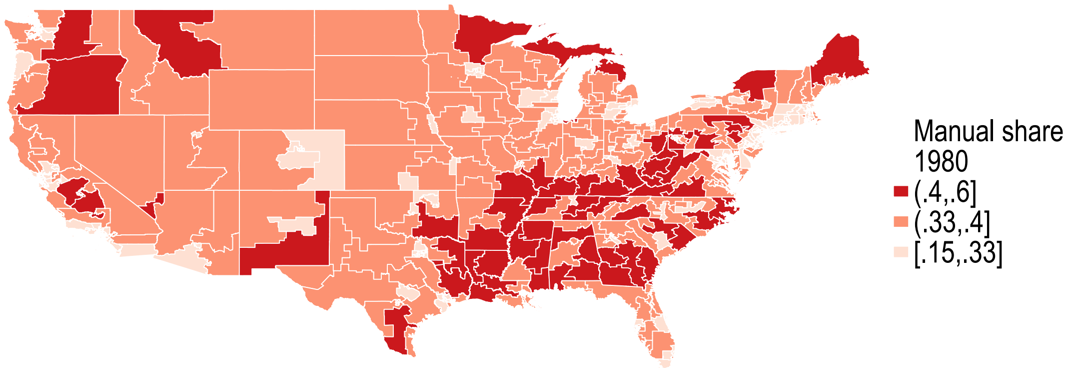
Appendix

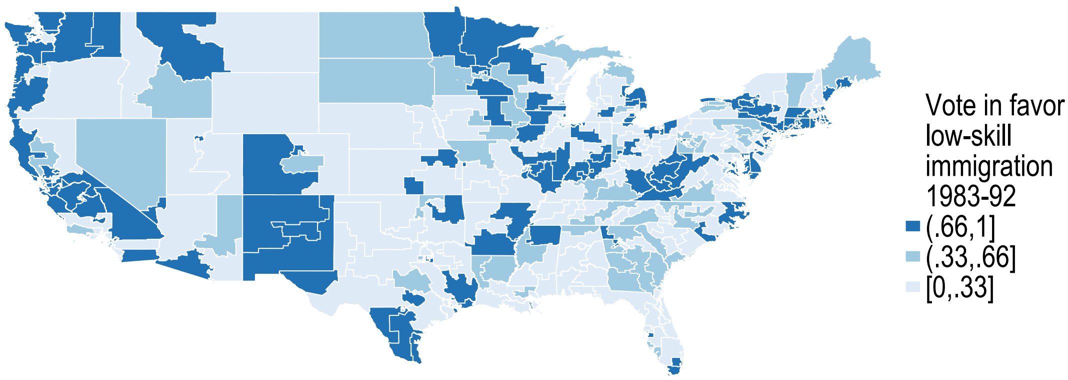
A Additional Figures and Tables

Figure A.1: Manual employment and pro-immigration voting

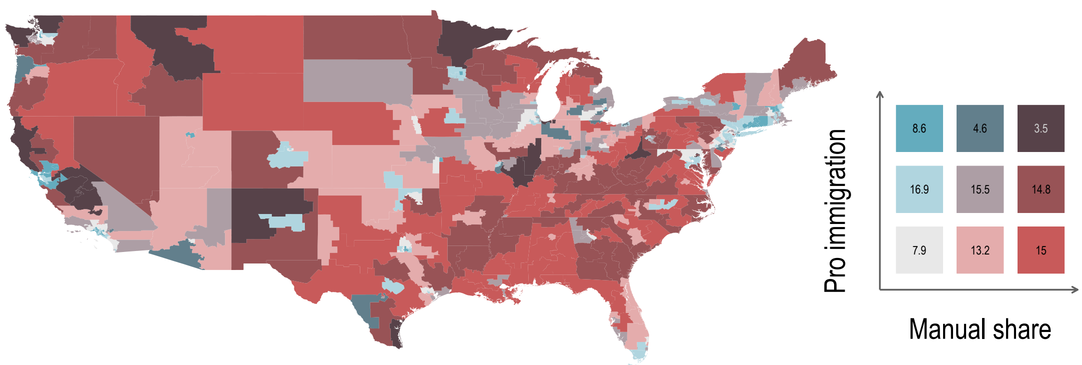
Panel A. Manual employment share 1980



Panel B. Vote on low skill immigration bills 1983-92

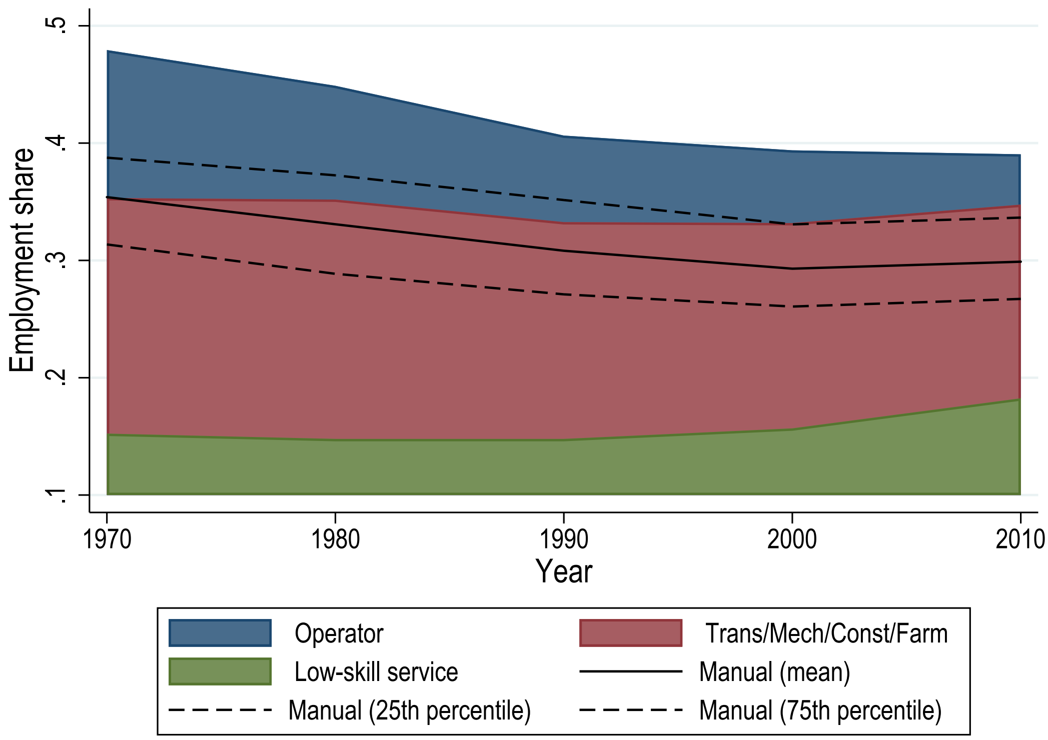


Panel C. Overlap manual employment share and immigration vote



Notes: The figures depict manual employment share and immigration voting in the 1980s across US congressional districts (1983-92 boundaries). The high resolution maps allows zooming into specific areas. Panel A depicts the manual employment share in 1980. Panel B depicts the share of votes in favor of liberalizing immigration policy 1983-92. The more orange an area Panel C depicts the correlation between the two variables (by terciles) in a bi-variate map. The bi-variate map depicts in (i) red a high manual share and anti-immigration stance, (ii) blue a low manual share and pro-immigration stance, (iii) white low manual share and anti-immigration stance, and (iv) black high manual share and pro-immigration stance. The values in the legend represent the percentage share of occurrences. The bivariate maps are constructed using the code by Naqvi (2022).

Figure A.2: Manual employment share 1970-2010



Notes: The graph depicts a breakdown of the manual employment share across congressional districts. It shows stacked average employment across manual intensive major occupation groups (i) low-skill services, (ii) transportation/mechanical/construction/mining/farm and (iii) machine operators/assemblers (see Autor & Dorn 2013). They are ordered by manual task intensity with low-skill services having the highest manual task content. The graph also depicts manual employment as constructed in Equation 1 at the mean, 25th and 75th percentile across congressional districts. As in the main analysis this is calculated for the US born population only. It illustrates the increase in manual employment (especially in the most manual intensive occupations) since the 1990s, while also highlighting that occupations routine and manual intensive (i.e. machine operators/assemblers) continued to decline in their importance even after 1990.

Table A.1: Immigration bills in US House of Representatives 1973-2014

	Cong	**Date**	**Bill**	**Keyword**	**Direction**	**Skill**	**Yes**	**No**
1	93rd	03.05.1973	HR 392	Employer Sanctions	Contra	Low	305	78
2	93rd	26.09.1973	HR 891	Rodino Bill	Contra	Low	337	31
3	98th	20.06.1984	HR 1510	Simpson-Mazzoli Act	Contra	Low	217	212
4	99th	09.10.1986	HR 3810	Immigration Reform and Control Act (IRCA)	Pro	Low	235	171
5	100th	21.04.1988	HR 4222	Amend Immigration and Nationality Act	Pro	Low	214	203
6	101st	03.10.1990	HR 4300	Immigration Act of 1990 (IMMACT)	Pro	Low	231	193
7	104th	21.03.1996	HR 2202	Immigration Control and Financial Responsibility Act	Contra	Low	333	87
8	105th	25.09.1998	HR 3736	Temporary Access to Skilled Workers and H-1B	Pro	High	288	134
9	109th	10.02.2005	HR 418	Real ID Act	Contra	Low	261	161
10	109th	16.12.2005	HR 4437	Border Protection, Antiterrorism, Illegal Immigration	Contra	Low	240	182
11	109th	14.09.2006	HR 6061	Secure Fence Act	Contra	Low	283	138
12	109th	21.09.2006	HR 6094	Community Protection Act of 2006	Contra	Low	328	95
13	109th	21.09.2006	HR 6095	Immigration Law Enforcement Act	Contra	Low	277	149
14	112th	29.11.2011	HR 3012	Fairness for High-Skilled Immigrants Act	Pro	High	389	15
15	112th	30.11.2012	HR 6429	STEM Jobs Act of 2012	Pro	High	245	140
16	113th	01.08.2014	HR 5272	Prohibit certain actions with regards to illegal aliens	Contra	Low	216	192
17	113th	4.12.2014	HR 5759	Preventing Executive Overreach on Immigration Act	Contra	Low	219	198

Notes: Contested immigration policy bills voted on in US House of Representatives between 1973-2014. Yes (No) comprises Yay (Nay), Paired Yea (Paired Nay) and Announced Yea (Announced Nay) votes. No votes are coded as missing values. Data on voting from Poole & Rosenthal (2000). More detailed information on the content of the bills is provided by `https://www.ncsl.org/research/immigration` and `https://www.congress.gov/bill` (last access: September 15, 2022)

Table A.2: Important occupations by task

Number	Manual	Routine	Abstract
1	Truck, delivery, & tractor drivers	Secretaries	Managers & administrators, n.e.c.
2	Primary school teachers	Cashiers	Salespersons, n.e.c.
3	Janitors	Bookkeepers, accounting & auditing clerks	Production supervisors or foremen
4	Waiter/waitress	Cooks, variously defined	Supervisors & proprietors of sales jobs
5	Nursing aides, orderlies, & attendants	General office clerks	Farmers (owners & tenants)
6	Laborers outside construction	Assemblers of electrical equipment	Accountants & auditors
7	Carpenters	Production checkers & inspectors	Child care workers
8	Farm workers	Typists	Secondary school teachers
9	Construction laborers	Welders & cutters	Office supervisors
10	Housekeepers, maids, & butlers	Bank tellers	Managers & specialists in marketing & public relations

Manual & routine task intensive occupations (Top 10): (1) Machine operators, n.e.c.; (2) Textile sewing machine operators; (3) Packers & packagers by hand; (4) Painters, construction & maintenance; (5) Masons, tilers, & carpet installers; (6) Punching & stamping press operatives; (7) Painting machine operators; (8) Vehicle washers & equipment cleaners; (9) Crane, derrick, winch, & hoist operators; (10) Packers, fillers, & wrappers

Manual & abstract task intensive occupations: (1) Kindergarten & earlier school teachers; (2) Locomotive operators (engineers & firemen); (3) Foresters & conservation scientists

Notes: The table presents the ten most important occupations in terms of employment in 1980 for each task. An occupation is recorded as intensive in a certain task when it ranks in the top 33% of wage share paid for this task across all occupation. Most occupations are either coded as manual, routine or abstract task intensive. The bottom of the table presents the occupations that are coded to be intensive in more than one task.

Table A.3: Descriptive statistics manual wage premium

Top 5 industry shares in 1950	
Construction	.073
Educational services	.042
Federal public administration	.039
Retail trade: Eating and drinking places	.034
Personal services: Private households	.032
Top 5 changes in manual wage premium	
Retail trade: Shoe stores	.443
Accounting, auditing, and bookkeeping services	.361
Personal services: Misc personal services	.353
Retail trade: Liquor stores	.189
Retail trade: Household appliance and radio stores	.128
Bottom 5 changes in manual wage premium	
Misc business services	-.312
Misc professional and related	-.313
Manufacturing: Footwear, except rubber	-.333
Manufacturing: Drugs and medicines	-.375
Manufacturing: Office and store machines	-.506

Notes: The table presents the 5 industries with the highest employment share in 1950 as well as the 5 industries with the strongest increase and decrease in the manual wage premium between 1950 and 2010.

Table A.4: Other data sources

Variable	Data sources
Union membership	Hirsch et al. (2001)
Republican	Poole & Rosenthal (2000)
DW-1 nominate	Poole & Rosenthal (2000)
Party voteshare	Federal Election Commission (1970-2014)
China-US IM	United States Census Bureau (1991); UN Comtrade (1991-2010)
China-US IM-EX	United States Census Bureau (1991); UN Comtrade (1991-2010)
NAFTA-US IM	United States Census Bureau (1991); UN Comtrade (1991-2010)
NAFTA-US IM-EX	United States Census Bureau (1991); UN Comtrade (1991-2010)
World-US IM	United States Census Bureau (1991); UN Comtrade (1991-2010)
World-US IM-EX	United States Census Bureau (1991); UN Comtrade (1991-2010)

Notes: This table presents information on the data sources for variables in the main analysis not discussed in detail in Section 2 and not based on US census data (Ruggles et al. 2019; Manson et al. 2019).

Table A.5: Summary Statistics

	Mean	**Std. dev.**	**Min**	**Max**	**Valid obs.**
A. Congressional voting dataset 1973-2014					
Pro migration vote	0.38	0.49	0.00	1.00	5,755
Manual share	0.31	0.06	0.14	0.51	5,755
MBTC	-0.02	0.02	-0.11	0.04	5,719
log(family income)	10.43	0.61	8.80	11.66	5,755
Poverty	0.16	0.11	0.02	0.69	5,755
Immigration	0.09	0.10	0.00	0.59	5,755
Hispanic	0.09	0.14	0.00	0.87	5,755
African-American	0.12	0.14	0.00	0.92	5,755
Unemployment rate	0.07	0.03	0.02	0.24	5,755
Age 65+	0.12	0.03	0.02	0.31	5,755
Republican	0.49	0.50	0.00	1.00	5,755
Republican voteshare	0.48	0.24	0.00	1.00	5,620
DW-1 nominate	0.07	0.46	-0.74	1.23	5,755
B. Voter attitudes dataset 2004 election					
Mayor problem immigration	0.01	0.11	0.00	1.00	79,217
Favor liber. immig.	0.14	0.34	0.00	1.00	19,427
Favor same immig.	0.24	0.43	0.00	1.00	19,427
Favor rest. immig.	0.62	0.49	0.00	1.00	19,427
Manual employment	0.21	0.41	0.00	1.00	79,217
Routine employment	0.11	0.31	0.00	1.00	79,217
Abstract employment	0.30	0.46	0.00	1.00	79,217

Notes: Panel A table reports the summary statistics for the main variables used in the paper for the dataset covering votes in the house of representatives on low-skill immigration policy. Summary statistics for the trade dataset are different due to the different number of votes in the house of representatives across periods. Panel B reports information on the individual attitudes dataset from the NAES (2004) opinion survey.

Table A.6: Specifications including 1950 controls

Dependent variable: Vote on low-skill immigration policy	Controls 1950*time-trend		Controls 1950*time FE	
	IV-Probit	Probit	IV-Probit	Probit
	(1)	(2)	(3)	(4)
Manual Share	-0.897***		-1.955***	
	(0.274)		(0.575)	
MBTC		-2.440**		-2.630**
		(1.054)		(1.059)
Controls 1950*time-trend	Yes	Yes	No	No
Controls 1950*time-FE	No	No	Yes	Yes
Observations	5698	5698	5698	5698

Notes: The table presents results using initial 1950 controls instead of contemporary controls in Table 3 column 5 and Table 4 column 5. Column 1-2 interacts the controls with a time-trend and column 3-4 with decade-fixed effects. Due to data limitations in the 1950 census three controls are slightly different using share of non-white & non-black population instead of Hispanic as well as county-level median income dummies for below 1000$ and above 4000$ instead of poverty and log family income. State FE and vote FE included. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: State-level results

Dependent variable: Vote on low-skill immigration policy	Missing vote excluded			Missing vote equal 0		
	2SLS	OLS	OLS	2SLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Manual Share	-6.946***			-5.891**		
	(2.649)			(2.307)		
MBTC		-11.18***			-11.31***	
		(2.420)			(2.405)	
MSH shift-share			-8.664***			-7.944***
			(1.748)			(1.685)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	662	662	662	804	804	804

Notes: The table presents additional results for manual share (Table 3 column 5) and manual-biased technological change (Table 4 column 5). It also presents results for the manual share shift-share variable complementary to manual-biased technological change (Table A.8 column 1). The table reexamines the main results at the state instead of the congressional district level allowing the use of classical two way fixed effects, which account for state and vote fixed effects. Presented estimates based on linear probability models as the dependent variable is the share of representative voting in favor of liberalizing immigration in a state. Note each congressional district/representative is giving the same weight independent of population. Missing votes not included in state-level dependent variable in columns 1-3 and treated as 0s in columns 4-6. Included controls are state FE, vote FE, poverty share, log family income, immigration share, Hispanic share, African-American share, unemployment rate, share age 65+. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Measurement of manual-biased technological change

Dependent variable: Vote on low-skill immigration policy						
	(1)	(2)	(3)	(4)	(5)	(6)
MSH shift-share	-2.948***					
	(0.664)					
MBTC (incl. 1950)		-2.955**				
		(1.193)				
MBTC (AD)			-7.273***			
			(1.361)			
MBTC (SH)				-4.465***		
				(1.333)		
MBTC (25%)					-4.150***	
					(1.108)	
MBTC (40%)						-1.826
						(1.485)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5719	5719	5719	5719	5719	5719

Notes: The table analyses the robustness of the main result to changing the way manual-biased technological change is measured. Column 1 uses the change in the manual employment share across industries at the national level interacted with the initial industry shares as explanatory variable constructed analogously to MBTC in Equation 2. This provides a complementary measure that directly measures the changing structure of employment triggered by MBTC. Column 2 presents the results not subtracting the 1950 manual wage premium. In column 3 the manual task intensity threshold is identical to Equation 16 of Autor & Dorn (2013) using log occupational tasks and in column 4 the threshold is based on the share of manual tasks in total tasks. In column 5 and 6 the manual task intensity threshold is changed from 33% to 25% and 40% of national employment, respectively. Included controls are state FE, vote FE, poverty share, log family income, immigration share, Hispanic share, African-American share, unemployment rate, share age 65+. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Technological change as instrument

Dependent variable: Vote on low-skill immigration policy				
	(1)	(2)	(3)	(4)
Manual Share	-2.887***	-3.915***		
	(0.318)	(1.247)		
Routine Task (35-55)			12.95***	10.04***
			(0.897)	(1.871)
Instrument	MBTC	MBTC	MBTC	MBTC
First stage coeff.	2.051***	.502***	-.141***	-.172***
	(.097)	(.067)	(.042)	(.041)
F-stat	448.535	55.733	11.391	17.819
Controls	No	Yes	No	Yes
Observations	5719	5719	5719	5719

Notes: IV-Probit estimates using MBTC as instrument underlying the relationship with automation. State FE and vote FE included in all specifications. Controls are poverty share, log family income, immigration share, Hispanic share, African-American share, unemployment rate, share age 65+. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: Votes on trade liberalization

	Bill (Cong.)	Description	Date	Direction	Yes-%
1	H.R. 10710 (93th)	Trade Act 1974	11.12.1973	Pro	.659
2	H.R. 4537 (96th)	Approval Tokyo Agreements	11.07.1979	Pro	.983
3	H.R. 4848 (100th)	Omnibus T&C Act	13.07.1988	Anti	.107
4	H.R. 5090 (100th)	Approval CUSFTA	09.08.1988	Pro	.902
5	H.Res. 101 (102nd)	Disapproving fast track	23.05.1991	Anti	.546
6	H.R.1876 (103rd)	Extension fast track	22.06.1993	Pro	.701
7	H.R.3450 (103rd)	Approval NAFTA	17.11.1993	Pro	.539
8	H.R.5110 (103rd)	Approval Uruguay Agreements	29.11.1994	Pro	.665
9	H.R.2621 (105rd)	Approval fast track	25.09.1998	Pro	.426
10	H.R. 3009 (107th)	Approval fast track	27.07.2002	Pro	.504
11	H.R. 2738 (108th)	US-Chile FTA	24.07.2003	Pro	.634
12	H.R. 2739 (108th)	US-Singapore FTA	24.07.2003	Pro	.637
13	H.R. 4759 (108th)	US-Australia FTA	14.07.2004	Pro	.742
14	H.R. 4842 (108th)	US-Morocco FTA	22.07.2004	Pro	.765
15	H.R. 3045 (109th)	CAFTA	28.07.2005	Pro	.502
16	H.R. 3078 (112th)	US-Colombia FTA	12.10.2011	Pro	.611
17	H.R. 3080 (112th)	US-Korea FTA	12.10.2011	Pro	.648

Notes: The table reports 17 votes on trade policy collected from Poole & Rosenthal (2000) for the time period of interest that are used in Table 8 for the placebo check. The table reports the number (congress), description, date and direction of the vote as well as the share of votes in favor of liberalizing trade policy. More detailed information on the content of the bills is provided by `https : //www.congress.gov/bill` (last access: September 15, 2022)

Table A.11: Representative support for immigration bills and re-election

Dependent variable: Re-election vote share representative	(1)	(2)	(3)	(4)
MBTC	0.130	0.889	0.806	0.381
	(0.328)	(0.791)	(0.812)	(0.840)
x Pro immigration	-0.539***	-0.967***	-1.094***	-1.390***
	(0.148)	(0.360)	(0.358)	(0.423)
x Democrat				0.665
				(0.425)
Representative FE	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Observations	5718	3218	3218	3218

Notes: The table presents OLS estimates of the effect of manual-biased technological change interacted with a (re-)elected representatives support for immigration policy and their party affiliation on the representatives re-election vote share later on. The first congressional section in which a representative voted on an immigration bill is used for constructing the representative's stance on immigration. Columns 2-4 focus on reelected representatives with election results prior to the first immigration policy vote not included in the sample. State FE and congress FE included in all specifications. Controls are poverty share, log family income, immigration share, Hispanic share, African-American share, unemployment rate, share age 65+. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Theoretical framework (Online publication only)

This section provides a theoretical framework corresponding to the stylized facts presented in Section 3. The economy in the model is a stylized version of the model presented in Acemoglu & Autor (2011) Section 4, where (capital-embedded) technology substitutes routine tasks provided by workers. This corresponds to the automation of routine tasks as the major driver of labor market changes in the US since 1990 as documented by Autor et al. (2003); Autor & Dorn (2013). This led to employment polarization, i.e. a rise in manual and abstract employment at the extremes of the skill distribution and a decline in routine employment at the middle of it. In my theoretical framework, this is modeled by a CES production function with manual, routine, and abstract inputs being complements and technology being a perfect substitute for routine labor. I add to this (i) low-skill immigration, and (ii) policy-makers setting immigration policy based on natives economic interests. The partial-equilibrium model illustrates how the automation of routine task can lead to a change in immigration policy. This occurs due to employment polarization expanding the share of natives in manual occupation that are in competition with low-skill immigrants.

B.1 Economy with employment polarization

Consider $d = 1, ..., D$ economies, each representing one US congressional district (D representing all congressional districts). For simplicity, each of these economies are represented by a single firm combining manual, routine and abstract inputs in a constant elasticity of substitution production function to produce a final good Y:

$$Y = \left(\alpha_d(K_M + L_M)^{\frac{\theta-1}{\theta}} + \beta_d(K_R + L_R)^{\frac{\theta-1}{\theta}} + (1 - \alpha_d - \beta_d)(K_A + L_A)^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}} \quad (3)$$

The parameter θ measures the elasticity of substitution (being complements, i.e. $\theta < 1$) between the three inputs. These inputs are either supplied by workers or capital-embedded technology. L_M, L_R, and L_A are the respective amount of manual, routine and abstract tasks supplied by workers.

K is the amount of capital-embedded technology adopted by a firm, which is a perfect substitute for labor supplying the respective task.[27] I focus on the automation of routine tasks ($K_R > 0$). This corresponds to routine tasks having been documented to be the ones most likely to have been substituted by technology since 1990 (Autor et al. 2003; Autor & Dorn 2013). This is depicted in Figure 4. K_R, for example, reflects the sudden adoption of personal computers in US workplaces. I assume $K_M = 0$ and $K_A = 0$. The symmetric CES function makes it easy to deduce any change to them as well (e.g. one can consider skill-biased technological change $K_M > 0$ corresponding to 1970-80 in Figure 4). I do not explicitly model the decisions of firms on how much routine task substituting technology they adopt as in my case it will be sufficient to show the effect of a change in K_R.[28] For generating employment polarization it is sufficient to think of K_R as following an increasing deterministic trend including a random component ϵ_d that

[27] This is very similar to the theoretical framework presented in Acemoglu & Restrepo (2020), but without different industries and only three tasks of which in the example only routine tasks will be replaced by automation.

[28] For example, adoption could be as in Autor & Dorn (2013) Eq.3 where firms choose to adopt more computer capital due to rising productivity of it over time.

varies across congressional districts. Firms vary by their fixed production technology (α_d, β_d) creating variation across congressional districts in the tasks supplied by workers even in the absence of technological change.

Given a specific K_d, each firm solves the following problem to maximize output Y:

$$\max_{M,R,A} Y - w_M L_M - w_R L_R - w_A L_A \tag{4}$$

Under the assumption that markets are perfectly competitive, the return on factor inputs will be at equilibrium equal to their marginal productivity. Consequently, combining the first order conditions of the optimal choice problem of the different labor inputs gives the manual-routine ($\hat{w}_{M|R}$), abstract-routine ($\hat{w}_{A|R}$) and abstract-manual ($\hat{w}_{A|M}$) wage premiums:

$$\begin{aligned} \hat{w}_{M|R} &= \frac{w_M}{w_R} = \frac{\alpha_d}{\beta_d}\left(\frac{K_R + L_R}{L_M}\right)^{\frac{1}{\theta}} \\ \hat{w}_{A|R} &= \frac{w_A}{w_R} = \frac{1-\alpha_d-\beta_d}{\beta_d}\left(\frac{K_R + L_R}{L_A}\right)^{\frac{1}{\theta}} \\ \hat{w}_{M|A} &= \frac{w_M}{w_A} = \frac{\alpha_d}{1-\alpha_d-\beta_d}\left(\frac{L_A}{L_M}\right)^{\frac{1}{\theta}} \end{aligned} \tag{5}$$

Manual, routine and abstract tasks are supplied by a set of native workers in d. These native workers i have one unit of labor and different abilities. Similar to Autor & Dorn (2013) all workers have homogeneous skills at performing manual tasks, but heterogeneous skills $\mu_i \in [0,1]$ for performing routine and abstract tasks. The supply of routine tasks is μ_i and abstract tasks is $g_A(\mu_i) = \mu_i^2$. This nested structure implies that individuals will be ordered along their ability level into the three tasks.[29] This reflects the pattern observed in the data that in general the lowest-skill workers perform manual, the medium-skill workers perform routine and the highest-skill workers perform abstract tasks.[30] This gives two cut-off conditions:

$$\mu_R^* = \hat{w}_{M|R} \tag{6}$$

$$\mu_A^* = \hat{w}_{A|R}^{-1} \tag{7}$$

In equation 6, μ_R^* is the skill level for which the routine tasks supplied relative to manual tasks is equal to the manual-routine wage premium, i.e. the skill level of the worker indifferent between supplying routine and manual tasks. In equation 7, μ_A^* is the skill level for which the routine tasks relative to the abstract tasks supplied is equal to the abstract-routine wage premium, i.e. the skill level of the worker indifferent between

[29] This holds for g_A being any other convex function with $g'_A > 0$ and $g''_A > 0$.

[30] One can imagine two alternative setups for individual skills: (i) The case with separate skill-levels for performing routine and abstract tasks. This would mean a third cut-off based on the abstract-manual wage premium $\hat{w}_{M|A}$ as some workers transition directly between abstract and manual tasks (those with low skills for routine tasks). (ii) The case of Autor & Dorn (2013), p.1562 where there are low-skill workers that optimize between supplying manual and routine tasks, and high-skill workers supply exclusively abstract tasks. In this case only the manual-routine wage premium cut-off $\hat{w}_{M|R}$ would matter as the supply of abstract tasks is fixed.

supplying routine and abstract tasks. The total supply of abstract, routine and manual tasks by native workers in the economy in district d is:

$$L_{M,N} = \int_0^{\mu_R^*} f(\mu_i)di \qquad L_R = \int_{\mu_R^*}^{\mu_A^*} f(\mu_i)di \qquad L_A = \int_{\mu_A^*}^{1} f(\mu_i)di \tag{8}$$

The subscript N denotes the aggregated manual tasks supplied by natives as through low-skill immigration the overall supply of manual tasks can increase. Tasks supplied by foreigners are denoted with subscript F, i.e. $L_M = L_{M,N} + W_D L_{M,F}$. W_D being the nationwide low-skill immigration policy with $W_D \in [0,1]$ with 0 being closed borders and 1 completely open borders. Low-skill immigrants are assumed to be prefect substitutes for natives supplying manual tasks (as for capital-embedded technology), but any degree of substitutability that is not complementarity will lead to similar conclusions.[31]

Thresholds, μ_R^* and μ_A^*, for natives allocation across tasks change with regards to technology in the following way:

$$\frac{\partial \mu_R^*}{\partial K_R} = \frac{\partial \hat{w}_{M|R}}{\partial K_R} = \left(\frac{\alpha_d}{\theta \beta_d} (K_R + L_R)^{\frac{1-\theta}{\theta}} L_M^{-\frac{1}{\theta}} \right) > 0 \tag{9}$$

$$\frac{\partial \mu_A^*}{\partial K_R} = \frac{\partial \hat{w}_{A|R}^{-1}}{\partial K_R} = -\left(\frac{\beta_d}{\theta(1-\alpha_d-\beta_d)} (K_R + L_R)^{-\frac{1+\theta}{\theta}} L_A^{\frac{1}{\theta}} \right) < 0 \tag{10}$$

An increase in K_R increases the manual-routine premium ($\hat{w}_{M|R}$) and abstract-routine premium ($\hat{w}_{A|R}$). Employment polarization occurs as technology substitutes routine tasks and the share of native individuals working in manual as well as abstract occupations rises. This corresponds to the stylized evidence presented in Figure 4 for the period 1990-2000. Different types of employment changes documented in Figure 4 can be easily modeled in this framework as well. For example, the employment changes that occurred 1970-80 —decrease at the bottom and increase in the middle and top of the skill distribution— could be alternatively generated by considering an increase in K_M (manual substituting technology) instead of K_R.

B.2 Immigration and immigration policy

The possibilities to vote on a new low-skill immigration policy (W'_D) occur unexpected. The restrictiveness of the policy to be voted on being a random draw from a normal distribution with regards to the current immigration policy $N(W_D, \sigma^2)$ with $W'_D \in [0,1]$. This simplified setting corresponds well to the empirical setup as vote fixed effects account for any overall differences across bills that are shaped by the process before the final passage vote. However, it should be noted that this does abstract considerably from reality as it excludes a large part of the political process leading up to the final passage vote. The selection of representatives (as shown in Table 10) is impacted by technological change as well, which in turn shapes the process of crafting bills to be voted on in the final passage vote. Consequently, rather than being random in its direction, in reality bills to be voted on will likely lean in the direction of the overall political sentiment on

[31] High-skill immigration is likely complementary even to natives supplying abstract tasks. This is one of the reasons I mostly do not consider high-skill immigration policies.

immigration policy of representatives (see Table A.1). The parameter σ^2 influences the severity of changes to low-skill immigration policy.

Due to the concentration of immigrants at the extremes of the US skill distribution, low-skilled immigrants in the model are assumed to exclusively work in manual occupations ($\mu_F = 0$).[32] Figure 2 highlights the relative over-representation of immigrants in manual occupations (see also Basso et al. 2017). A change in low-skill immigration policy W_D corresponds to an increase or decrease in the supply of manual tasks through changing $L_{M,F}$. Native workers or representatives are myopic in the way that they take into account natives' labor market adjustments to the inflow of immigrants.[33] In the myopic case the size of the policy change $\Delta L_{M,F}$ is irrelevant for perceptions on the gains from immigration policy as all manual workers expect a drop in their wages from an increase in immigration and vice versa:

$$\frac{\partial w_M}{\partial L_{M,F}} < 0 \qquad\qquad \frac{\partial w_R}{\partial L_{M,F}} > 0 \qquad\qquad \frac{\partial w_A}{\partial L_{M,F}} > 0 \tag{11}$$

This formally underlines that natives supplying routine and abstract tasks expect to gain from low-skill immigration while natives supplying manual tasks lose out from low-skill immigration. This corresponds to the evidence presented in Table 1. In turn, this labor market competition determines attitudes on immigration (see Table 2).

The location choice of immigrants can be summarized as $f(w_M, \tau_{i,d})$ where w_M is the manual wage that an immigrant receives and $\tau_{i,d}$ is a migration cost that varies across districts by immigrants (e.g. due to travel distance, family ties, etc).[34] Importantly, immigrant location choice (deportation in the case of $\Delta L_{M,F} < 0$) across congressional districts d has no impact on attitudes of natives as long as the expectation is that local immigrant numbers adjust in the same direction as nation-wide immigration. This is due to the magnitude of the expected wage impact across individuals having no effect on the representatives decisions as it is based on a median-voter equilibrium.[35]

[32] One can think of this as being due to language barriers or a need for US documentation (educational/occupational licenses) in non-manual occupations. This, of course, might only be temporary and as with obtaining citizenship, (legal) migrants might be able to enter more skill-demanding occupations in the medium- to long-run as language skills improve or they receive accreditation of their license/degrees in the US.

[33] In the case of perfect foresight representatives will take into account the share of individuals that gain from adjusting their task supply away from manual tasks ($w'_R\mu_i > w_M \in \mu_i < \mu^*_R$). This being a share of all natives who adjust to an increase in low-skill immigration by supplying routine instead of manual tasks (μ^*_R decreases to μ'^*_R). Alternatively, large enough rigidities for natives when changing occupation from one task to another —e.g. retraining costs— lead to identical conclusions as in the myopic case.

[34] Instead of having a constant supply of immigrants $L_{M,F}$ willing to move to the US one can model the emigration decision based on: w_F the wage in the immigrants country of origin needing to be lower than w_M minus the migration cost $\tau_{i,d}$ (optimizing across congressional districts based on $f(w_M, \tau_{i,d})$). Further, W_D determines the migration cost $\tau_{i,d}$ rather than the share of immigrant inflows and w_F increases with respect to immigration. This would determine the immigration equilibrium for both countries. However, this does not add anything to the models predictions on immigration policy making (at least in the median-voter equilibrium used), so that I abstract from the emigration decision in the outlined way.

[35] The current level of low-skill immigration $L_{M,F}$ —in contrast to $\Delta L_{M,F}$— in a congressional district has a (positive) impact on immigration attitudes in the model as it led to a decline in the share of native workers in manual tasks. This is because the model does not in any way take into account the magnitude of competition between natives and immigrants along the skill distribution (only whether there is a positive or negative wage impact on the median voter from immigration matters). In the data, the degree of competition between immigrants and natives in a congressional district clearly plays an important role

The representatives votes on the new low-skill immigration policy W'_d based on a median-voter equilibrium as described by Downs (1957). The natives median ability level $\bar{\mu}$ will determine the representatives vote (depicted below is a bill that would liberalize immigration policy $W'_D > W_D$):

$$W'_d = \begin{cases} W'_d = 0 & if \quad \bar{\mu} \in (0, \mu^*_R) \\ W'_d = 1 & if \quad \bar{\mu} \in (\mu^*_R, \mu^*_A) \\ W'_d = 1 & if \quad \bar{\mu} \in (\mu^*_A, 1) \end{cases} \qquad if \qquad W'_D > W_D \tag{12}$$

$W'_d = 1$ represents a representative voting in favor of liberalizing low-skill immigration policy, while $W'_d = 0$ represent a vote against it. The voting pattern is reversed if the new immigration policy is more restrictive than the current one ($W'_D < W_D$). This corresponds well to the stylized evidence on voting behavior of representatives with regards to task-shares across congressional districts (Figure 3). Subsequently, if the majority of representatives voted in favor of the new immigration policy, it gets adopted.

μ^*_R is the key determinant of the representatives voting behavior representing the native manual employment share. Accordingly, representatives from congressional districts with a higher manual employment share should vote in favor of restricting low-skill immigration. This is confirmed by the more thorough empirical results presented in Table 3. The IV-strategy presented in Panel B corresponds to exploiting the fixed differences in α_d across congressional districts.

The automation of routine tasks K_R leads to more restrictive immigration policy. This is due to its complementarity to manual tasks (one type of manual-biased technological change). Equation 9 shows this clearly. An increase in K_R leads to an increase in μ^*_R corresponding to a change in the manual-routine wage premium. This is confirmed by the empirical evidence presented in Table 4.[36]

as the share of low-skill immigrants as well as the interaction between immigration and manual-biased technological change are leading to representatives voting in favor of restricting low-skill immigration (see Table C.5). A further factor in the medium to long-term not considered in the theoretical framework is that low-skill immigration might reduce incentives to innovate and adopt K_M, while increasing incentives for K_R and K_A due to the increase in relative wages for the latter.

[36] Another type of (negative) manual-biased technological change would be K_M leading to the substitution of manual tasks and more favorable immigration policy. For some industries/individuals the occupational choice in this case might be exclusively between manual and abstract tasks. Accordingly, in the main empirical specification I use the manual premium with regards to the medium wage across industries as the main variable. Results are similar using the manual-routine wage premium after controlling for other wage premiums in Table 6.

C Additional robustness checks (Online publication only)

C.1 Shift-share variable

This section describes in detail the variation exploited in the shift-share variables, focusing in particular on the main variable which interacts the industry-level manual premium with initial industry employment shares in 1950. I follow Borusyak et al. (2022) as the key for identification in my settings is the exogeneity of the shifters rather than the shares.

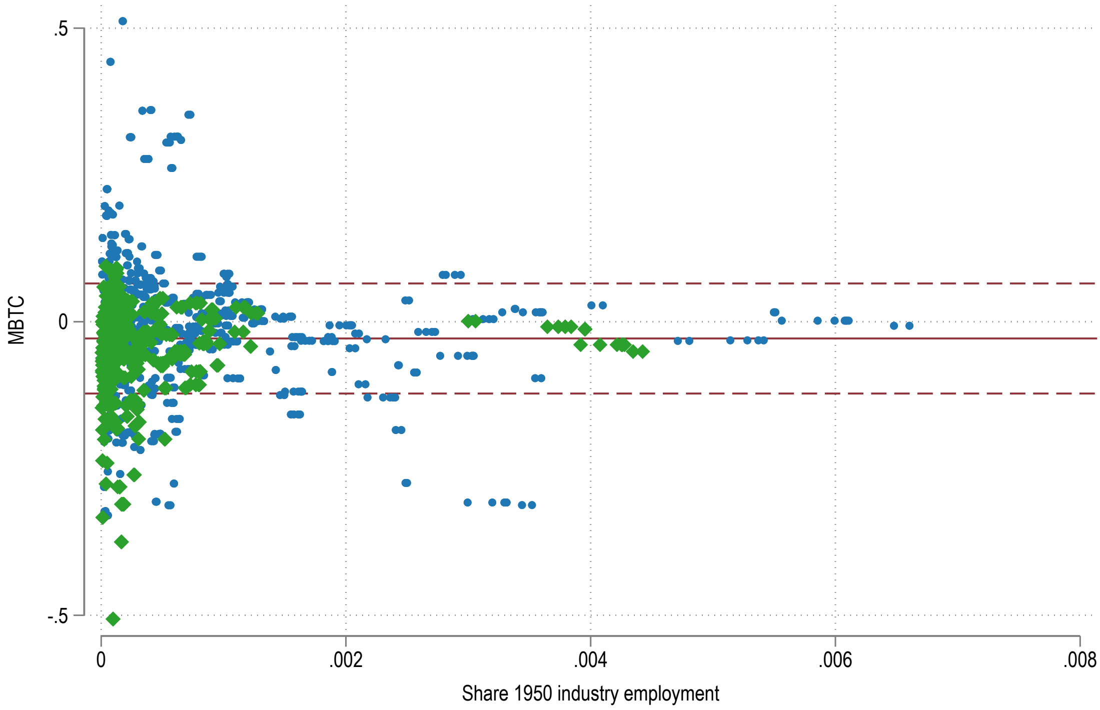
Figure C.1 starts by illustrating that there are indeed a considerable number of independent industry-level shocks (a visualization of Table 1 in Borusyak et al. 2022). It depicts that the shocks are well dispersed and that their are no large industry shares that account for more than 1% of total employment in a specific decade. The green diamonds and blue dots represent industries in the manufacturing and service sector, respectively. It highlights that manual-biased technological change was more complementary in the service sector, while manual tasks were substituted more in manufacturing. This seems inline with growth in employment from automation being in the service sector (Autor & Dorn 2013), while manufacturing experienced more manual task replacing technological change (see e.g. Beaudry & Green 2005; Beaudry et al. 2010; Lewis 2011). The later indeed including plausibly the adoption of industrial robots, which mainly replaced manual-routine jobs along the assembly line Acemoglu & Restrepo (2020).

The effective (1/HHI) industry level sample size is 540 due to the considerable number of small industries (by employment share) in the sample. Even at the more aggregate 2-digit level the effective sample remains sizable with 93. This suggests that there is still considerable industry-level variation available when shocks are serially correlated or clustered by groups. Only when excluding additionally the time dimension the effective sample becomes relatively small with 26.

Table C.1 depicts the correlation between the set of baseline controls measured in 1950 and the two main potential shift-share variables the one using the industry-level manual premium (columns 1-4) and the one using the industry-level manual share (columns 5-8) as shifters. The former being the MBTC variable and the latter the MSH shift-share variable. MBTC shocks appear as-good-as-random as the variable is uncorrelated with the 1950 variables. The MSH shift-share variable appears correlated with racial characteristics of areas in 1950. The latter is not necessarily meaning that results for this variable are biased in the empirical analysis, however it does suggest that changes in the manual employment share might be not as good as random across industries without adding the appropriate set of controls and might capture underlying trends associated with these variables. Accordingly, along with the conceptual reasons highlighted in the paper, MBTC seems the most credible proxy for manual-biased technological change in the analysis.

Table C.2 completes the evaluation of the shift-share variable converting the analysis into a dataset of weighted shock-level aggregates. The corresponding results at the industry level are presented for the main MBTC variable in Panel A, the alternative MSH shift-share variable in Panel B and the IV-manual share specification using initial manual intensity in 1950 in Panel C. Column 1 presents the coefficient including the baseline controls, industry weights, excluding the agricultural sector and clustered standard errors at the 2-digit industry level following Adao et al. (2019). Column 2 controls for 1-digit industry fixed effects. Column 3 excludes industry outliers being the top 5% and bottom 5% of respective industry shocks. Column 4 and 5 only include industries in the man-

Figure C.1: Visualization shock summary stats



Notes: The figure illustrates the variation in industry shares and shocks across industries. Green diamonds are industries in the manufacturing sector and blue dots are industries in the service sector. The x-axis depicts the share of the industry of the total in 1950 and the y-axis the respective MBTC by year. Weighted shock mean is -.029 with a standard deviation of .118 (inter-quartile-range .109) depicted in the graph by the solid red and dashed lines. Largest 3-digit industry share is .007 and largest 2-digit industry share is .097. Nr. shocks=2527, Nr.3-digit industries=143, Nr.2-digit industries=64. The 3-digit-year 1/HHI=539.721, 2-digit-year 1/HHI=92.998 and 2-digit 1/HHI=26.260.

ufacturing and service sector, respectively. Most interestingly, and in line with Autor & Dorn (2013), the effect appears larger in the service sector, while manufacturing seems less impacted. More broadly, these results rule out that the results using the shift-share variables are driven by particular industries or are specific to some broader industrial sectors.

C.2 Other economic factors

This section controls for a set of additional economic factors that measure the specialization of congressional districts in Table C.3. First, manual-biased technological change in a congressional district might be correlated with long-run differences in the importance of manual employment across congressional districts.Column 1 includes the manual employment share in 1950. It shows that both the manual-biased technological change and the manual employment share in 1950 have their expected negative signs, but notably only MBTC accounting for recent technological change is now significant.

Column 2 further explores the role played by competition between natives and low-skill immigrants focusing on college education in the literature so far (Mayda 2006; Facchini & Steinhardt 2011). In line with previous findings a higher share of college educated individuals increases the likelihood that a representative will vote in favor of liberalizing low-skill immigration, however the effect of manual-biased technological change remains

Table C.1: Correlation shift-share variables with 1950 observables

Dependent variable:	MBTC				MSH shift-share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Poverty	-0.018			-0.002	0.101***			-0.026
	(0.015)			(0.016)	(0.019)			(0.023)
High income	-0.004			0.001	-0.013*			-0.001
	(0.006)			(0.007)	(0.007)			(0.007)
African-American		-0.022**		-0.020*		0.109***		0.115***
		(0.009)		(0.011)		(0.013)		(0.017)
Other race		0.082		0.063		0.320***		0.256***
		(0.065)		(0.041)		(0.090)		(0.081)
Immigration		-0.033		-0.044		-0.063		-0.090*
		(0.033)		(0.037)		(0.041)		(0.046)
Unemployment			0.048	0.064			-0.001	0.167*
			(0.091)	(0.102)			(0.083)	(0.093)
Age 65+			0.051	0.029			-0.337***	-0.002
			(0.062)	(0.069)			(0.087)	(0.105)
Observations	2134	2142	2142	2134	2134	2142	2142	2134

Notes: The table presents the relationship between MBTC as well as the manual share (MSH) shift-share variable and 1950 observables across congressional districts and decades. Robust standard errors clustered at the sate-decade level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

similar. This suggests that competition due to changing tasks performed in the labor market and through differences in education are two distinct mechanism that affect voting behavior of representatives on low-skill immigration.Column 3 separates the educational composition by tasks. This helps ruling out that the change in the wage premium might be driven by changes in the relationship between job tasks performed and the human capital required for them. This relates to a concern that arises based on Autor & Handel (2013) where wages might provide a bad proxy for task demand due to changes in the relationship between tasks performed and human-capital required. Notably, this point is most likely to underestimate the impact of an increase in MBTC as higher levels of education are associated with more favorable attitudes towards immigration. Indeed, the effect of education appears to depend on labor market competition. In contrast to routine and abstract employment, in manual employment a higher college share of natives even more decreases support of representatives for liberalizing immigration policy. One reasons for this might be that educated voters are more likely to turnout in elections and for this reason have more influence on the voting behavior of representatives Sondheimer & Green 2010. This heterogeneity in the effect of education might hint at the fact that education is in general negatively correlated with manual employment and that what really matters are solely competition due to occupational tasks. To the best of my knowledge there is no research so far that thoroughly investigates the intersection between occupational tasks, education and support for immigration. However, most importantly for this paper, the coefficient for MBTC is robust, which rules out that results are driven by changes in the educational composition of occupational tasks.

Over the study period union membership has more than halved. Trade unions usually have been opposed to increasing immigration inflows fearing a deterioration of wages and working conditions through an extension of the labor force (see Gimpel & Edwards 1999). In addition, changes in union membership might have affected wages differently across

Table C.2: Shift-share analysis

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)	(4)	(5)
Panel A. Manual-biased technological change					
MBTC	-6.676***	-7.220***	-9.721***	-4.675*	-12.36***
	(2.131)	(2.121)	(1.764)	(2.379)	(0.922)
Panel B. Manual share shift-share					
MSH shift-share	-2.991**	-4.714***	-8.983***	-4.479**	-5.727***
	(1.487)	(1.633)	(1.009)	(2.028)	(1.357)
2-digit industry-clusters	Yes	Yes	Yes	Yes	Yes
1-digit industry FE	No	Yes	Yes	Yes	Yes
Excluding outliers	No	No	Yes	No	No
Agricultural sector	No	No	No	No	No
Manufacturing sector	Yes	Yes	Yes	Yes	No
Service sector	Yes	Yes	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations (industry)	1893	1893	1704	850	1043

Notes: The table presents the analysis of the effects at the industry-level as suggested in Borusyak et al. (2022). Estimation weighted by industry employment. All columns include the full vector of controls from the baseline specifications: state FE, vote FE, poverty share, log family income, immigration share, Hispanic share, African-American share, unemployment rate, share age 65+. Panel A presents results for MBTC, Panel B for MSH shift-share, and Column 1 presents results for the re-centered baseline estimation using OLS (agricultural sector dropped) with standard errors clustered on 2-digit industries. Column 2 includes 1-digit industry fixed effects. Column 3 excludes outlier industries (top and bottom 5%). Column 4 and 5 only include industries in the manufacturing and service sector, respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

occupations within industries. Column 4 accounts for the changing importance of trade unions in the US labor market. The share of trade union members appears to have indeed a negative effect, however the effect is insignificant. Technological change plausibly varies between urban and rural economies and this difference also shapes changing opinions on immigration. Column 5 accounts for differences between rural and urban labor markets with representatives from districts with more constituents in rural areas being more likely to vote to restrict low-skill immigration. Column 6 accounts for a congressional district's employment share in five major industry categories accounting for the broad specialization of districts in specific products and services: transport, retail, manufacturing, construction and agriculture. This exercise is similar to previous findings controlling for 1-digit industry fixed effects in the setup by Borusyak et al. (2022). Importantly, in all these specifications again the coefficient for MBTC remains similar in magnitude and significance.

C.3 Trade exposure

Apart from technological change, trade in goods appears to have been the major factor in recent labor market developments in the US, in particular in the form of rising Chinese import competition and integration into NAFTA (see e.g. Autor & Dorn 2013; Autor et al. 2013*a*; Benguria 2020; Choi et al. 2021). In particular, Chinese competition has been highlighted to also have contributed to increased support for nativist politicians and

Table C.3: Robustness checks - Economic specialization

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)	(4)	(5)	(6)
MBTC	-4.339***	-3.947***	-3.483***	-4.135***	-4.664***	-5.702***
	(1.423)	(1.342)	(1.282)	(1.394)	(1.414)	(1.424)
Historical Manual Task	-0.473					
	(0.402)					
College		1.763***				
		(0.261)				
College share (manual)			-4.604***			
			(0.792)			
College share (routine)			4.527***			
			(0.933)			
College share (abstract)			1.808***			
			(0.362)			
Union Membership				-0.388		
				(0.614)		
Rural					-0.394***	
					(0.0909)	
Transport						-2.132**
						(0.859)
Retail						1.459
						(1.007)
Manufacturing						-1.258***
						(0.195)
Construction						-2.546***
						(0.798)
Agriculture						-1.453***
						(0.465)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5719	5719	5719	5719	5719	5719

Notes: The table analyses the robustness of MBTC to controlling for additional labor market channels. Presented estimates extend on column 5 of Table 4 reporting marginal effects at means for Probit regressions. Robust standard errors clustered on state-vote in parentheses. Controls are state FE, vote FE, poverty share, log family income, immigration share, Hispanic share, African-American share, unemployment rate, share age 65+. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

political polarization (see e.g. Colantone & Stanig 2017 and Autor et al. 2020). Other papers have studied the political consequences of trade shock in other contexts: Japans trade integration in the 1980s (Nishioka & Olson 2022), World War 1 trade disruptions on political support for independence in British India (Bonfatti & Brey 2020) and drop in German exports on support for the Nazi party in the 1930s (Brey & Facchini 2021). Bombardini et al. (2020) goes even further highlighting that US representatives at least in the 1990s could have expected the negative consequences of Chinese imports to the the US.

One might be concerned that manual-biased technological change is correlated with increases in foreign competition at the local level. To rule this out, I control for increased trade competition across congressional districts and the effect it might have had on immigration policy in Table C.4. I construct measures of trade penetration in levels corresponding to the differenced version used by Autor et al. (2013*a*). The details on the construction of the specification used can be found in Appendix Section D. Columns 1 and 2 present the effect of import penetration (in 1000$) per employee from China across congressional districts. Both coefficients, imports (column 1) and net imports (column 2), are negative and significant. Accordingly, rising competition from China made representatives more likely to vote in favor of restricting low-skill immigration. Columns 3 and 4 show no corresponding political impact due to increased trade within NAFTA. Columns 5 and 6 show also a minor effect for total US trade. This plausibly reflects the rising importance of trade with China within total US trade that is clearly observable in columns 1 and 2. Trade competition however seems to be rather a complementary explanation for tighter immigration legislation as the main variable of interest is little affected by the inclusion of the variables controlling for Chinese import competition. This actually seems consequential when considering that automation mainly led to a decline in non-traded routine occupations, like clerks and secretaries, and an increase in manual occupations in the low-skill services sector. Accordingly, occupations most affected by automation appear in general to be non-traded, so that there is little possibility for correlation between the two shocks across local labor markets (see also Autor et al. 2013*b*).

Table C.4: Robustness checks - China & NAFTA trade shock

Dependent variable: Vote on low-skill immigration policy	China		NAFTA		World	
	IM	IM-EX	IM	IM-EX	IM	IM-EX
	(1)	(2)	(3)	(4)	(5)	(6)
MBTC	-4.247***	-4.234***	-4.218***	-4.300***	-4.165***	-4.165***
	(1.388)	(1.388)	(1.394)	(1.388)	(1.389)	(1.391)
Trade shock	-0.006**	-0.006**	-0.001	0.004	-0.001*	-0.001
	(0.003)	(0.003)	(0.003)	(0.004)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5719	5719	5719	5719	5719	5719

Notes: The table analyses the robustness of MBTC to controlling for the different trade shocks. Presented estimates extend on column 5 of Table 4 reporting marginal effects at means for Probit regressions. Trade data before 1990 set to 0 for China and interpolated for NAFTA (Canada & Mexico) and World using aggregate trade flows due to no HS6 data available. Controls are state FE, vote FE, poverty share, log family income, immigration share, Hispanic share, African-American share, unemployment rate, share age 65+. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.4 Composition of immigrants

Another concern might be that the observed effect is driven by differential inflows of immigrants. Notably, both the relocation of natives into different occupations (Peri & Sparber 2009) as well as the perception of immigrants by natives might be related to immigrants' skill-level (Mayda et al. 2018; Moriconi et al. 2018). The way the MBTC variable is constructed makes it implausible that it is influenced by local migration inflows, however it might be the case that local technological change alters the composition of immigrants that move to a congressional district. This reflects an alternative mechanism

Table C.5: Robustness checks - Immigrant composition

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)	(4)	(5)
MBTC	-3.482**	-3.064**	-4.243***	-4.099***	-2.456
	(1.383)	(1.374)	(1.396)	(1.420)	(1.569)
x Immigration					-13.96**
					(6.045)
Immigration manual occupation	-0.894***				
	(0.156)				
Immigration college degree		1.142***			
		(0.215)			
Immigration unemployed			-0.537		
			(0.411)		
Immigration Hispanic				-0.112	
				(0.169)	
Controls	Yes	Yes	Yes	Yes	Yes
Observations	5719	5719	5719	5719	5719

Notes: The table analyses the robustness of MBTC to controlling for the composition of local immigration. Presented estimates extend on column 5 of Table 4 reporting marginal effects at means for Probit regressions. Controls are state FE, vote FE, poverty share, log family income, immigration share, Hispanic share, African-American share, unemployment rate, share age 65+. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

for the observed impact of MBTC on voting behavior. To rule out that the observed effect of MBTC is due to changes in the composition of immigrants in a congressional district I control not only for the overall immigrant population, but also the composition of immigration.

Column 1 of Table C.5 accounts for the share of immigrants that work in manual occupations. In line with previous evidence a higher share of immigrants that work in manual occupations reduces support of a representative for liberalizing low-skill immigration policy. Column 2 controls for the share of immigrants with a college degree and column 3 for the share of unemployed immigrants. A higher college share of immigrants has a positive effect, while higher immigrant unemployment has a negative (insignificant) impact. Column 4 controls for the share of immigrants that has Hispanic origins to account for cultural factors, which does not seem to play an important role. The effect of manual-biased technological change is unchanged across these specifications highlighting that the observed effect is driven by changes in the specialization of natives and not by altering the composition of immigrant inflows. Finally, one might expect that the effect of MBTC is strongest in areas where indeed there is a lot of immigration. Column 5 highlight that MBTC has a larger impact when there has been a lot of immigration into a congressional district. This again supports that the effect of MBTC is through labor market competition between natives and immigrants and that while status concerns if at all only play a secondary role.

D Data appendix (Online publication only)

Data coverage

IPUMS data (Ruggles et al. 2019) is available at the following geographic areas: State Economic Areas in 1950 (not including Alaska and Hawaii); County Groups in 1970 and 1980; Public Use Microdata Areas in 1990, 2000 and 2010. The national random sample covers 1% of the population in 1950 and 2010, 2% of the population in 1970, and 5% of the population in 1980, 1990 and 2000. The variables relying on the use of individual level data, i.e. the main explanatory variables requiring individual level data, are constructed based on US citizens by birth or individuals that have been naturalized and are over the age of 18. Individuals living in prisons and psychiatric institutions are excluded. For economic and non-economic variables used as controls I use data from NHGIS (Manson et al. 2019) available at the county and congressional district level. NHGIS data, while being geographically more provides less detailed variable Variables at the congressional district level from NHGIS and corresponding ones constructed from IPUMS individual records are highly correlated and results are similar when using data from IPUMS to construct controls.

Congressional district shapefiles are obtained form Lewis et al. (2013), while the remaining shapefile's geographical areas required are obtained from IPUMS and NHGIS for the geographical areas covered in the dataset. I convert data from the respective census geographical areas, denoted by subscript c, to congressional districts, denoted by d, by using population (pop_c) and area-share ($area_c$) of the census district as weights:

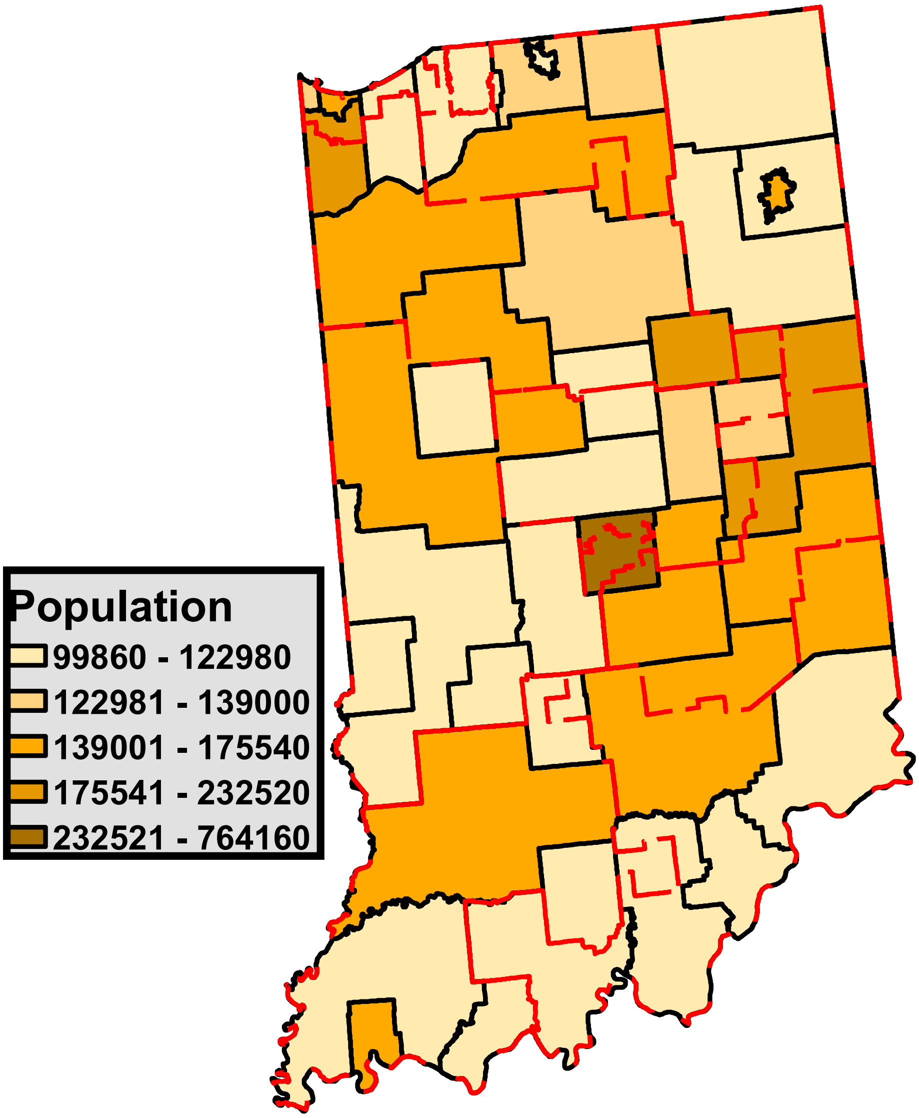
$$Var_d = \frac{\sum area_c * pop_c * Var_c}{\sum area_c * pop_c}$$

As the congressional districts are redefined based on the census three years later, I merge for example data from the 1980 census to the time period 1983-1992 (98th-102nd congress). This is illustrated in Figure D.1. In the cases where data is readily available from NGHIS at the congressional district level, I use this data. This is the case for the majority of the variables obtained from this source.

Task Content Measures for Occupations

I use the measures for manual, routine and abstract tasks inputs preformed for each census occupation code from Autor & Dorn (2013). These three task aggregates are based on the following variables in the Dictionary of Occupational Titles [US Department of Labor 1977]: (i) the manual tasks performed is based on "eye-hand-foot coordination" of an occupation; (ii) the routine task is an average of the variables, "set limits, tolerances, and standards" and "finger dexterity"; (iii) the abstract task measure is the average of "direction control and planning" and "GED Math". In the Dictionary of Occupational Titles an occupation consists of multiple tasks that are performed at a varying degree of intensity. Detailed information on the tasks measures can be found in the Appendices of Autor et al. (2003) and Autor & Dorn (2013). To account for automation altering the immigrants task composition and leading to an increased share of low-skill immigrants, as documented by Basso et al. (2017), I construct my task share measures using exclusively citizens –US born and naturalized– over the age of 25 and living outside of group quarters.

Figure D.1: Matching across geographic areas



Notes: Map illustrating the conversion of data from 1980 county groups to 98th-102nd congressional districts for the state of Indiana using the overlapping area and county population. Source: IPUMS data [Ruggles et al. 2019]

China Trade Shock

The measure of exposure to trade is constructed as follows (using China as an example as used in Autor et al. 2013*a*):

$$IP_{n,t} = \sum_{i=1}^{I} \frac{L_{n,91,i}}{L_{n,91}} \frac{TR_{t,i}^{CHN}}{L_{91,i}}$$

where for each US industry i, $TR_{t,i}^{CHN}$ is the amount of trade with China (in 2007$) in years 1991,2000 and 2010 (either defined as Imports only or as Imports minus Exports). I use 1991 as the initial year as it is the first one for which the necessary disaggregated bilateral trade data is available. For 1970 and 1980 I set $TR_{t,i}^{CHN}$ equal to zero. This assumption seems plausible as China only accounted for less than 1% of total US trade with China (Wang 2013). Trade is than adjusted by total US employment in industry. Finally, the industry specific measure of trade penetration is weighted by the share of industry employment in total employment of a district. Data collected from United States Census Bureau (1991) and UN Comtrade (1991-2010). I analogously construct the same measure for NAFTA and total US trade. These trade flows are interpolated for 1970 and 1980 using aggregate trade flows.

E Results excluded from final version (only for editor and referee)

Table E.1: Linear estimation of baseline results

Dependent variable: Vote on low-skill immigration policy

	(1)	(2)
Panel A: OLS results for Table 3		
Manual share	-0.173	-0.958***
	(0.127)	(0.189)
Controls	No	Yes
Observations	5719	5719
Panel B: 2SLS results for Table 3		
Manual share	-2.409***	-2.437***
	(0.297)	(0.550)
Controls	No	Yes
Observations	5719	5719
Panel C: OLS results for Table 4		
MBTC	-4.722***	-2.912***
	(0.937)	(0.741)
Controls	No	Yes
Observations	5719	5719

Notes: Corresponding results using OLS and 2SLS for baseline estimates presented in Table 3 and Table 4. State FE and vote FE included in all specifications. Controls are poverty share, log family income, immigration share, Hispanic share, African-American share, unemployment rate, share age 65+.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.2: Technological change, specialization and status concerns

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)	(4)
MBTC	-4.452***	-8.115***	13.10*	-4.362***
	(1.403)	(2.476)	(6.735)	(1.410)
MBTC*manual		14.01*	-138.8***	
		(7.463)	(45.29)	
MBTC*manual^2			268.8***	
			(79.75)	
Manual share	-1.516***	-1.403***	-1.529***	
	(0.445)	(0.447)	(0.449)	
MBTC*positive				2.040
				(1.330)
Controls	Yes	Yes	Yes	Yes
Observations	5719	5719	5719	5719

Notes: The table presents a interactions between MBTC and (i) the manual share and (ii) whether manual wages increased. Controls are state FE, vote FE, poverty share, log family income, immigration share, Hispanic share, African-American share, unemployment rate, share age 65+. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.3: Relationship MBTC and MSH shift-share

Dependent variable: MSH shift-share	(1)	(2)	(3)	(4)	(5)	(6)
MBTC	0.701***	0.535***	0.635***	0.698***	0.715***	0.713***
	(0.0561)	(0.0511)	(0.0475)	(0.0454)	(0.0443)	(0.0444)
State & Year FE	No	Yes	Yes	Yes	Yes	Yes
Income controls	No	No	Yes	Yes	Yes	Yes
Racial controls	No	No	No	Yes	Yes	Yes
Unemployment	No	No	No	No	Yes	Yes
Age 65+	No	No	No	No	No	Yes

Notes: Table presents the relationship between MBTC and MSH shift-share variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$