The Effect of Recent Technological Change on US Immigration Policy *

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Abstract

Did recent technological change, in the form of automation, affect immigration policy in the United States? I argue that as automation shifted employment from routine to manual occupations at the bottom end of the skill distribution, it increased competition between natives and immigrants, consequently leading to increased support for restricting low-skill immigration. I formalise this hypothesis theoretically in a partial equilibrium model with constant elasticity of substitution in which technology leads to employment polarization, and policy makers can vote on immigration legislation. I empirically evaluate these predictions by analysing voting on low-skill immigration bills in the House of Representatives during the period 1973-2014. First, I find evidence that policy makers who represent congressional districts with a higher share of manual employment are more likely to support restricting low-skill immigration. Second, I provide empirical evidence that representatives of districts which experienced more manual-biased technological change are more likely to support restricting low-skill immigration. Finally, I provide evidence that this did not affect trade policy, which is in line with automation having increased employment in occupations exposed to low-skill immigration, but not those exposed to international trade.

JEL Classifications: F22; J61; K37; O30
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1 Introduction

Immigration and immigration legislation have been a key area of policy debate in the United States since independence (Hatton & Williamson 2005). The US House of Representatives voted on more than a dozen bills regulating immigration since 1970 alone. During the same period the number of immigrants to the US increased from a relatively low level, when compared to the age of mass migration, to numbers not observed before.

Public views on immigration differ greatly between individuals. For example, one important determinant is competition with immigrants in the labour market. Low-skilled workers are considerably more likely to prefer limiting immigrant inflows than their high-skilled counterparts (Scheve & Slaughter 2001; Mayda 2006; O'Rourke & Sinnott 2006).[1] For political incumbents, casting roll-call votes ranks among the most visible activities to take clear policy positions and communicate them to their constituents (Mayhew 1974). Consistent with this, Facchini & Steinhardt (2011) find that the degree of potential labour market competition between natives and low-skill immigrants explains representatives' voting behaviour on immigration policy.[2] This raises the question, whether recent technological change, in the form of automation (see Autor et al. 2003; Acemoglu & Autor 2011; Autor & Dorn 2013; Goos et al. 2014), has affected US immigration policy through shifting employment from routine to manual occupations, that face more competition from low-skill immigrants. In particular, the relative complementarity of automation with manual compared to routine tasks at the bottom end of the skill distribution, i.e. manual-biased technological change, appears crucial here, while the corresponding effect of automation on demand for abstract relative to routine tasks at the top end of the skill distribution should not influence competition between natives and low-skill immigrants.[3]

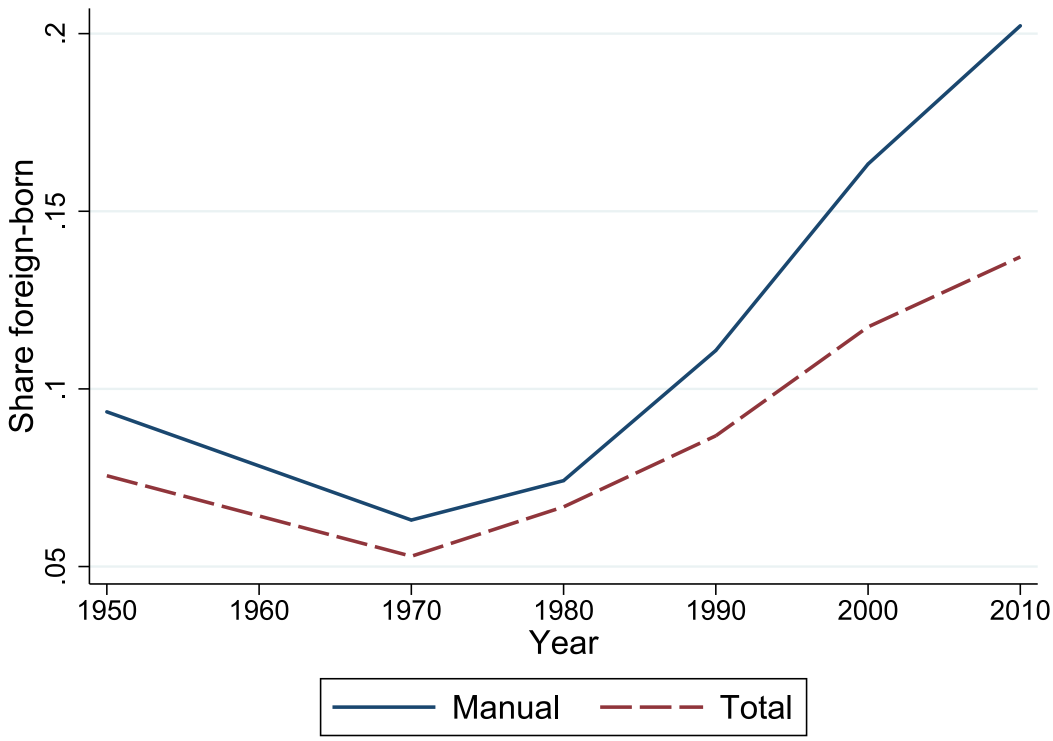
This paper studies the role of technological change in the making of immigration policy. In particular, I study (i) the extent to which local manual employment is related to representatives being in favour of stricter low-skill immigration policies, and (ii) whether recent technological change affected the voting behaviour of representatives.

[1] The overall impact of immigration on local wages has been a vividly debated issue. Most of this literature is reviewed in Dustmann et al. (2016) and O'Rourke (2019). However, that immigration depressed wages at the lower end of the skill distribution has been well documented by a set of recent papers (e.g. Dustmann et al. 2013; Mandelman & Zlate Forthcoming; Allen et al. 2018). Burstein et al. (2020) also highlight that the impact of competition from immigration on natives is much larger in non-traded compared to traded sectors.

[2] Note that I use the term native to refer to individuals with the right to vote (including previous cohorts of immigrants), while immigrant refers to individuals that have migrated to the US (legally or illegally), but do not have the right to vote.

[3] The latter effect of higher complementarity of automation with abstract compared to routine tasks might influence competition between natives and high-skill immigrants if these are substitutes in abstract occupation. However, as high-skill immigration is less contested and the House of Representatives has only voted on three bills focussing on this issue I will focus exclusively on the effect of recent technological change on low-skill immigration legislation.

Figure 1: Share of migrants in manual employment 1950-2010

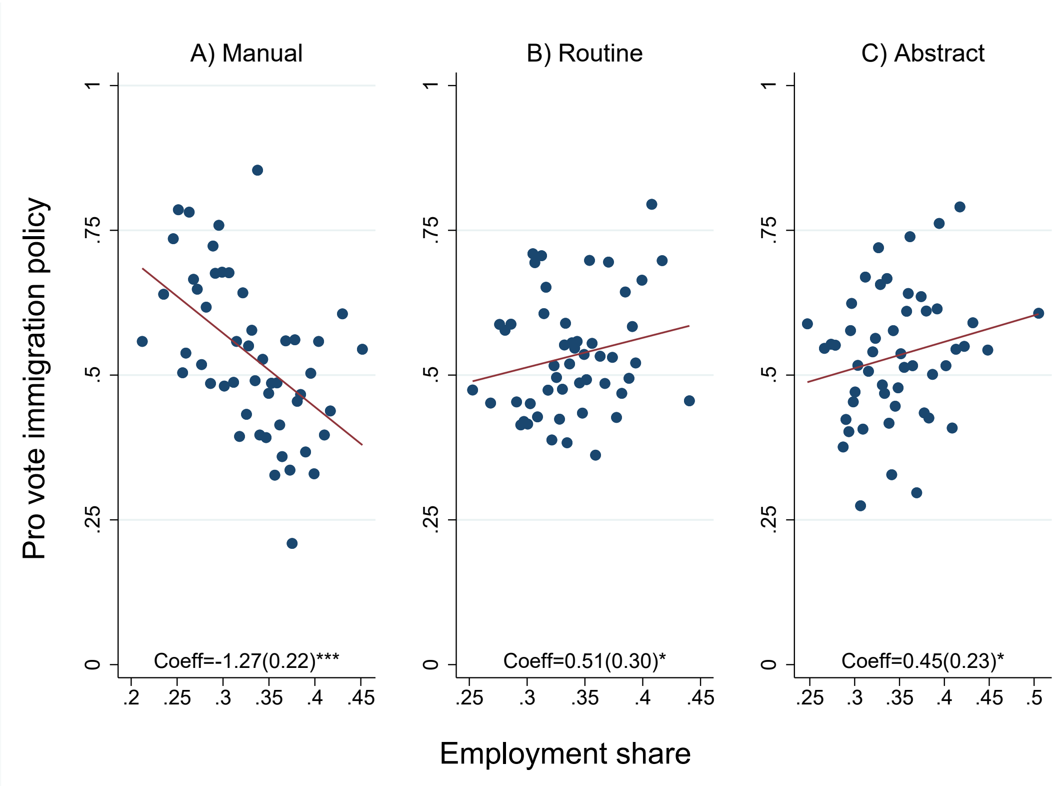


Notes: The figure illustrates the share of foreign-born individuals in manual employment in total US manual employment from 1950 to 2010. It also depicts the share of foreign-born individuals in the total US population. Manual employment is defined based on an occupation being in the top-33% of manual task intensity in 1980. A detailed description on the construction of manual employment and task intensity is provided in Section 3.

I examine these questions theoretically and empirically. First, I formalise the hypothesis that automation, which led to a shift from manual to routine employment, increased competition between natives and immigrants, and consequently lead to increased support for restricting low-skill immigration in a theoretical model. Second, I empirically evaluate the theoretical predictions by analysing 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.

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 reflects 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 1 highlights the consistent over-representation of foreign-born individuals in manual occupations, like agricultural, construction and low-skill services. Accordingly, natives in routine employment experience little competition from low-skill immigrants, while natives in manual employment are in strong competition with low-skill immigrants. This is also supported by evidence that natives move into jobs more intensive in communication-language tasks due to immigration (see the seminal paper by Peri & Sparber 2009).

Figure 2: Employment tasks and voting on immigration policy

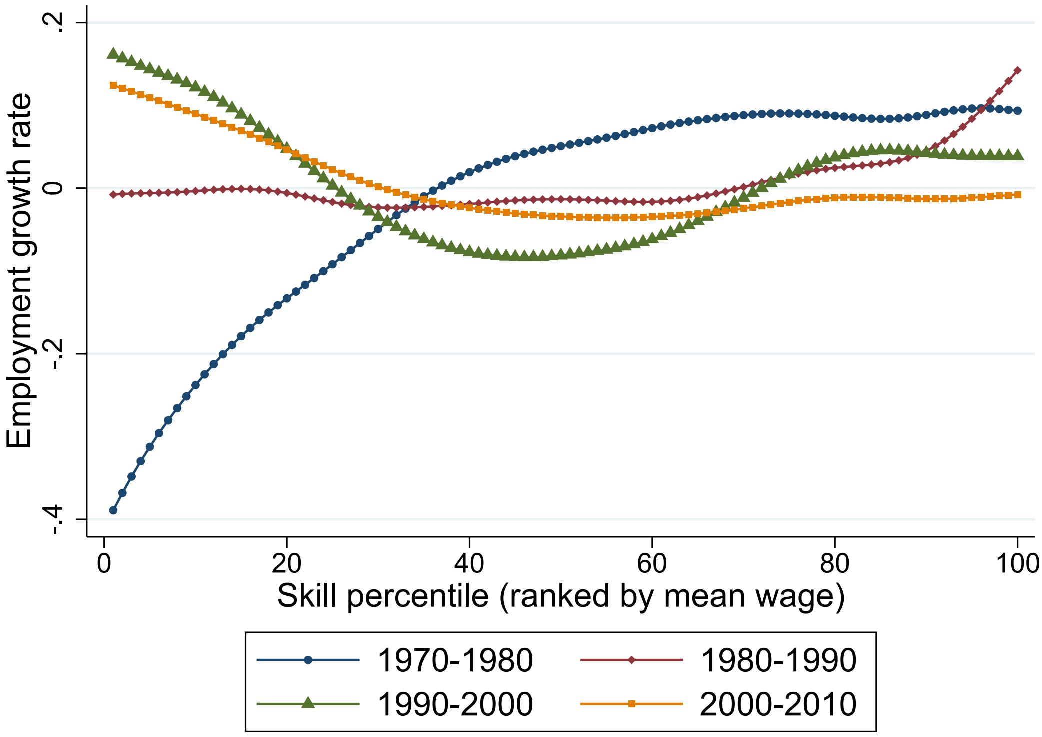


Notes: Employment share of natives across tasks in 1980 and voting on liberalizing low-skill immigration between 1983 and 1992 across corresponding congressional districts. Classification based on occupations being in the top 33% of task intensity at the national level. Employment data is taken from the census and matched to the respective votes reported in Table A.1. A detailed description on the construction of employment shares is provided in Section 3. Overall differences across votes subtracted. N=1673 in 50 bins.

If labour market competition between natives and low-skill immigrants in manual employment is indeed greater, one would expect this to affect policy preferences. Accordingly, 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 favour of liberalizing low-skill immigration. In line with this, Figure 2 shows that representatives of congressional districts that had a higher manual employment share in 1980 were more likely to vote in favour of restricting low-skill immigration 1983-1992, while the opposite is the case for representatives in a district with a high routine or abstract employment share.

Recent technological change in the US, in particular automation (see Autor et al. 2003; Acemoglu & Autor 2011; Autor & Dorn 2013; Goos et al. 2014), led to consider-

Figure 3: US employment growth by skill percentile



Notes: The figure displays smoothed US employment growth rates ranked by skill percentile for decades 1970-2010. The figure highlights the transition from skill-biased technological change (1970-1980) to employment polarization (1980-2010). The 2000s might even be described as unskilled biased. Employment growth rates are measured as the deviation from the average employment growth rate in the respective decade. The skill percentile of occupations is constructed based on the mean hourly wage in 1980.

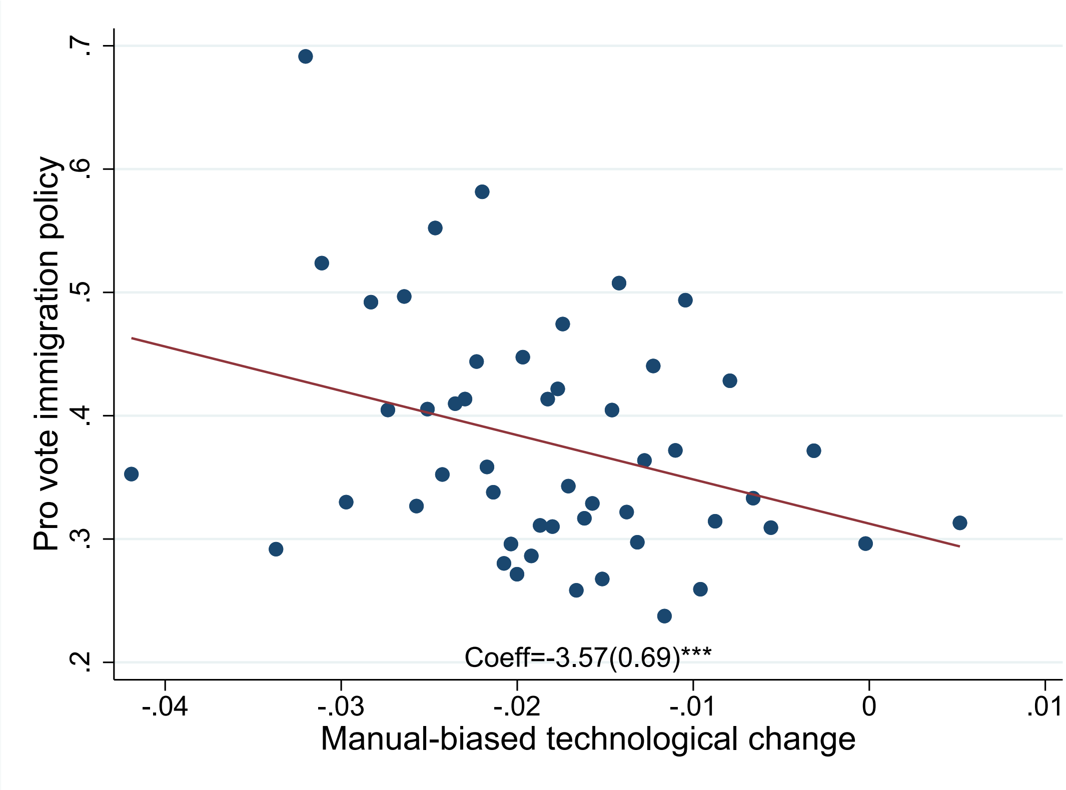
able labour market polarization in which employment declined in routine occupations, but expanded in manual ones at the bottom end of the skill distribution.[4] Figure 3 illustrates this recent change in US employment growth along the skill distribution from 1970-2010. This suggests that while up to 1990 employment growth mostly occurred at the upper end of the skill distribution, since 1990 employment growth increased at the bottom end. This would suggest that until 1990 the share of natives in competition with low-skill immigrants was decreasing, while afterwards it increased again. This in turn should affect representatives votes on immigration policy. In general, one would expect that representatives become more likely to vote in favour of restricting low-skill immigration in areas where technological change was more favourable to manual employment increasing through the share of natives in competition with low-skill immigrants.[5] This is

[4] 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.

[5] This might not necessarily be due to natives moving from routine occupations, which are usually communication-language task intensive, to manual occupations, but rather by making routine occupations

highlighted in Figure 4 which shows that representatives from congressional districts that experienced more manual-biased technological change are more likely to vote in favour of restricting low-skill immigration.[6] Manual-biased technological change is measured as the change in the manual wage premium—the wage in manual occupations relative to other occupations—by industry at the national level since 1950 interacted with the initial industry structure of a congressional district in 1950. Accordingly, this measure proxies for technological change leading to a change in demand for manual tasks relative to other tasks across congressional districts.

Figure 4: Technological change and migration voting



Notes: The figure displays the relationship between manual-biased technological change and support for liberalizing low-skill immigration policy across congressional districts. The manual-biased technological change variable measures the complementarity of recent technological change that occurred since 1950 with manual employment across congressional districts. A detailed description on the construction of the manual-biased technological change variable is provided in Section 3. Overall differences across votes subtracted. N=5719 in 50 bins.

This outlined pattern is formalized in a partial equilibrium model in which technological change leads to employment polarization, low-skill immigrants compete with natives

less attractive for natives initially working in manual occupation to relocate towards due to increased immigration pressure (see also Peri & Sparber 2009).

[6]Notably in Section 5 I will even provide evidence that exposure to manual-biased technological change altered the voting behaviour of the same elected representative and not just had an effect through the replacement of pro- with anti-immigration representatives (i.e. reflecting an adjustment in voting behaviour along the intensive margin).

in manual employment and policy-makers respond to their constituencies' preferences towards immigration. First, my model predicts that in districts with a higher manual employment share the representative is more likely to support restricting low-skill immigration. Second, technological change which is complementary to manual tasks—for example the case of automation—increases the support for restricting low-skill immigration.[7]

I test these two theoretical predictions empirically. I find that a one percentage point higher manual employment share in a congressional district makes it 3.7 percentage points less likely that a representative votes in favour of liberalizing low-skill immigration. Further, I construct a measure of manual-biased technological change by looking at the national level change in the manual wage premium by industry over time, exploiting the fact that the geographic distribution of industries is predetermined and that the possibility to implement technological changes differs across industries. I find that a one percentage point increase in the manual wage premium increases the likelihood of a representative voting in favour of restricting low-skill immigration by 3.9 percentage points. This is consistent with the theoretical prediction that automation has made it less likely that representatives vote in favour of liberalizing low-skill immigration policy. Notably, I do not find any corresponding effect of technological change on voting on trade liberalization.[8]

My findings hold when considering a set of alternative explanations that might be correlated with exposure to manual-biased technological change. A first concern I rule out is that areas with more low-skilled natives, that are also more averse to immigration (see e.g. Mayda 2006; Hainmueller & Hiscox 2010; Facchini & Steinhardt 2011), are more exposed to manual-biased technological change at the same time as immigration to the US starts to rise. A second concern I rule out is that the observed effect is driven by the composition of immigrants (see Mayda et al. 2018; Moriconi et al. 2018) into certain areas that might be influenced by changes in technology. A third concern that can be ruled out is that the effect is associated with increases in political polarization and changes in the elected politicians. A final concern I rule out is that the effect is driven by a correlation between changes in technology and rising trade exposure across occupations and labour markets (see Colantone & Stanig 2017; Autor et al. 2020).

My paper contributes to the literature in the following way. First, several papers have studied the economic determinants of attitudes towards immigrants and immigration

[7] I focus in the empirical analysis on manual-biased technological change, rather than just automation for the following reasons: (i) the nature of technological change varies considerably across the time period 1970-2010 with automation accelerating only at the end and (ii) the key driving force is the shift into or out of manual employment caused by technological change which is plausibly better proxied for by changes in the manual wage premium than measures of automation as the latter also leads to a shift from routine to abstract employment at the top end of the skill distribution creating considerable noise.

[8] Autor et al. (2013*b*) note that exposure to automation and Chinese import competition are largely uncorrelated and affect different local labour 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 appear largely non-tradable and should not be exposed to foreign competition.

policy-making in the US. In particular, the role of substitutability between migrants and natives in the labour market (see Goldin 1994; Gonzalez & Kamdar 2000;Scheve & Slaughter 2001; Fetzer 2006; Mayda 2006; Facchini & Mayda 2008; Hainmueller & Hiscox 2010 Facchini & Steinhardt (2011) and Conconi et al. 2020).[9] I add to this literature through emphasizing the role played by key tasks performed within occupations and their role in shaping the substitutability between natives and immigrants and consequently voting on immigration legislation.

Second, it adds to an emerging literature focussing on how economic shocks affect support for nativist and protectionist political parties and policies. While most attention here has been on the political consequences of rising Chinese trade exposure in the US and Europe (see e.g. Feigenbaum & Hall 2015; Che et al. 2016; Colantone & Stanig 2017; Colantone & Stanig 2019; Autor et al. 2020), some recent studies have started to look at the impact of technological change. Frey et al. (2018) find that areas affected by the implementation of more industrial robots were more likely to vote for Donald Trump in the 2016 US Presidential Election. Gallego et al. (2018) find that in the UK individuals in industries that introduced more information and communications technology are more likely to support the UK Independence Party. However, they also highlight that the winners from automation were more likely to support mainstream parties. My paper contributes to this literature in the following ways: It focusses on the effect of technological change on policy outcomes rather than individual attitudes ot support for parties.[10] This seems important as an increase in support for extremist parties might not necessarily translate into changes in policy if these parties remain at the fringes. Also, I highlight that the effect of recent technological change increased support for restricting low-skill immigration, but did not have a corresponding effect on support for trade liberalization. This seems in line with automation having increased employment in occupations exposed to low-skill immigration, but unaffected by foreign competition.[11]

The remainder of the paper is organized as follows. Section 2 presents a theoretical framework. Section 3 describes the data and Section 4 outlines the empirical strategy and presents my main results. Section 5 evaluates the sensitivity of the key results and presents additional findings. Finally, Section 6 concludes the paper.

[9] Closely related to this Otto & Steinhardt (2014) and Halla et al. (2017) emphasize that inflows of immigrants increase support for anti-immigration parties with Mayda et al. (2018) and Moriconi et al. (2018) emphasizing the differential impact between inflows of low-skill versus high-skill immigrants with the former leading to increased support for anti-immigration parties, while the latter has the opposite effect.

[10] Many bills were highly contested and decided by as little as 5 votes out of 429. So while my outcome is the voting behaviour of a congressional district's representative the estimated effect size for manual-biased technological change suggests this played an important role for overall outcomes in many cases.

[11] That automation increased employment mainly in non-tradable sectors, rather than traded ones, might also have been crucial for the observed effect on policy outcomes as recent evidence by Burstein et al. (2020) suggests that local labour market competition between natives and immigrants is much larger in the former set of occupations than the later.

2 Theoretical Framework

This section aims at providing a theoretical framework to illustrate how employment polarization caused by technological change (see e.g. Autor et al. 2003 and Autor & Dorn 2013) can lead to a change in immigration policy. To do this, I set up a partial-equilibrium model with constant elasticity of substitution of factor inputs (manual, routine, abstract) in the production process, individuals choosing their level of education and policy-makers deciding on the supply of immigrants based on their constituents' preferences.

2.1 Production

Consider $d = 1, ..., D$ economies, each representing one US congressional district (with D representing all congressional districts). Each of these economies is characterized by a representative firm. Representative firms vary by their routine task automating technology ($Z_{d,t}$) and fixed production technology (α_d, β_d). I assume $Z_{d,t}$ to vary across (i) time, characterizing general advances in the automation of routine tasks, and (ii) districts, reflecting that there is some idiosyncratic variation across representative firms in the possibility to automate routine task (e.g. differences across industries). Further, the differences in α_d and β_d create local comparative advantages, which leads to fixed differences across districts in occupational specialisation across manual, routine and abstract intensive tasks. Firms combine labour inputs A, R and M in a constant elasticity of substitution production function to produce a final good Y:

$$Y = \left(\alpha_d M^{\frac{\theta-1}{\theta}} + \beta_d (Z_{d,t} R)^{\frac{\theta-1}{\theta}} + (1 - \alpha_d - \beta_d) A^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}} \tag{1}$$

The parameter θ measures the elasticity of substitution (being complements, i.e. $\theta < 1$) between the three inputs. A is the amount of abstract tasks performed. R is the amount of routine tasks. M is the amount of manual tasks performed. A, R, M are all supplied by the labour force while $Z_{d,t}$ reflects the tasks performed by automation technology.[12] Given $Z_{d,t}$ at time t each firm solves the following problem to maximise output:

$$\max_{M,R,A} Y - w_M M - w_R R - w_A A \tag{2}$$

Under the assumption that markets are perfectly competitive, the return on factor inputs will be at equilibrium equal to their marginal productivities. Consequently, com-

[12] Classical skill-biased technological change could be characterized by $Z_{d,t}$ augmenting M instead of R. In this case it is analogous to show that policy-makers become more favourable towards low-skill immigration policy due to the decline in the manual employment share as technology is substituting instead of complementing manual labour inputs.

bining the first order conditions of the optimal choice problem of the different labour inputs gives the manual($\hat{w}_M$) and abstract ($\hat{w}_A$) task wage premiums:

$$\hat{w}_M = \frac{w_M}{w_R} = \frac{\alpha_d}{\beta_d}\left(\frac{R}{M}\right)^{\frac{1}{\theta}} Z_{d,t}^{\frac{1-\theta}{\theta}} \tag{3}$$

$$\hat{w}_A = \frac{w_A}{w_R} = \frac{1-\alpha_d-\beta_d}{\beta_d}\left(\frac{R}{A}\right)^{\frac{1}{\theta}} Z_{d,t}^{\frac{1-\theta}{\theta}} \tag{4}$$

Themanual and abstract task wage premiums are increasing in $Z_{d,t}$ leading to the polarization of wages due to technology being complementary to manual and abstract inputs in the production process, while substituting for routine ones. This affects the employment decision of individuals and leads to employment polarization.

2.2 Individuals' occupation choice

Each congressional district is populated by a set of native individuals. Individuals i have ability levels $\mu_i \geq 1$, distributed $F(\mu_i)$. Given $Z_{d,t}$ at time t individuals face the following occupation choices: (i) they can either work in manual occupations, (ii) obtain some education equivalent to a high-school degree/vocational training required for routine occupations, or (iii) obtain a college-degree to work in abstract occupations. Education costs are proportional to consumption, decreasing in μ_i and increasing in the complexity of the occupation. When an individual decides to obtain the level of education which is required for a routine occupation, the individual's consumption is adjusted by the learning cost $g_R(\mu_i) \in (0,1)$. Further, an individual can decide to obtain the level of education required for an abstract occupation with the additional learning cost being $g_A(\mu_i) \in (0,1)$. For both types of education $T \in (R, A)$ the cost is decreasing in ability $g'_T(\mu_i) > 0$. Consequently, consumption of individuals performing manual tasks is $c_M = w_M$; individuals performing routine tasks consume $c_{i,R} = g_R(\mu_i)w_R$ and individuals performing abstract tasks consume $c_{i,A} = g_R(\mu_i)g_A(\mu_i)w_A$. Given the learning costs, equilibrium wages for manual, routine and abstract occupations are ordered accordingly $w_A > w_R > w_M$. The education decision of individuals follows the respective cut-off conditions:

$$g_R(\mu_R^*) = \hat{w}_M = \frac{w_M}{w_R} \tag{5}$$

$$g_A(\mu_A^*) = \frac{1}{\hat{w}_A} = \frac{w_R}{w_A} \tag{6}$$

Consequently, individuals take up the following occupations depending on their ability; (i) manual if $\mu_i \in (1, \mu_R^*)$, (ii) routine if $\mu_i \in (\mu_R^*, \mu_A^*)$ and (iii) abstract if $\mu_i \in (\mu_A^*, \infty)$.

The total supply of abstract, routine and manual tasks by natives in the economy in district d at point t is:

$$
\begin{aligned}
A &= \int_{\mu_A^*}^{\infty} f(\mu_i)di \\
R &= \int_{\mu_R^*}^{\mu_A^*} f(\mu_i)di \\
M_N &= \int_{1}^{\mu_R^*} f(\mu_i)di
\end{aligned}
\tag{7}
$$

The subscript N denotes the aggregated manual tasks supplied by natives as through immigration the overall supply of manual tasks can be increases. Tasks supplied by foreigners are denoted with subscript F, i.e. $M = M_N + W_D M_F$. W_D is the nationwide low-skill immigration policy either allowing low-skill immigration ($W_D = 1$) or restricting it ($W_D = 0$). $Z_{d,t}$ is the only factor in the model changing exogenously across t which leads to a reallocation of labour across sectors between periods t and $t+1$ in a congressional district. Formally, thresholds μ_R^* and μ_A^* change with regards to technology in the following way:[13]

$$
\frac{\partial \mu_R^*}{\partial Z_{d,t}} = g_R^{-1} \left(\frac{(1-\theta)\alpha_d}{\theta \beta_d} \left(\frac{R}{M} \right)^{\frac{1}{\theta}} Z_{d,t}^{\frac{1-2\theta}{\theta}} \right) > 0 \tag{8}
$$

$$
\frac{\partial \mu_A^*}{\partial Z_{d,t}} = g_A^{-1} \left(\frac{(\theta-1)\beta_d}{\theta(1-\alpha_d-\beta_d)} \left(\frac{A}{R} \right)^{\frac{1}{\theta}} Z_{d,t}^{-\frac{1}{\theta}} \right) < 0 \tag{9}
$$

This highlights that when technology increases, a higher share of individuals decide to work in manual and abstract occupations compared to routine occupations. This is because the marginal return of routine tasks compared to manual tasks decreases, while the marginal return of abstract tasks compared to routine tasks increases.

[13] Analogously to Basso et al. (2017) and Mandelman & Zlate (Forthcoming) a higher amount of low-skill immigrants M_F, through changing wages, affects the education decision leading to less natives in manual occupations. Notably, the expectation about the number of immigrants does in general not change when a policy change of the local representative occurs. This only occurs (for all districts) if the pivotal representative is expected to change his vote. In turn, this will lead to an additional reallocation of locals across tasks. In this case, the reallocation effect of technology from routine towards manual tasks is even stronger (due to $\frac{\partial M}{\partial Z_{d,t}} < 0$).

2.3 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 work in manual occupations.[14] For this reason a change in low-skill immigration policy W_D is equivalent to an increase or decrease in the supply of aggregate manual tasks. In each period t the politician votes on setting low-skill immigration policy W_D.[15] Accordingly, an increase in a factor of production decreases the wage paid for the factor itself while increasing the wage of the other factors of production:

$$\frac{\partial w_M}{\partial M_F} = -\frac{w_M(w_R R + w_A A)}{\theta M Y} < 0 \tag{10}$$

$$\frac{\partial w_R}{\partial M_F} = \frac{w_R w_M}{\theta Y} > 0 \tag{11}$$

$$\frac{\partial w_A}{\partial M_F} = \frac{w_A w_M}{\theta Y} > 0 \tag{12}$$

This highlights that individuals working in routine and abstract task intensive occupations gain from low-skill immigration while individuals working in occupations intensive in manual tasks lose out from low-skill immigration. I assume the vote of a politician on low-skill immigration policy W_d is based on a median-voter equilibrium as described by

[14] The fact that low-skill immigrants supply manual tasks more intensively than natives, as shown in Figure 1, has also been highlighted by Basso et al. (2017).

[15] I model this as a binary choice for representatives between having immigration or not to reflect that when voting on a final bill in the house of representatives they are only able to vote "yes" or "no", but cannot vote for their preferred level of immigration. This binary setup also corresponds to the outcome variable of interest in the empirical analysis.

Downs (1957). Accordingly, the politician will focus on the effect immigration has on the median voter, characterized by the ability level $\bar{\mu}$:[16]

$$W_d = \begin{cases} W_d = 0 \quad if \quad \bar{\mu} \in (1, \mu_R^*) \\ W_d = 1 \quad if \quad \bar{\mu} \in (\mu_R^*, \mu_A^*) \\ W_d = 1 \quad if \quad \bar{\mu} \in (\mu_A^*, \infty) \end{cases} \tag{14}$$

Finally, all the votes are summed up setting the new national immigration policy:

$$W_D = \begin{cases} W_D = 0 \quad if \quad \frac{\sum W_d}{D} < \frac{1}{2} \\ W_D = 1 \quad if \quad \frac{\sum W_d}{D} > \frac{1}{2} \end{cases} \tag{15}$$

The key element for the decision of the representative to be in favour of restricting low-skill immigration is the size of the manual share of natives in a congressional district, which depends on two underlying factors; (i) the fixed local comparative advantage and (ii) technological change complementary to manual tasks. Accordingly, the spatial equilibrium of the model provides two main empirical implications that I will test in Section 4:

1. Higher α_d: Representatives of districts that have a fixed comparative advantage in manual task intensive production, and for this reason a higher share of natives in manual occupations, will be more likely to vote in favour of restricting low-skilled immigration.

2. Increase in $Z_{d,t}$: Manual-biased technological change, through increasing the wage premium for manual tasks, will make it more likely that a representative will vote in favour of restricting low-skilled immigration.

Two elements omitted from the model deserve some additional consideration. First, the assumption that natives are not mobile across regions. Allowing for internal migration in my set-up would lead to similar results as regions being more strongly affected by technological change would attract more abstract and manual task intensive individuals, while areas with lower levels of technological progress would observe an out-migration of those groups. This would not change the association between technology and the voting behaviour. However, if only high-skilled labour is mobile at the local level, it might be observed that, in areas with high rates of technological change, the manual employment

[16] One can simply extend this to allow for an orthogonal dimension of immigration that influences a representatives decision that varies across congressional districts d. For example, $p_d \in [0, 1]$ is the share of individuals prioritizing other factors over economic gains and $c_d \in [0, 1]$ is the share of individuals being in favour of restricting immigration based on these other reasons in d. Accordingly, the representative votes on low-skill immigration based on his constituency's preferences in the following way:

$$W_d = \begin{cases} W_d = 0 \quad if \quad p_d c_d + (1 - p_d)\frac{M_N}{M_N + R + A} > \frac{1}{2} \\ W_d = 1 \quad if \quad p_d c_d + (1 - p_d)\frac{M_N}{M_N + R + A} < \frac{1}{2} \end{cases} \tag{13}$$

share is decreasing. This would lead to a local representative in a district subject to high level of technological progress becoming more favourable towards liberalizing low-skill immigration policy. The nationwide effect between technology and voting behaviour would remain the same, while local measurement would be biased against my hypothesis. However, labour mobility mitigating local economic shocks is also faced by other papers (e.g. the local differences in exposure to Chinese trade Autor et al. 2013*a*), where there is little evidence of adjustment through internal migration of low-skilled workers.

Second, I assume immigrants are split equally across areas. However, it appears possible that immigrants select into districts more strongly affected by automation (see e.g. Basso et al. 2017; Mandelman & Zlate Forthcoming). This might slow natives' reallocation from routine to manual occupations. Accordingly, it is crucial to observe the share of manual occupations in native rather than in total employment to correctly observe attitudes towards low-skill immigration induced by natives' competition with them. In addition, local wages for different occupations are not fully representative of the effect of technological change. I circumvent this issue in the empirical part of the paper by exploiting the quasi-fixed local industry mix and the within industry specific technological change at the national level over time.

3 Data

I use US house of representatives roll call data from Poole & Rosenthal (2000) to obtain information on the voting behaviour of legislators for 17 bills focussing on immigration policy between 1973 and 2014, updating the list of immigration bills identified by Facchini & Steinhardt (2011). Following their methodology, I use bills that focus on legal and illegal immigration, which are most directly linked to the inflow of foreign labour. Furthermore, 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. A full list of bills is presented in Table A.1 of the Appendix. I code these bills into primarily focussing on low-skill immigration or high-skill immigration legislation and bills being in favour or against increasing the number of immigrants. I exclude bills coded as relating to high-skill immigration from the main analysis as they, in contrast to low-skill immigration bills, should be unaffected by manual-biased technological change as it does not impact natives' competition with high-skill immigrants.

I combine the voting data with individual level economic information matched to congressional districts from the Census Integrated Public Use Micro Samples [IPUMS-USA; Ruggles et al. 2019].[17] The most rigorous way of testing the hypothesis that manual-

[17]IPUMS data 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

biased technological change influences policy-makers to tighten immigration policy would be by identifying when the introduction of new technologies leads to the median voter changing his occupation from routine or abstract employment to manual employment. Unfortunately, technological change $Z_{d,t}$ and the median voter identified by ability μ_i are unobservable. But as data on individual wages and occupations and their respective task intensity is available, it is possible to construct measures of the overall task intensity as well as changes in the wage premium for a certain task across congressional districts. I combine the IPUMS data on individuals' occupations with information on manual, routine and abstract task intensity of occupations in 1980 from Autor & Dorn (2013) denoted $T_{i,80} = \{M|R|A\}$.[18] However, occupations vary in their overall task content. For this reason, I estimate the share of an occupation's wage that is paid for the manual tasks performed to obtain a measure of relative task intensity. I first use a hedonic regression on the hourly wage to price the manual, routine and abstract tasks in 1980, with the estimated wage rate of a respective task denoted $\hat{w}_{T,80}$.[19] After this I divide the estimated wage paid for manual tasks performed by the total estimated wage paid for all tasks. Accordingly, the manual wage share for individual i is:

$$MW_{i,80} = \frac{\hat{w}_{M,80} M_{i,80}}{\sum\limits_{T=\{M,R,A\}} \hat{w}_{T,80} T_{i,80}} \tag{16}$$

with $MW_{i,80}$ being constant across individuals and time for each occupation. I use the estimated wage share related to manual tasks $MW_{i,80}$ in an occupation as the measure of relative manual task intensity, ordering all occupations along their relative task intensities. Appendix Table A.2 provides information on the top-10 manual, routine and abstract intensive occupations by employment in 1980. Following this, I construct the manual employment share across congressional district and years based on the share of individuals

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. See Figure C.1 in the Appendix for more details on the conversion of data across geographical areas. For economic and non-economic variables used as controls I use data from Manson et al. (2019) available at the congressional district level. Variables at the congressional district level from Manson et al. (2019) and corresponding ones constructed from Ruggles et al. (2019) individual records are highly correlated and results are similar when using data from Ruggles et al. (2019) to construct controls.

[18] Appendix C provides additional information on the different tasks.

[19] 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 exclude the top and lowest 1% of observations for the hourly wage data in case reported hours (usually for last week) are not representative of weekly hours worked over the whole year.

that hold an occupation that was in the top 33% of manual task intensive occupations at the national level in 1980 (analogous to the threshold used in Autor & Dorn 2013):

$$MSH_{d,t} = \frac{\sum_{i=1}^{I} L_{d,t,i} * 1[MW_{i,80} > MW_{i,80}^{P66}]}{\sum_{i=1}^{I} L_{d,t,i}} \tag{17}$$

The considerable variation in the manual employment share across the US in 1980 is illustrated in Figure A.1 in the Appendix.

To investigate whether technological change has influenced the voting behaviour of representatives I need to measure the complementarity/substitutability of technological change with manual tasks. I do this by exploiting changes in the manual wage premium across congressional districts. This is based on the assumption that if technological change is complementary to manual tasks, i.e. increasing demand for them relative to other tasks, this will raise the relative wage paid for manual tasks compared to other tasks.

A key obstacle is that local supply shocks in manual tasks, for example through immigration, led to a change in the manual wage premium that is not related to demand changes due to manual-biased technological change. Accordingly, 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 due to technological change but be unaffected by local supply shocks. For this, I exploit the fact that the possibility of implementing new technologies varies by industries and that this is determined at the national level. Accordingly, I construct the following Bartik-type variable ($MBTC_{d,t}$) that measures the local manual-biased technological change experienced by a congressional district through combining industry-level changes in the manual wage premium at the national level since 1950 with the pre-existing distribution of industries across areas:

$$MBTC_{d,t} = \sum_{j=1}^{J} EmpSH_{j,d,1950} \times \Delta \left(\frac{\bar{w}_{M,j,t}}{\bar{w}_{j,t}} \right) \tag{18}$$

$EmpSH_{j,d,1950}$ describes the employment share of industry $j \in j, ..., J$ in 1950 for a congressional district. I interact this with the industry manual wage premium, which I construct by dividing the median hourly wage in the US among native workers in industry j working in manual occupations ($\bar{w}_{M,j,t}$) by the median wage of industry j ($\bar{w}_{j,t}$) in decade t.[20] A potential source of variations in the manual wage premium between industries—not

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

related to technological change—are time-fixed industry characteristics. To account for this unobserved heterogeneity I subtract the industry specific manual wage premium in the initial year 1950 from the observed manual wage premium in decade t: $\Delta\left(\frac{\bar{w}_{M,j,t}}{\bar{w}_{j,t}}\right) = \frac{\bar{w}_{M,j,t}}{\bar{w}_{j,t}} - \frac{\bar{w}_{M,j,1950}}{\bar{w}_{j,1950}}$. This Bartik-type variable is a logical proxy for the varying degree of substitutability/complementarity of technological change with manual employment across districts assuming that intra-industry wage changes reflect changes in demand for certain tasks and are driven by the adoption of new technologies (see Katz & Murphy 1992; Krueger 1993). Crucially, focussing on the intra-industry change in the wage premium is not related to overall changes in demand or foreign competition faced by an industry, but only reflects relative changes in the demand for manual tasks compared to other tasks within an industry's production function.

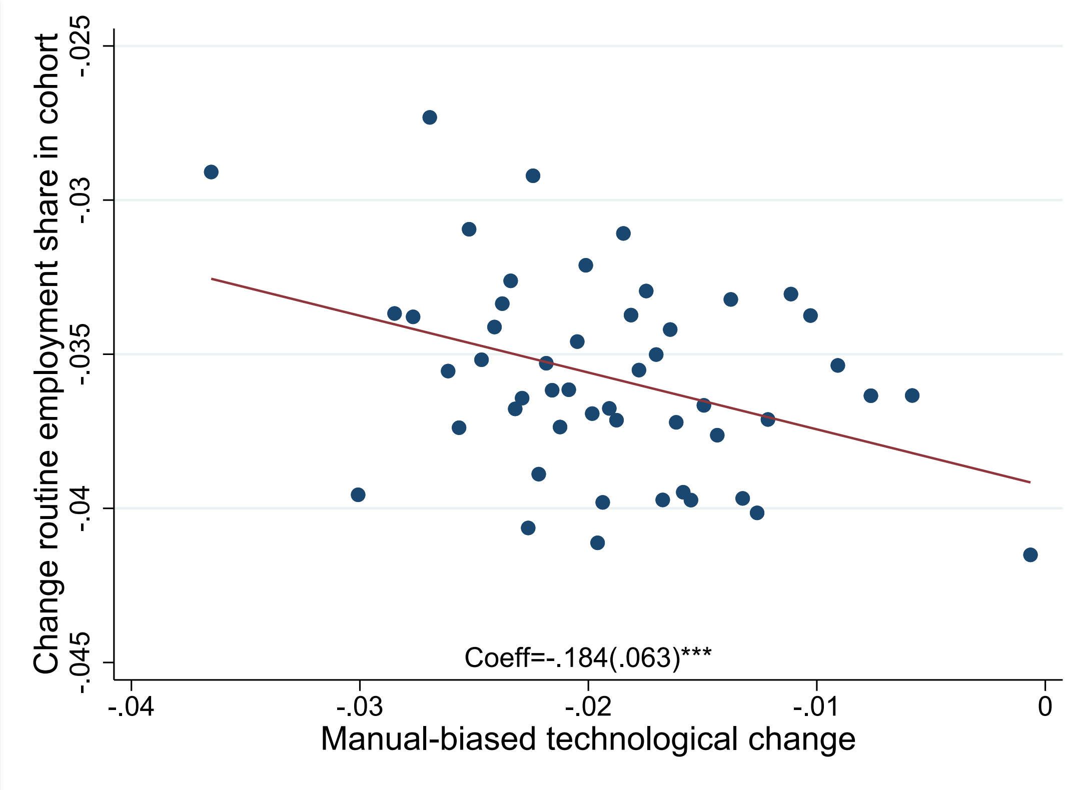
It should be highlighted that while the outlined measure is not affected by changes in the trade in goods at the industry level, recent advances in transportation and communications technology have made it increasingly possible to separate tasks in time and space within a production process (see e.g. Feenstra & Hanson 1999; Grossman & Rossi-Hansberg 2008). This "offshoring" of tasks within the production process certainly could affect the relative price of manual compared to other tasks within an industry at the national level and will accordingly be captured in my measure of manual-biased technological change. Importantly, this is in line with the aim of the measure to capture any type of technological change biased towards manual tasks compared to other tasks. Here, it is however important to point out that while offshoring had some important effects on US labour markets, the results in Autor & Dorn (2013) suggest that offshorability did not play a role in the growth in demand for manual tasks at the bottom end of the skill distribution. So, while feasible, it does not appear to be the case that manual tasks are offshored at any different rate than routine and abstract tasks.

Accordingly, congressional districts in which technological change was more biased towards manual task, e.g. due to automation, should observe a greater decline in routine employment. Figure 5 underlines this, it illustrates that in congressional districts that experienced more manual-biased technological change, more individuals leave routine employment.[21] Automation, of course, while likely the most important type of technological change in the period of interest, is not the only form of technological change. The adoption of skill-biased technologies might still have been more important than automation in

[21]The individual census records are repeated cross-sections and do not report specific individuals over time. For this reason, I cannot observe individual's employment transition directly. Instead I focus on the change in routine employment of cohorts over the previous 10 years. That is the change in the share of routine employment for individuals aged 35-55 in t compared to the same cohort when they were aged 25-45 in t-10 in congressional districts. In this case it seems unlikely that these individuals change from routine to abstract employment as their obtained occupation is fixed so that they can only change to occupations that require less or equivalent qualifications, i.e. reflecting a transition from routine to manual employment. Focussing on cohorts also circumvents the issues that the observed change in routine employment might be due to individuals that have not entered the labour market in t-10 changing educational choices or migrating as well as that older individuals might change their retirement decisions.

certain industries potentially leading to a transition from manual towards routine or abstract employment (e.g. in manufacturing industries, see Beaudry & Green 2005; Beaudry et al. 2010; Lewis 2011). Also, skill-biased technologies were likely more important than automation technologies for overall technological change till the 1980s (see Figure 3). Importantly, the impact of different types of technologies is consistently accounted for by my measure of manual-biased technological change as it simply captures how any type of technological change affected the relative demand for manual tasks compared to other tasks.

Figure 5: Manual-biased technological change and automation



Notes: The figure displays the relationship between manual-biased technological change and automation as measured by the decline in the routine task share within a cohort (age 35-55 in t and 25-45 in t-10). The observation are for congressional districts and census years 1970, 1980, 1990, 2000 and 2010. State and year differences accounted for. N=2142 in 50 bins.

Table A.3 in the Appendix provides an idea of what drives 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 thr manual wages premium, while industries in the manufacturing, business and professional services sectors have experienced the strongest decline in the manual wage premium.[22]

[22]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

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. Appendix Table A.4 presents the data sources for the remaining variables used as controls in the empirical analysis. Appendix Table A.5 presents summary statistics.

4 Empirical Analysis

4.1 Tasks and voting on immigration

The first thing I evaluate is whether differences in the manual employment share influence representatives voting behaviour on low-skill immigration policy. For this I estimate the following Probit equations:

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

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. Accordingly, I move from the commonly used theoretical framework of the median voter model to estimating more standard marginal effects reflecting the complexity the representative faces in actually observing the median voter and having to vote on a large bundle of different bills, not just immigration policy, that the median voter cares about. $X'_{d,t}$ is a vector of controls including congressional district and representative characteristics. Finally, γ_s and γ_t denote state and vote fixed effects, respectively.[23] To simplify interpretation the estimation tables report marginal effects (at means) which represent the change in probability of a representative voting in favour of liberalizing low-skill

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.

[23] 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. Also, as I'm interested in the quasi-fixed differences in manual intensity across congressional districts in this section even if possible congressional district fixed effect would be problematic as they would account for all of the important variation between congressional districts. If controlling for them my estimation would instead only capture the remaining changes in manual employment over time due to demand (technology) and supply (migration) factors.

immigration due to a change in the independent variable. Table 1 presents the Probit estimates for the measure capturing the manual employment share of a representative's congressional district on voting outcomes.

Table 1: Effect manual task share on immigration policy

Dependent variable: Vote on low-skill immigration policy (1=Pro; 0=Against)	(1)	(2)	(3)	(4)	(5)	(6)
Manual share	-0.223	-3.435***	-2.287***	-1.107**	-1.332***	-1.356***
	(0.166)	(0.433)	(0.426)	(0.443)	(0.443)	(0.440)
	[0.258]	[0.433]	[0.372]	[0.399]	[0.397]	[0.397]
log(family income)		-0.317*	-0.0550	-0.0584	0.0387	0.0538
		(0.175)	(0.164)	(0.155)	(0.145)	(0.148)
Poverty		3.465***	2.074***	0.587	0.499	0.513
		(0.498)	(0.426)	(0.470)	(0.452)	(0.448)
Republican			-0.551***	-0.497***	-0.494***	-0.493***
			(0.0256)	(0.0253)	(0.0255)	(0.0254)
Foreign-born				0.848***	0.880***	0.858***
				(0.265)	(0.264)	(0.270)
Hispanic				0.516***	0.349**	0.374**
				(0.169)	(0.160)	(0.174)
African-American				0.725***	0.568***	0.578***
				(0.117)	(0.123)	(0.126)
Unemployment rate					2.645***	2.672***
					(0.791)	(0.792)
Age 65+						0.220
						(0.396)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Vote fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5755	5755	5755	5755	5755	5755
Pseudo R^2	0.167	0.258	0.412	0.437	0.439	0.439

Notes: The table presents the effect of the manual employment share on voting on low-skill immigration policy. Vote in favour of more immigration coded as 1 and 0 otherwise. The table reports marginal effects at means of probit regressions. Panel A of Table A.6 in the Appendix presents the corresponding OLS results. Robust standard errors clustered on state-vote in parentheses. Clustered on representatives in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column 1 in Table 1 shows that the effect of the manual employment share has the expected negative sign, however the effect is insignificant. A potential issue here is that manual employment is correlated with lower incomes. Notably, an abundant literature has highlighted the role of the welfare state channel as influencing individual and legislator attitudes on immigration policy (Hanson et al. 2007; Dustmann & Preston 2007; Facchini & Mayda 2009). Accordingly, legislators from wealthier constituencies are expected to exhibit less favourable attitudes towards low-skill immigrants as their constituencies carry the main fiscal burden of immigration. Consequently in column 2 I account for this confounding effect of the welfare state channel through controlling for average incomes and poverty share. Indeed, the coefficient suggests that representatives of richer areas are more averse to immigration. When disentangling the income effect and the subsequent higher fiscal cost of migration through redistribution from the competition of natives and migrants in manual tasks, I find that the estimated effect of the manual employment share increases considerably in magnitude and is now highly significant. A second concern is that representatives' party affiliation shapes voting on immigration policy (see Gimpel & Edwards 1999). Column 3 controls for Republican representatives showing they are indeed more averse to increasing immigration. A third concern 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 shows that, in line with previous studies, the share of Hispanics and African-Americans has a positive effect on voting in favour of low-skill immigration. Note, also that when controlling for race and origin the importance of the welfare channel disappears. A fourth concern is that tighter labour markets might affect manual employment as well as support for liberalizing immigration policy. Accordingly, column 5 controls for the unemployment rate. I find that there is a positive relationship between the unemployment rate and support for liberalizing immigration policy. While counter-intuitive a positive correlation between a congressional district's unemployment rate and voting behaviour has been previously observed in the empirical literature (Gimpel & Edwards 1999; Facchini & Steinhardt 2011). This positive effect appears driven by the 1970s and 80s, while in later periods the effect turns negative (see also footnote 25). Accordingly, one explanation for the positive association between unemployment and pro-immigration voting of representatives might be the strong role of labour unions at the time, which were traditionally anti-immigration and might have also been associated with higher unemployment rates (see e.g. Gimpel & Edwards 1999). Most importantly, the effect of the manual employment share is nearly unaffected when controlling for the unemployment rate. A final concern is that an ageing population requires more manual employment in care services, often provided by immigrants, but age 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, however this appears to be of little importance. A sizeable negative and significant relationship is observable in columns 2-6 between the size of the manual employment share and representatives support for liberalizing immigration policy. The benchmark specification (column 6) suggests that a one percentage point higher manual employment share is associated with the representative being 1.36 percent less likely to vote in favour of liberalizing low-skill immigration policy.

Table 1 so far explored the relationship between the manual employment share in a congressional district at the start of the period and subsequent voting decisions of congressmen on low-skill immigration bills in the following decade. Variation in the manual employment share can be attributed to; (i) fixed differences in the production structure, (ii) demand and (iii) supply shocks. To illustrate this, consider the observed manual employment share at point t as fixed differences in the production structure MSH_d^* and idiosyncratic shocks $v_{d,t}$:

$$MSH_{d,t} = MSH_d^* + v_{d,t}$$

Changes to the manual employment share due to unobserved factors $v_{d,t}$ are not necessarily a problem for identification as long as they are affecting a representatives vote on low-skill immigration purely through changing the competition between natives and migrants. However, certain idiosyncratic shocks $v_{d,t}$ might affect a representatives' voting behaviour not just through changing manual employment, but also through another channel. For example, a short-run boom in demand for a congressional district's routine-task intensive manufacturing outputs might lead to a reallocation of low-skilled workers from manual to routine occupations. However, this will likely also locally reduce financial anxiety more generally, which has a direct effect on individual attitudes towards immigration (see Goldstein & Peters 2014). This would lead to an upward biased OLS estimate on the effect of the manual employment share on representatives' voting on immigration policy. A corresponding demand shock for manual task intensive products (e.g. agricultural products) would have the reverse effect and lead to a downward biased OLS estimate. In addition, even short-run idiosyncratic shocks $v_{d,t}$ that are not directly affecting voting outcomes create the issue of introducing considerable measurement error at the time the vote on immigration policy actually occurs leading to regression dilution. I deal with the outlined concerns by following the approach of Autor & Dorn (2013) to construct a long-run, quasi-fixed measure of employment, but for manual rather than routine employment.

To do this I use the historical differences in industries across areas in 1950 combined with the nationwide manual employment share for industries in 1950:

$$\overline{MSH}_{d,1950} = \sum_{j=1}^{J} EmpSH_{j,d,1950} \times MSH_{j,-d,1950}$$

$MSH_{j,-d,1950}$ describes the manual employment share in a given industry in the whole of the US excluding area d and $EmpSH_{j,d,1950}$ is the local employment share of industry j in 1950. Accordingly, $\overline{MSH}_{d,1950}$ provides me with a predicted value of the long run, quasi-fixed manual employment share for each congressional district MSH_d^* unaffected by any local shocks $v_{d,t}$. I interact $\overline{MSH}_{d,1950}$ with decade dummies D_t giving the following first-stage equations:

$$\widehat{MSH}_{d,t} = \sum_{t=Decade} \phi_t * \overline{MSH}_{d,1950} * D_t + X'_{d,t}\beta + \gamma_s + \gamma_t + \varepsilon_{d,t}$$

Table 2 presents the corresponding IV-Probit results. The first-stage, presented at the bottom of the table, shows that the used instruments are highly predictive of the observed manual employment share. Also observable is that the magnitude of the predictive relationship decreases over time as initial conditions become less important. The IV-estimates for the effect of the manual employment share on the voting behaviour of representatives increase in magnitude compared to the OLS-estimates and are now similar in size across all specifications presented in Table 2.

The IV-Probit marginal effect in column 6 of Table 2 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 favour of restricting low-skilled immigration. This suggests that even though far less than half of voters are in competition with low skill immigrants, an increase in share of natives in manual employment still influences a representative's voting behaviour. Indeed, the marginal effect of the manual employment share on representative's voting behaviour is largest at 29% with an effect of -3.46. One might interpret this as the pivotal median voter that has a decisive influence on a representatives voting decision on low-skill immigration policy being most frequently located towards the bottom-end of the skill distribution rather than at the middle as one might a priori expect.

4.2 The effect of technological change

So far, my estimates highlighted the relationship between relatively fixed differences in the competition of natives and low-skill immigrants across congressional districts in the labour market and the effect it has on the voting behaviour on immigration policy of representatives. We now turn to the second question: did recent technological change lead to changes in the voting behaviour of representatives.

First, I ask whether manual-biased technological change made representatives more likely to vote in favour of restricting immigration policy. To analyse 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 $MBTC_{d,t}$ on the voting outcome $Vote_{d,t}$ of a representative from congressional district d at time t. As described in Section 3, $MBTC_{d,t}$ proxies for manual-biased technological change by capturing the demand driven variation in the manual wage premium that occurred since 1950 across congressional districts d and decades t.

Second, I examine whether manual-biased technological change, in the form of automation, through causing declining routine employment led to representatives voting in

Table 2: IV-effect manual task share on immigration policy

Dependent variable: Vote on low-skill immigration policy (1=Pro; 0=Against)	(1)	(2)	(3)	(4)	(5)	(6)
Manual share	-2.697***	-3.883***	-3.591***	-2.199**	-3.313***	-3.368***
	(0.368)	(0.385)	(0.490)	(0.859)	(0.965)	(1.000)
	[0.537]	[0.427]	[0.473]	[0.841]	[0.939]	[0.971]
Controls	See controls included in Table 1					
F-stat (1st stage)	296.6	135.1	131.3	115.1	125.0	123.6
Endogeneity test	0.000	0.000	0.001	0.064	0.005	0.005
Observations	5719	5719	5719	5719	5719	5719
First-Stage:						
Manual share 1950*D_{1970}	1.009***	0.760***	0.727***	0.637***	0.648***	0.649***
	(0.045)	(0.042)	(0.044)	(0.046)	(0.047)	(0.048)
Manual share 1950*D_{1980}	0.964***	0.647***	0.647***	0.544***	0.505***	0.500***
	(0.033)	(0.031)	(0.031)	(0.025)	(0.022)	(0.022)
Manual share 1950*D_{1990}	0.912***	0.469***	0.462***	0.400***	0.387***	0.384***
	(0.049)	(0.038)	(0.036)	(0.044)	(0.047)	(0.046)
Manual share 1950*D_{2000}	0.762***	0.356***	0.347***	0.249***	0.245***	0.242***
	(0.030)	(0.021)	(0.021)	(0.024)	(0.023)	(0.023)
Manual share 1950*D_{2010}	0.757***	0.357***	0.330***	0.253***	0.242***	0.232***
	(0.038)	(0.037)	(0.040)	(0.041)	(0.041)	(0.042)

Notes: The table presents the effect of the manual employment share on voting on low-skill immigration policy. Vote in favour of more immigration coded as 1 and 0 otherwise. The estimates are IV-Probit estimates corresponding to column 1-6 of Table 1. The estimates report marginal effects at means. Panel B of Table A.6 in the Appendix presents the corresponding 2SLS results. Robust standard errors clustered on state-vote in parentheses. Clustered on representatives in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

favour of restricting low-skill immigration. For this I estimate the following IV Probit specification and first stage:

$$prob(Vote_{d,t} = 1|Z_{d,t}) = \Phi(\delta \Delta RSH^{Cohort}_{d,t} + X'_{d,t}\beta + \gamma_s + \gamma_t)$$

$$\Delta RSH^{Cohort}_{d,t} = \varphi MBTC_{d,t} + X'_{d,t}\beta + \gamma_s + \gamma_t$$

where $\Delta RSH^{Cohort}_{d,t}$ is the change in the share of a cohorts' routine employment over the previous 10 years. Accordingly, it measures the recent change in routine employment for the same group of individuals when aged 35-55 years in t compared to when 25-45 years old in $t-10$. I instrument this change with the observed manual-biased technological change ($MBTC_{d,t}$) across congressional districts in the first stage. This should illustrate the mechanism through which recent technological change affected representatives voting on immigration policy, i.e. through the automation of routine tasks. However, it should be noted that given the varied nature and effects of technological change, it is not possible to fully rule out that the estimated effects are (partly) driven by other forces than through the transition out of routine occupations. For this reason, I view the effect of the change in cohort routine employment presented here more as suggestive, rather than conclusive evidence on the effect of automation of routine tasks on voting on low-skill immigration policy.

Nevertheless, while it is not possible to rule out every channel, other than the transition out of routine into manual employment, via which manual-biased technological change may effect voting on immigration policy, I present both the IV-Probit and the corresponding reduced form estimates across all specifications. Even if the exclusion restriction did not hold, the reduced form specifications would still identify the effect of manual-biased technological on representative's voting decision under the weaker assumption that manual-biased technological change is uncorrelated with other determinants of the outcome variable of interest. So while the latter cannot narrow the effect down to automation specifically, it provides conclusive evidence on the important role of technological change more broadly for the setting of immigration policy.

Table 3 Panel A presents the Probit estimates which analyse the effect of manual-biased technological change on the voting behaviour of representatives. In line with expectations the coefficient for the manual-biased technological change, i.e. manual premium, variable is negative. This implies that areas where technological change was more favourable to manual tasks compared to other tasks representatives 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, party affiliation, migration networks, labour market conditions and demographic factors.The baseline specification in column 6 suggests that a one percentage point increase in manual-biased technological change makes it 3.8 percent less likely that a representative votes for liberalizing low-skill immigration. 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 8.0% less likely to be in favour of liberalizing low-skill immigration policy.

Table 3 Panel B presents the IV-Probit results looking at the effect of changes in a cohorts routine employment share in the previous period instrumented with manual-biased technological change. The first stage estimate suggests that manual-biased technological change indeed captures the automation of routine tasks that occurred as an increase in it is related to transition out of routine employment. The second stage depicts a positive coefficient for the cohort change in the routine employment share. Accordingly, individuals changing from routine to manual occupations and the corresponding increase in natives competition with low-skill immigrants leads to the local representative becoming more likely to vote in favour of restricting low-skill immigration. This result suggests that the possibility of the automation of routine tasks, corresponding to manual-biased technological change, increased the likelihood of representatives voting in favour of restricting low-skill immigration policy in the US. The estimated effect of a change in a cohorts routine employment share is considerable as the marginal effect suggests that at mean each 1 percentage point decline in routine employment made the representative 10.6% more likely to vote in favour of restricting low-skill immigration. Accordingly, the individuals affected seem pivotal in influencing a policy makers voting behaviour on low-skill immigration policies.

Table 3: Effect of technological change on immigration policy

Dependent variable: Vote on low-skill immigration policy (1=Pro; 0=Against)	(1)	(2)	(3)	(4)	(5)	(6)
A. Effect manual-biased technological change						
MBTC	-5.270***	-4.926***	-3.639***	-3.213**	-3.827***	-3.827***
	(1.151)	(1.305)	(1.347)	(1.328)	(1.381)	(1.381)
	[1.737]	[1.663]	[1.433]	[1.402]	[1.433]	[1.433]
Controls	See controls included in Table 1					
Observations	5719	5719	5719	5719	5719	5719
Pseudo R-sq	0.171	0.235	0.395	0.424	0.427	0.427
B. Channel: Automation of routine tasks						
Δ Routine task (35-55)	12.95***	10.54***	9.426***	9.035***	9.539***	10.58***
	(0.896)	(1.929)	(2.587)	(2.505)	(2.234)	(2.670)
	[1.371]	[2.449]	[3.006]	[2.951]	[2.711]	[3.229]
First stage (MBTC)	-0.140***	-0.150***	-0.147***	-0.175***	-0.166***	-0.169***
	(0.042)	(0.043)	(0.043)	(0.042)	(0.041)	(0.041)
F-stat (1st stage)	11.269	12.011	11.647	17.534	16.086	17.332

Notes: Panel A presents the effect of manual-biased technological change (MBTC) on voting on low-skill immigration policy. Vote in favour of more immigration coded as 1 and 0 otherwise. The table reports marginal effects at means from probit regressions. Panel C of Table A.6 in the Appendix presents the corresponding OLS results. Panel B presents IV-probit estimates were the decline over the last 10 years in routine employment for a cohort (aged 35-55 in period t and 25-45 in $t-1$) is estimated with the manual-biased technological change. This corresponds to automation being a key way in how manual-biased technological change affects the voting behaviour of representatives. Robust standard errors clustered on state-vote in parentheses. Clustered on representatives in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Additional evidence

This section presents additional evidence. First, Section 5.1 analyses the sensitivity of my measure for manual-biased technological change to variations in its specification. Second, Section 5.2 provides a falsification exercise where manual-biased technological change that occurs in the future is regressed on votes on low-skill immigration policy that occurred before. Third, Section 5.3 considers alternative explanations: (i) economic specialization, (ii) the skill composition of immigrants, (iii) political polarization and (iv) trade exposure.

Fourth, Section 5.4 studies whether technological change had also an impact on US trade policy.

5.1 Measurement

An important concern is that the estimated effect of manual-biased technological change is sensitive to changes in the definition of the variable. Table 4 analyses this by considering alternative ways of constructing the measure for manual-biased technological change. In column 1, I use a narrower definition of manual task intensity, classifying only the top 25% of occupations as manual instead of the top 33%. The coefficient on the measure of manual-biased technological change is nearly identical to my preferred specification (column 6 of Table 3). Column 2 presents the result when the definition of manual task intensity is instead widened to 40%. The coefficient decreases sightly in magnitude and becomes borderline insignificant. This seems consequential considering that through extending the definition of manual task intensity the measure is more likely contaminated by occupations falsely classified as being manual task intensive, when indeed they are more intensive in routine or abstract tasks. This leads to an increase in random measurement error in the explanatory variable, which compared to the baseline specification reduces the magnitude of the coefficient. In column 3, I replace the change in the manual wage premium with the change in manual employment across industries as proxy of manual-biased technological change. In contrast to the manual premium, this measure reflects the realized change in manual employment across industries at the national level rather than the change in demand for certain tasks across industries.[24] The estimated effect confirms previous results. The size of the coefficient suggests that a one standard deviation (3.3 percentage points) increase in manual employment since the 1950s leads to a representative being 6.4% less likely to be in favour of liberalizing low-skill immigration policy which is roughly equivalent to the effect measured by the manual wage premium.

Table 5 confirms that results are robust with respect to the timing of legislation, the geography of immigration and voting on high-skill immigration. In column 1, the sample of bills is restricted to the 2000s, a period characterized by considerable automation of routine occupations and a large number of roll call votes on bills aimed at restricting low-skill immigration.[25] Column 2 presents the effect for the periods before 2000.

[24] I prefer manual premium as measure of manual-biased technological change as it compares wages between occupations in the same industry with similar working hours and days, while changes in the employment share in a industry might be more likely subject to the extension of part-time employment at the bottom end of the skill distribution. Indeed, changes in relative wages across tasks should be the driving force behind workers reallocation within industries, so that the later is an intermediate outcome of the former. In line with this, the manual wage premium is the driving force behind workers reallocation across tasks in Equation 5 of the model.

[25] Interestingly, when looking at later time-periods the coefficient on the unemployment rate turns negative and insignificant, which is in line with expectations. The positive coefficient on the unemployment rate in the baseline specification appears to be exclusively driven by the 1970s & 1980s.

Table 4: Measurement of manual-biased technological change

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)
Manual premium (25%)	-3.822***		
	(1.076)		
Manual premium (40%)		-2.359	
		(1.440)	
Δ Manual employment since 1950			-1.953***
			(0.622)
Controls	Yes	Yes	Yes
Observations	5719	5719	5719

Notes: The table analyses the robustness of the main result to changing the way manual-biased technological change is measured. The manual task intensity threshold is changed from 33% to 25% and 40% of national employment in column 1 and 2, respectively. Column 3 uses the change in the manual employment share at the national level interacted with the initial industry shares as explanatory variable instead of the manual wage premium. Presented estimates include all controls from column 6 of Table 3. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column 3 exclusively focuses on states with a high immigrant share (the 15 states with the highest foreigner share during the study period). Column 4 instead excludes these 15 high-immigration states. The coefficient on my main explanatory variable remains similar to the benchmark specification across columns 1-4 suggesting that manual-biased technological change had a similar marginal effect across different time-periods and geographic regions. Rather than restricting the sample, column 5 includes votes on high-skilled immigration. A vote in favour of bills aimed at increasing high-skilled immigration has been coded as a "0", whereas a vote against it as "1". This is done as manual-biased technological change should, if at all, decrease competition of natives with high-skilled immigrants.[26] Extending the sample to include votes on high-skilled immigration seems to reduce the coefficient size as the link between manual-biased technological change and competition with high-skilled workers is likely weaker, but remains significant.

5.2 Falsification exercise

Another concern is that manual-biased technological change might be a symptom of increasing anti-immigration sentiment rather than a cause. 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

[26] I also evaluated whether abstract-biased technological change increased support for restricting high-skill immigration, however I did not find any significant effect. This might simply reflect the limited number of bills (3) focussing on high skill immigration that were voted on in the house of representatives. In particular, as there is only limited time variation available as these three bills were passed in 1998, 2011 and 2012, respectively.

Table 5: Robustness checks - Effect across sub-samples

Dependent variable: Vote on low-skill immigration policy

	Bills 2000s	Bills pre-2000	High immigration states	Low immigration states	High-skill bills included
	(1)	(2)	(3)	(4)	(5)
MBTC	-4.387*	-3.857**	-3.599*	-3.755***	-2.191**
	(2.351)	(1.943)	(2.126)	(1.100)	(0.976)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1968	2798	2423	3296	6919

Notes: The table analyses the robustness of manual-biased technological change (MBTC) across different sub-samples of the data. Presented estimates extend on column 6 of Table 3 reporting marginal effects at means for Probit regressions. Column 1 and 2 study the effect on votes in the 2000s and pre-2000, respectively. Column 3 (4) comprises (excludes) the following 15 states with the highest foreigner share: Arizona, California, Connecticut, Florida, Hawaii, Illinois, Maryland, Massachusetts, Nevada, New Jersey, New Mexico, New York, Rhode Island and Washington. Column 5 also includes high-immigration bills, which are coded in the opposite direction to low-skill immigration bills as high-skill immigration should be complementary to manual employment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

immigration and increased manual-biased technological change, I conduct a falsification exercise by regressing past voting outcomes on future manual-biased technological change.

For this, I construct measures of manual-biased technological change for congressional districts that will occur over the next 10, 20 and 30 years. Table 6 shows the correlation between voting outcomes and the change in future manual-biased technological change. Column 1 looks at future manual-biased technological change 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. In column 1 an insignificant, positive relationship between voting in favour of liberalizing low-skill immigration policy and future manual-biased technological change can be observed, while in column 2 and 3 the relationship turns negative, but remains insignificant. This exercise demonstrates that representatives of congressional districts that will experience more manual-biased technological change in the future were not becoming more unfavourable towards low-skill immigration beforehand.

5.3 Alternative explanations

This section shows that the main results are robust to accounting for alternative explanations. I focus on the robustness of manual-biased technological change, but corresponding robustness checks are presented for the manual employment share in Appendix B.

5.3.1 Economic specialization

I start with controlling for a set of additional economic factors that measure the specialization of congressional districts in Table 7. A first concern is that the degree of manual-

Table 6: Falsification exercise

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)
MBTC (t+10)	1.285		
	(2.981)		
MBTC (t+20)		-1.714	
		(1.857)	
MBTC (t+30)			-0.923
			(1.861)
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. Presented estimates include all controls from column 6 of Table 3. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

biased technological change in a congressional district might be correlated with long-run differences in the importance of manual employment between congressional districts capturing the quasi-fixed higher competition between natives and low-skill immigrants rather than changes to it due to technology. Accordingly, 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 and are significant. This implicitly alleviates potential concerns that the effect of changes in technology since 1950 on the level of voting behaviour at point t are both driven by the initial level of manual employment at the start. Indeed there is little correlation between the historical manual employment share in 1950 and exposure to manual-biased technological change (correlation=-0.038) since 1950 and even this correlation suggests that areas initially less manual intensive experienced more manual-biased technological change, which would reduce the magnitude of the observed effect. This seems also in line with the minimal increase in magnitude of the coefficient compared to the baseline.

In column 2, I further explore the role played by competition between natives and low-skill immigrants (see Mayda 2006; Hainmueller & Hiscox 2010; Facchini & Steinhardt 2011). In particular, I modify the benchmark specification to include the share of college graduates at the start of the period as an alternative measure to control for competition between natives and low-skilled immigrants based on education levels as used for example by Facchini & Steinhardt (2011). As expected a higher share of highly-skilled individuals increases the likelihood that a representative will vote in favour of liberalizing low-skill immigration, however the effect of manual-biased technological change remains the same. This seems to suggest that competition due to changing tasks performed in the labour market and through education are two distinct mechanism that affect voting behaviour of representatives on low-skill immigration.[27]

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 labour force (see Gimpel & Edwards 1999). In addition, changes in union membership might have affected wages differently across occupations within industries. Column 3 accounts for the changing importance of trade unions in the US labour market. The share of trade union members appears to have indeed a negative effect, however the effect is not significant.

Another concern is that technological change varies between urban and rural economies and that this difference also shapes changing opinions on immigration. Column 4 accounts for differences between rural and urban labour markets with representatives from districts with more constituents in rural areas being slightly more likely to vote to restrict low-skill immigration, also the effect is again insignificant.

Finally, column 5 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. Again there is a general correlation between substitutability of low-skill immigrants with natives (apart from in agriculture) and the voting behaviour of representatives observable. I observe a strong negative effect of a higher employment share in construction, manufacturing and transport industries on the likelihood of representatives liberalizing low-skill immigration. This again does not weaken the observed effect of manual-biased technological change, if at all it's importance increases by controlling for major industry differences across congressional districts.

These results rule out that the effect observed for manual-biased technological change is simply driven by it being distributed across the US in a way that is correlated with the low skill share of employment. This is important as low skilled natives, not just for economic reasons, have been documented to be more likely to be against immigration and vote for parties that are anti-immigration.

5.3.2 Composition of immigrants

Next I evaluate whether the observed effect is driven by differential inflows of immigrants. Notably, both the relocation of natives into different occupations (see 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 manual-biased technological

[27]The manual employment share and the college share are highly negatively correlated across congressional districts. But as observable in Table B.2 in the Appendix competition characterized by tasks and education are not fully overlapping and both coefficients despite decreasing in magnitude have their expected sign and are significant.

Table 7: Robustness checks - Economic specialization

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)	(4)	(5)
MBTC	-4.274***	-3.728***	-3.785***	-3.986***	-5.099***
	(1.395)	(1.328)	(1.391)	(1.389)	(1.381)
Historical manual share	-1.172***				
	(0.380)				
College		1.723***			
		(0.252)			
Union membership			-0.309		
			(0.596)		
Rural				-0.132	
				(0.086)	
Transport					-1.902**
					(0.876)
Retail					2.032**
					(0.960)
Manufacturing					-1.054***
					(0.184)
Construction					-2.366***
					(0.827)
Agriculture					-0.322
					(0.455)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	5719	5719	5719	5719	5719

Notes: The table analyses the robustness of manual-biased technological change (MBTC) to controlling for additional labour market channels. Presented estimates extend on column 6 of Table 3 reporting marginal effects at means for Probit regressions. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

change 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. To rule out that the observed effect of manual-biased technological change is due to changes in the composition of immigrants in a congressional district I control not just for the share of foreign born individuals in the population, but also the composition of immigration in a congressional district.

Column 1 and 2 of Table 8 account for the share of immigrants that work in manual and abstract occupations, respectively.[28] 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, while a higher share of immigrants that work in abstract occupations increases it. Column 3 controls for the share of immigrants with a college degree and column 4 for the share of unemployed immigrants. A higher college

[28]Corresponding robustness checks for the manual employment share are presented in Appendix Table B.1.

share of immigrants has a positive effect, while higher immigrant unemployment has a negative impact. Column 5 controls for the share of immigrants that has Hispanic origins to account for cultural factors, which does not seem to have an impact. 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.

Table 8: Robustness checks - Immigrant composition

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)	(4)	(5)
MBTC	-3.349**	-3.194**	-2.919**	-4.025***	-3.981***
	(1.371)	(1.347)	(1.358)	(1.393)	(1.391)
Share foreigners manual occupation	-0.721***				
	(0.170)				
Share foreigners abstract occupation		0.911***			
		(0.157)			
Share foreigners college degree			1.066***		
			(0.210)		
Share foreigners unemployed				-1.203***	
				(0.425)	
Share foreigners Hispanic					0.171
					(0.155)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	5719	5719	5719	5719	5719

Notes: The table analyses the robustness of manual-biased technological change (MBTC) to controlling for the composition of local immigration. Presented estimates extend on column 6 of Table 3 reporting marginal effects at means for Probit regressions. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3.3 Political polarization

Up to this point, I controlled for the ideology of a legislator by using party affiliation. This however might not be a sufficient proxy for a representative's true views on low-skill immigration and increasing political polarization, not just on immigration, in the US. Table 9 explores the impact of differences between legislators in further detail. Column 1 of Table 9 includes being a member of the republican party as a time-varying dummy control. By doing so, I allow for the degree of party influence on members' roll call votes to vary over the studied time period (see Snyder Jr & Groseclose 2000). It is clearly observable that republican representatives have become more averse to low-skill immigration over time compared to democrats.

Column 2 controls for the DW-1 nominate score as measure of a politicians left-right (or liberal-conservative) orientation and DW-2 nominate score reflecting secondary cultural political issues in particular civil rights for African-Americans or gun-rights as constructed by Poole & Rosenthal (2000). Accordingly, these measures account for the political ideologies of representatives beyond party affiliation. These measures should account for the general polarization of US politics over recent decades (Poole & Rosenthal 1984; Hare & Poole 2014). Having a more conservative attitude towards economic and cultural issues, even after controlling for party affiliation, makes it less likely that a representative votes in favour of liberalizing low-skill immigration.

Column 3 includes the share of votes the democratic candidate received as recorded by the Federal Election Commission (1970-2014), which seems to have a small positive but insignificant effect. This accounts for how competitive the election in a congressional district was for a democratic/republican representative.

These different characteristics might however still not fully account for a legislator's position on immigration, as a number of other individual characteristics are unobservable. These characteristics might be related to the task and industry composition of a congressional district. For this reason, I estimate column 4 including individual legislator fixed effects. This controls for time-invariant unobservable characteristics of representatives, therefore only exploiting the variation in manual-biased technological change across time while a representative remains in office. Accordingly, I estimate whether a representative adjusts his support for low-skill immigration policy with regards to the changing degree of manual-biased technological change in his congressional district. Importantly, the sign and significance of my key explanatory variables remains similar to the baseline specification across column 1 to 4 of Table 9.

5.3.4 Trade exposure

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). Also, apart from technological change, trade in goods appears to have been the major factor in recent labour market developments in the US, in particular in the form of rising Chinese import competition (see Autor & Dorn 2013; Autor et al. 2013*a*).

One might be concerned that manual-biased technological change is correlated with increases in foreign competition, in particular from China, at the local level.[29] To rule this out, I control for increased Chinese competition across congressional districts and the effect it might have had on immigration policy in Table 10. The political consequences that China's integration into the world economy had on US politics has been highlighted for example by Colantone & Stanig (2017) and Autor et al. (2020). I construct a measures of trade penetration in levels corresponding to the differenced version used by Autor et al.

[29] Trade shocks can also affect internal migration patterns and legislation (see e.g. Facchini et al. 2019; Tian 2020), which in addition to its adverse economic consequences (Autor et al. 2020), might be another way it influences voting outcomes that is not captured by the included controls so far. Even if to the best of my knowledge there is no evidence that internal migration in the US changed substantially due to the China trade shock.

Table 9: Robustness checks - Other political factors

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)	(4)
Manual premium	-5.020***	-4.977***	-3.614***	-5.092***
	(1.517)	(1.395)	(1.372)	(1.721)
Republican (93rd-97th)	-0.0221			
	(0.053)			
Republican (98th-102nd)	-0.285***			
	(0.035)			
Republican (103rd-107th)	-0.535***			
	(0.078)			
Republican (108th-112th)	-0.803***			
	(0.040)			
Republican (113th-117th)	-1.286***			
	(0.078)			
DW-1 nominate		-0.873***		
		(0.070)		
DW-2 nominate		-0.130***		
		(0.035)		
Democrat voteshare			0.074	
			(0.058)	
Representative fixed effects	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes
Observations	5719	5719	5578	5719

Notes: The table analyses the robustness of manual-biased technological change (MBTC) to controlling for a vast set of other political factors. Presented estimates include all controls from column (6) of Table 3. Columns 1, 2 and 3 report marginal effects at means for Probit regressions. Column 4 is estimated using OLS due to the high number of fixed effects. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(2013*a*). The details of the specification used can be found in Appendix Section C. Column 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 favour of restricting low-skill immigration. 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.[30] This is actually less surprising 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. That is the types of occupations most affected by automation are in general not affected by trade, so that there is little possibility for correlation between the two shocks across local labour markets (see also Autor et al. 2013*b*).

[30]Corresponding robustness checks for the manual employment share are presented in Appendix Table B.4.

Table 10: Robustness checks - China trade shock

Dependent variable: Vote on low-skill immigration policy		
	(1)	(2)
MBTC	-3.862***	-3.862***
	(1.382)	(1.382)
China-US IM	-0.009***	
	(0.003)	
China-US IM-EX		-0.008***
		(0.003)
Controls	Yes	Yes
Observations	5719	5719

Notes: The table analyses the robustness of manual-biased technological change (MBTC) to controlling for the China trade shock. Presented estimates extend on column 6 of Table 3 reporting marginal effects at means for Probit regressions. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.4 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 should not have increased exposure to foreign competition. This is because as noted before most of the jobs lost as well as created are in non-trade sectors (see 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 affected by manual-biased technological change. 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 labour market changes. In contrast, if there is no observable effect of manual-biased technological change 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 labour market.

Table 11 presents the results of manual-biased technological change on the voting behaviour 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.7. 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 a good placebo test for whether technological change affected voting on immigration policy due to increasing competition between natives and low-skill immigrants or rather due to other factors. Column 1 shows that the effect of manual-biased technological change 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 3. Columns 2-6 shows that when controlling for other factors the effect of manual-biased technological change on trade policy remains insignificant and even changes sign across specifications. This finding supports the argument that manual-biased technological change affects voting on immigration policy through increasing competition in the labour market between natives and immigrants in the US as it does not appear to have fostered general discontent against globalization.[31]

Table 11: Effect manual-biased technological change on trade policy

Dependent variable: Vote on liberalizing trade policy (1=Pro; 0=Against)						
	(1)	(2)	(3)	(4)	(5)	(6)
MBTC	-0.836	0.211	-0.202	-0.728	-0.363	-0.384
	(0.969)	(0.990)	(1.006)	(1.014)	(1.019)	(1.018)
log(family income)		0.204***	0.326***	0.393***	0.325***	0.277***
		(0.054)	(0.054)	(0.060)	(0.063)	(0.065)
Poverty		-1.219***	0.199	0.685***	0.857***	0.829***
		(0.160)	(0.161)	(0.205)	(0.213)	(0.213)
Republican			0.417***	0.398***	0.396***	0.394***
			(0.013)	(0.014)	(0.014)	(0.014)
Foreign-born				-0.124	-0.185	-0.146
				(0.122)	(0.123)	(0.124)
Hispanic				-0.038	0.078	-0.002
				(0.083)	(0.090)	(0.096)
African-American				-0.265***	-0.163***	-0.202***
				(0.054)	(0.062)	(0.064)
Unemployment rate					-1.831***	-1.866***
					(0.532)	(0.533)
Age 65+						-0.677**
						(0.263)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Vote fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7153	7153	7153	7153	7153	7153
Pseudo R-sq	0.149	0.184	0.297	0.300	0.301	0.302

Notes: The table presents the effect of manual-biased technological change (MBTC) on voting on trade policy. Vote in favour 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.7. Robust standard errors clustered on state-vote in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[31] Table 12 in the Appendix presents the effect of the China shock on voting to liberalize trade policy. In contrast to technological change, the effect of the China trade shock is comparable and significant for both voting on liberalizing trade and immigration. This is despite most bills focussing on legislation not related to US-China trade.

In contrast to this, trade shocks did not just increase representatives' support for restricting low-skill immigration, but also increased support for restricting free trade. This is highlighted in Table 12 which shows that rising Chinese import competition led representatives to be less favourable to free trade (not just with China). This suggests that in contrast to recent technological change increasing competition from China fostered discontent with globalization overall not just trade policy. Understanding why Chinese competition has such broader consequences compared to technological change is left for further analysis.

Table 12: Effect of China shock on trade liberalization

Dependent variable:	Vote on liberalizing trade policy	
	(1)	(2)
MBTC	-0.326	-0.323
	(1.019)	(1.019)
China-US IM	-0.005**	
	(0.002)	
China-US IM-EX		-0.005**
		(0.002)
Controls	Yes	Yes
Observations	7153	7153

Notes: The table analyses the effect of manual-biased technological change (MBTC) and the China trade shock on voting to liberalize trade policy. Presented estimates extend on column 6 of Table 11 reporting marginal effects at means for Probit regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusions

This chapter documents that recent technological change that favoured manual tasks, for example automation, led to a tightening of low-skill immigration policy in the United States. This is because it increased the share of natives in manual employment that are in competition with low-skill immigrants, which in turn affects representatives' voting behaviour on low-skill immigration bills.

This finding is based on theoretical as well as empirical evidence. The empirical results are obtained by combining US Census data, which provides measures for manual employment and manual-biased technological change, with US House of Representatives roll call votes on immigration policy across congressional districts from 1970-2014. First, the obtained results highlight that the task composition of congressional districts matters and the degree of substitutability between natives and low-skill immigrants influences representatives' voting on low-skill immigration policy. Second, they provide evidence that representatives of congressional districts which were more exposed to manual-biased technological change increased their support for restricting low-skill immigration. Further, there is evidence that in particular the automation of routine tasks played an important role in the restriction of low-skill immigration to the US.

Importantly, manual-biased technological change did not have a corresponding effect on trade policy. This is consistent with the change in voting behaviour of representatives being due to increased competition in the labour markets between natives and low-skill immigrants rather than more broad discontent with globalization. This is in marked contrast to increased import competition from China, which I find increased support for policies restricting trade as well as immigration.

These results help explain how competition between natives and immigrants in certain tasks shapes US immigration policy. It also highlights the way in which new technologies can increase support for nativist politics through changing this competition. Here it seems particularly important that, in contrast to exposure to foreign competition, technology appears to change support for nativist political parties and politicians only through changing views on immigration, but not trade. These results provide important new insights into the mechanism of how technological change and trade shocks have led to the recently documented rise of extremist politics in Western democracies.

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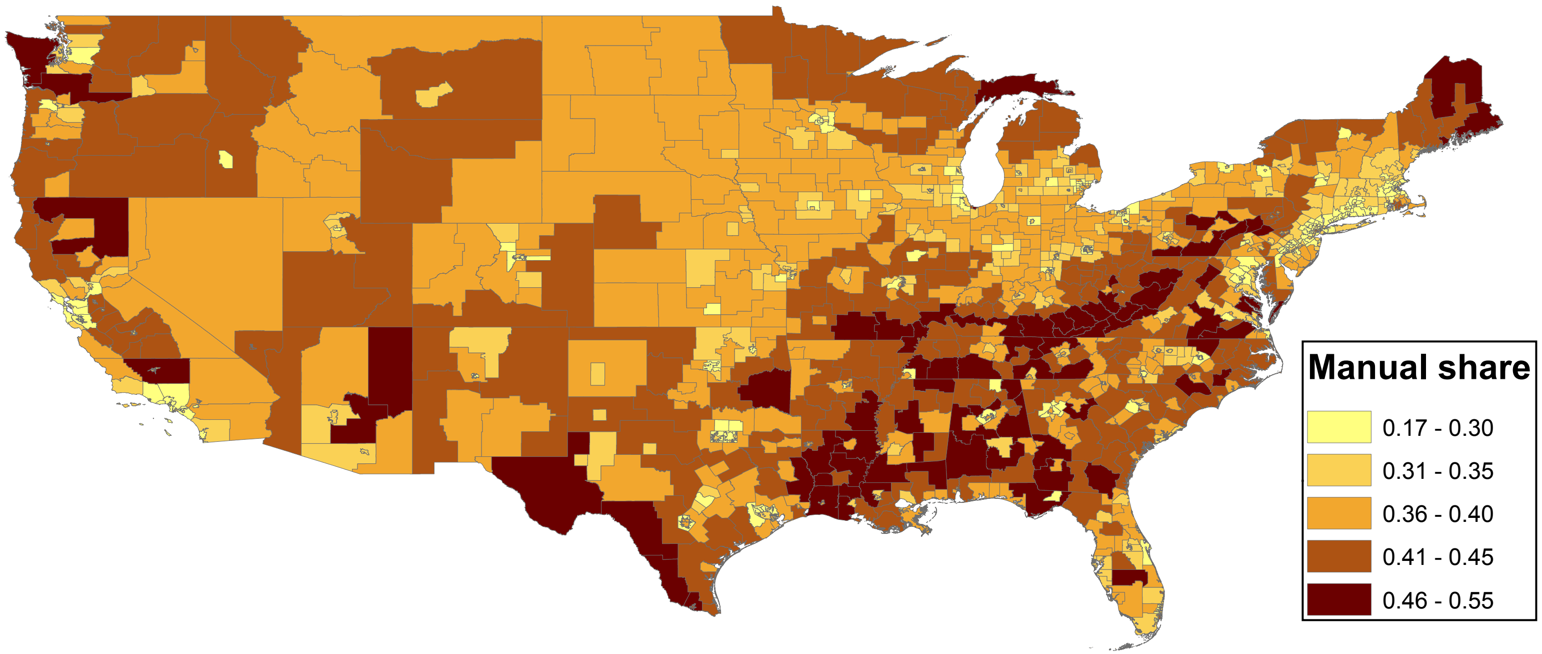
Appendix

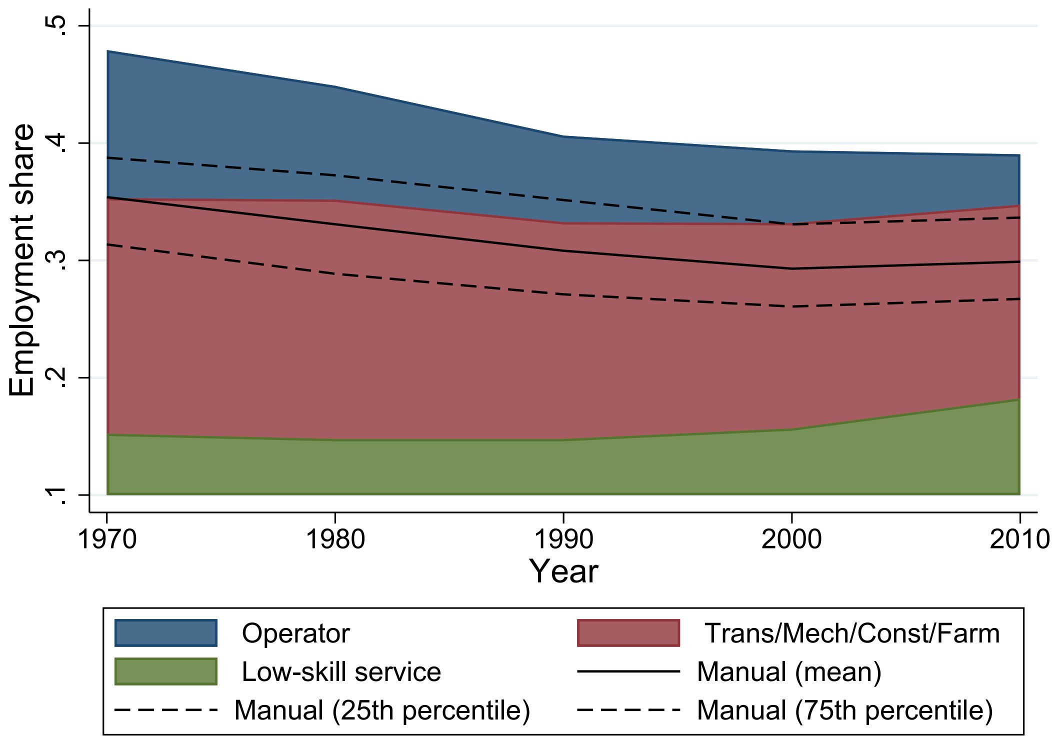
A Additional Figures and Tables

Figure A.1: Manual employment share across the US in 1980



Notes: Manual employment share in 1980 across the mainland US. The data is constructed from individual level IPUMS data and depicted for 1980 county groups (the smallest geographical level for which data is available). Alaska and Hawaii not shown but included in the dataset.

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 17 at the mean, 25th and 75th percentile across congressional districts. 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).

Table A.2: Important occupations by task

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

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

Manual & abstract task intensive occupations: (1) Kindergarten and earlier school teachers; (2) Locomotive operators (engineers and firemen); (3) Foresters and 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: Data sources of control variables

Variable	**Data sources**
log(family income)	Manson et al. (2019)
Poverty	Manson et al. (2019)
Republican	Poole & Rosenthal (2000)
Foreign-born	Manson et al. (2019)
Hispanic	Manson et al. (2019)
African-American	Manson et al. (2019)
Unemployment rate	Manson et al. (2019)
Age 65+	Manson et al. (2019)
College	Manson et al. (2019)
Union membership	Hirsch et al. (2001)
Rural	Manson et al. (2019)
Transport	Manson et al. (2019)
Retail	Manson et al. (2019)
Manufacturing	Manson et al. (2019)
Construction	Manson et al. (2019)
Agriculture	Manson et al. (2019)
DW-1 nominate	Poole & Rosenthal (2000)
DW-2 nominate	Poole & Rosenthal (2000)
Democrat 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)

Notes: This table presents information on the data sources of variables used as controls which have not been discussed in detail in Section 3.

Table A.5: Summary Statistics

	Mean	**Std. dev.**	**Min**	**Max**	**Valid obs.**
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
Historical manual share	0.42	0.03	0.32	0.59	5,719
MBTC	-0.02	0.02	-0.11	0.04	5,719
Manual premium (25%)	-0.02	0.02	-0.10	0.04	5,719
Manual premium (40%)	-0.00	0.02	-0.07	0.06	5,719
Manual employment	-0.08	0.03	-0.21	0.01	5,719
Δ Routine task (35-55)	-0.04	0.03	-0.12	0.09	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
Republican	0.49	0.50	0.00	1.00	5,755
Foreign-born	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
College	0.20	0.10	0.04	0.69	5,755
Union membership	0.18	0.09	0.03	0.42	5,755
Rural	0.23	0.21	0.00	0.87	5,755
Transport	0.05	0.02	0.02	0.12	5,755
Retail	0.14	0.03	0.07	0.23	5,755
Manufacturing	0.18	0.09	0.02	0.53	5,755
Construction	0.06	0.02	0.01	0.17	5,755
Agriculture	0.03	0.04	0.00	0.29	5,755
DW-1 nominate	0.07	0.46	-0.74	1.23	5,755
DW-2 nominate	0.07	0.39	-1.51	1.24	5,755
Democrat voteshare	0.52	0.25	0.00	1.00	5,620
China-US IM	1.04	6.32	0.00	287.26	5,755
China-US IM-EX	0.92	5.67	-1.97	252.25	5,755

Notes: This 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.

Table A.6: Linear estimation of baseline results

Dependent variable: Vote on low-skill immigration policy

Panel A: OLS results for Table 1

	(1)	(2)
Manual share	-0.173	-0.958***
	(0.127)	(0.189)
Controls	No	Yes
Observations	5719	5719

Panel B: 2SLS results for Table 2

	(1)	(2)
Manual share	-2.409***	-2.437***
	(0.297)	(0.550)
Controls	No	Yes
Observations	5719	5719

Panel C: OLS results for Table 3

	(1)	(2)
Manual premium	-4.722***	-1.912***
	(0.937)	(0.741)
Controls	No	Yes
Observations	5719	5719

Notes: Corresponding results using OLS and 2SLS for baseline estimates presented in Table 1, Table 2 and Table 3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Votes on trade liberalization

	Bill (Cong.)	Description	Date	Direction	Yes-share
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 extension 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 11 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 favour of liberalizing trade policy.

B Additional robustness checks (Not for publication)

This section of the Appendix presents the robustness checks for the manual task share. Table B.2 accounts for other economic factors. In particular, it highlights that there is considerable difference between the effect of tasks performed in the labour market with the education level as well as with the broad industrial sectors an individual is employed in. Table B.3 controls for a set of additional political factors including letting the effect of party affiliation vary by decade, democratic vote share and DW-nominate scores. The coefficient for the manual task share remains negative across all specifications. I do not include the specification using representative fixed effects as the instrumentation strategy relies on the initial manual task share in 1950 interacted with time fixed effects so that including representative fixed effects captures nearly all variation apart from that which occurs due to redistricting while the representative is in office. Finally, Table B.4 accounts for the impact of increased US trade with China and highlights.

Table B.1: Robustness checks II - Immigrant composition

Dependent variable: Vote on low-skill immigration policy	(1)	(2)	(3)	(4)	(5)
Manual share	-2.427**	-2.500***	-2.618***	-3.360***	-2.842***
	(1.002)	(0.911)	(0.949)	(1.008)	(0.959)
Share foreigners manual occupation	-0.202				
	(0.229)				
Share foreigners abstract occupation		0.471***			
		(0.174)			
Share foreigners college degree			0.420*		
			(0.234)		
Share foreigners unemployed				-0.456	
				(0.387)	
Share foreigners Hispanic					0.266*
					(0.147)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	5719	5719	5719	5719	5719

Notes: Presented estimates extend on column 6 of Table 2 reporting marginal effects at means for IV-Probit regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Robustness checks II - Other economic factors

Dependent variable: Vote on low-skill immigration policy				
	(1)	(2)	(3)	(4)
Manual share	-2.009**	-3.333***	-6.193***	-2.421**
	(0.941)	(0.841)	(1.054)	(1.128)
College	0.852**			
	(0.356)			
Union membership		-0.0677		
		(0.348)		
Rural			0.543***	
			(0.129)	
Transport				-1.119
				(0.834)
Retail				0.839
				(0.739)
Manufacturing				-0.827***
				(0.308)
Construction				-0.232
				(1.024)
Agriculture				0.663
				(0.694)
Controls	Yes	Yes	Yes	Yes
Observations	5719	5719	5719	5719

Notes: Presented estimates extend on column 6 of Table 2 reporting marginal effects at means for IV-Probit regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Robustness checks II - Other political factors

Dependent variable: Vote on low-skill immigration policy			
	(1)	(2)	(3)
Manual share	-1.861***	-2.629***	-2.626***
	(0.679)	(0.725)	(0.742)
Republican (93rd-97th)	-0.024		
	(0.037)		
Republican (98th-102nd)	-0.236***		
	(0.023)		
Republican (103rd-107th)	-0.432***		
	(0.067)		
Republican (108th-112th)	-0.651***		
	(0.041)		
Republican (113th-117th)	-1.044***		
	(0.060)		
Democrat voteshare		0.052	
		(0.041)	
DW-1 nominate			-0.729***
			(0.054)
DW-2 nominate			-0.084***
			(0.029)
Controls	Yes	Yes	Yes
Observations	5719	5578	5719

Notes: Presented estimates extend on column 6 of Table 2 reporting marginal effects at means for IV-Probit regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: Robustness checks II - China trade shock

Dependent variable: Vote on low-skill immigration policy		
	(1)	(2)
Manual share	-3.349***	-3.356***
	(0.822)	(0.822)
China-US IM	-0.006**	
	(0.003)	
China-US IM-EX		-0.005**
		(0.003)
Controls	Yes	Yes
Observations	5719	5719

Notes:Presented estimates extend on column 6 of Table 2 reporting marginal effects at means for IV-Probit regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Data appendix (Not for publication)

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.

Converting Data across Geographic Areas

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:[32]

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

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 C.1. In the cases where data is readily available from Manson et al. (2019) at the congressional district level, I use this data. This is the case for the majority of the control variables.

China Trade Shock

The measure of exposure to Chinese trade is constructed as follows:

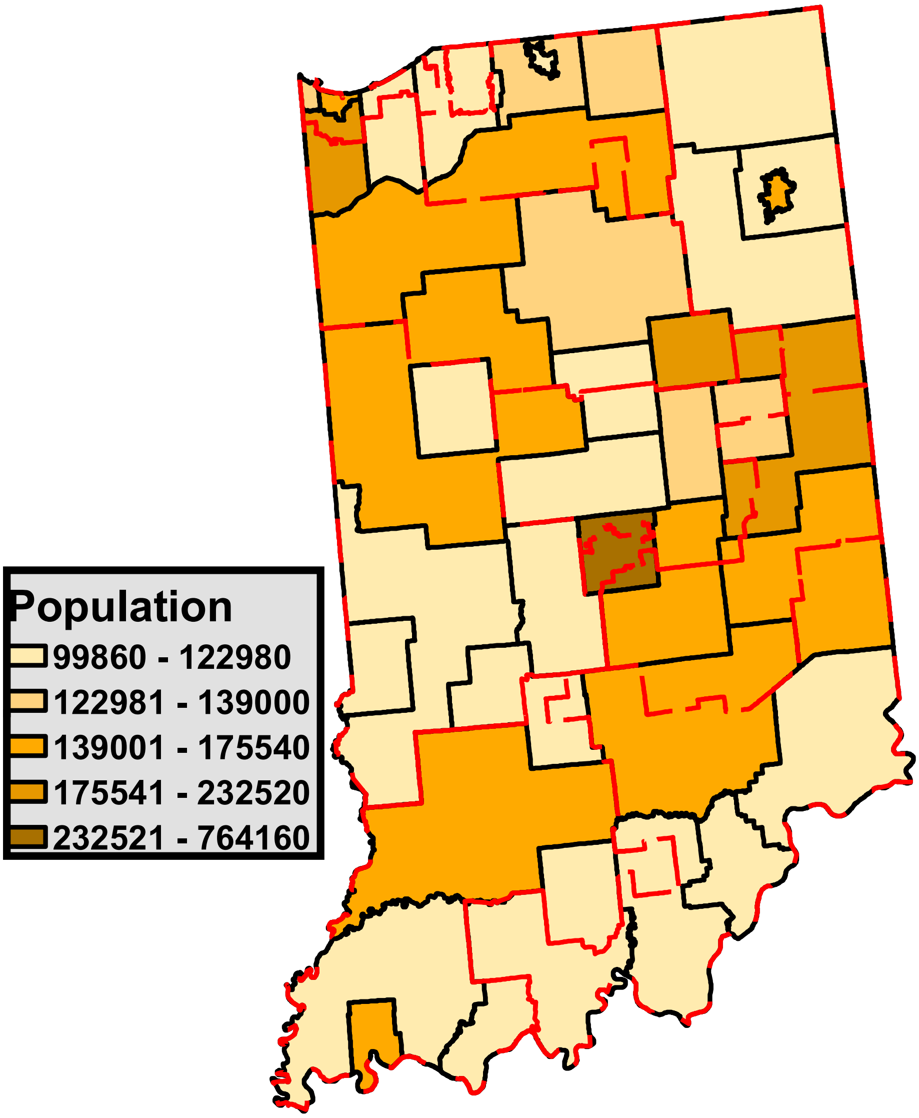
$$IP_{n,t} = \sum_{i=1}^{I} \frac{L_{n,91,i}}{L_{n,91}} \frac{TR_{t,i}^{CHN}}{L_{91,i}}$$

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.[33] Trade is than adjusted by total US employment in industry. Finally, the industry specific measure

[32] Congressional district shapefiles are obtained form Lewis et al. (2013), while the remaining shapefile's geographical areas required are obtained from Ruggles et al. (2019) for areas used in IPUMS-USA and Manson et al. (2019) for counties.

[33] This assumption seems plausible as China only accounted for less than 1% of total US trade with China (being mostly balanced) (Wang 2013). This likely relates to Congress conferring contingent Most

Figure C.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]

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).

Favored Nation status to China only on January the 24, 1980. Compared to this trade with China accounted for 14.3% of total US trade in 2010.