Spatial Misallocation of Native Labor and Immigration*

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Abstract

We document that immigrants played an outsized role in one of the biggest reallocations of workers in the US since World War II: the shift in population from the Rust Belt to the Sun Belt. Motivated by this observation, this paper asks how much do immigrant workers contribute to US economic growth through the spatial reallocation channel. We first provide empirical evidence using US Census data that, in terms of labor-market earnings, immigrants sort themselves better across locations than natives. We then use a Roy model of occupational choice to measure frictions to labor reallocation separately for natives and immigrant workers. The standard deviation of the wedge between earnings and utility, the model-based measure of frictions, is more than three times larger for natives than for immigrant workers. We run equilibrium counterfactuals in which we evaluate the effect of varying the share of immigrant workers on aggregate US productivity. We find that in 2018 aggregate labor productivity in the US is hump-shaped in the share of immigrant workers. The hump shape reflects the net effect of two underlying forces. First, there is a misallocation effect: increasing the share of immigrant workers increases labor productivity by ameliorating the misallocation of native labor. The second effect reflects a change in endowment: increasing the share of immigrant workers lowers labor productivity because these workers are, on average, less productive than natives.

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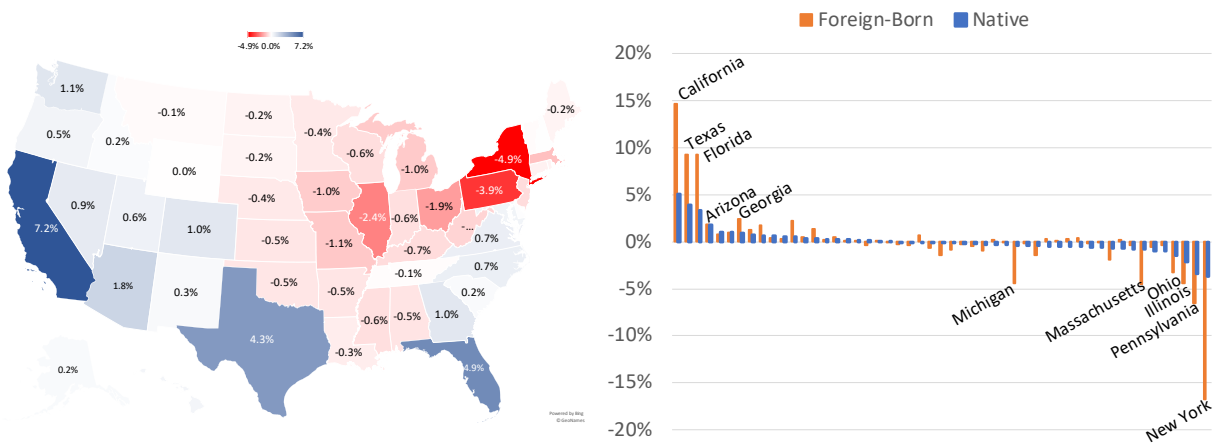
1 Introduction

The process of economic growth involves significant reallocation of workers across space. The post-WWII shift in the distribution of population and economic activity from Rust Belt states to Sun Belt states is a prominent example. Between 1940 and 2018, California, Texas and Florida's share of the US working age population increased by 16 percent, as shown in Figure 1a. A lesser-known fact is that these shifts in the distribution of workers towards Sun Belt states was much more pronounced for the foreign-born, as shown in Figure 1b. This observation suggests that foreign-born workers play a disproportionate role in greasing the wheels of economic growth by reallocating to where labor is most needed. Motivated by these facts, we ask how much do foreign-born workers contribute to US economic growth through the channel of spatial reallocation?



(a) Total

(b) By Nativity Status

Figure 1: Change in the Distribution of US Working-Age Population, 1940-2018

Source. IPUMS-USA and own calculations
Notes. The value in a state is the share of US workers in that state in 2018 minus the share in US workers in that state in 1940. Values in each series add up to zero. Panel b: States are ordered by the size of the blue bars.

We begin by documenting that wages play a more important role in the location choices of foreign-born workers. We regress the real wage per hour of workers on their nativity status and location in US Census data. We find that foreign-born workers tend to locate in states with high real wages. For example, without location controls, aggregate data indicate that foreign-born workers earned a wage premium in 2018. Once we control for location, however, the premium vanishes indicating that the higher wages of foreign-born workers can be attributed to their choice of location. Similarly, in decades where the aggregate data indicate there is a wage-gap between foreign-born and native workers, the inclusion of location controls further widens the gap. These findings are robust to controlling for

worker characteristics such as age, sex, education, industry and occupation. Overall, these findings suggest that wages play a stronger role in the location choices of foreign-born workers, as compared to natives.

The importance of wages for foreign-born workers implies that these workers are more likely to reside in locations where they are most productive. However, people might choose locations for reasons other than wages, which we refer to as frictions. For example, Glaeser and Tobio (2008) find that while rising productivity was the main driver of reallocation to the Sun Belt states, weather-amenity improvements (such as air conditioning) and flexible housing supply also played a role. Kennan and Walker (2011) argue that incorporating home bias into preferences is necessary to explain why a large fraction of all movers involve people returning to their home location. In order to correctly attribute location choices to productivity, we need to distinguish the part of the location decision due to productivity from the part of the location decision due to other factors, which we refer to as a wedge. While there might be measures available for the some components of the wedge, such as amenities, other components are intrinsically unobservable, such as home bias. Therefore, we need to impose further structure to recover productivity and wedge from the data. We do so by using a Roy model that features labor markets across space. The Roy framework allows us to recover the wedge – the ratio of utility to earnings – from compensating differentials that rationalize the observed location choices of workers. The dispersion in the wedge measures the extent to which agents are subject to reallocation frictions. We recover the wedge separately for native and foreign-born workers.

Our identification strategy consists of exploiting variation across markets to infer the wedge, and so reallocation frictions, and exploiting variation within markets to infer productivities. We find that the foreign-born population is subject to lower reallocation frictions than the native population. In particular, we find that the dispersion of the wedge of the foreign-born is two to four times lower than that of natives. However, we also find that the native population tends to be more productive than the foreign-born population. With the measurements at hand, we quantify the contribution of immigration to US economic growth by running counterfactuals in which we change the fraction of foreign-born workers in the economy. In order to make these counterfactuals meaningful, we specify a production structure for the economy, which determines the precise way in which prices, and therefore migration flows, respond to the change in the fraction of foreign-born workers.

Our counterfactuals indicate that US aggregate productivity is hump-shaped in the share of foreign-born workers. The US in 2018 is to the left of the peak: the share of foreign-born workers in the US is 18%, while aggregate labor productivity peaks at 22%. The hump shape reflects the net effect of two underlying forces. First, there is a misallocation effect: increasing the share of foreign-born workers increases labor productivity by

ameliorating the moving cost friction. The second effect reflects a change in endowment: increasing the share of foreign-born workers lowers labor productivity because these workers are, on average, less productive than natives. The misallocation effect dominates for low levels of immigration, while the endowment effect dominates after the peak at 22.45%.

Related Literature. The debate on the impacts of immigration on various aspects of the economy dates back to at least the seminal papers by Borjas (1987) and Card (1990). The traditional debate, however, has been focused on the labor-market impact of immigration (see Peri (2016) for a review and Burstein, Hanson, Tian and Vogel (2020) and Piyapromdee (2021) for recent contributions). More recently, there has been a growing body of work addressing the productivity effects of immigration. A number of papers have looked at the link between immigration and innovation (Sequeira, Nunn and Qian, 2019; Burchardi, Chaney, Hassan, Tarquinio and Terry, 2020; Arkolakis, Lee and Peters, 2020; Bernstein, Diamond, McQuade and Pousada, 2019, e.g.). We contribute to this literature on the productivity effects of immigration by highlighting a different channel, spatial reallocation, by which immigration affects long-run economic growth.

Recent empirical work has found that differences in location choices of immigrants and natives play a distinctive role in explaining various outcomes. For example, Abramitzky, Boustan, Jacome and Perez (2021) find that children of immigrants have higher rates of upward mobility than children of the US-born, in part, because they settle in locations that offer better prospects for their children. Cadena and Kovak (2016) find that immigrants play an important role in smoothing regional economic fluctuations because their location choices are more responsive to economic shocks than natives. In our empirical exercise we find that location plays an equally important role in explaining a different outcome: the difference in labor-market earnings between immigrant and US-born workers.

While most of the literature on immigration has focused on frictionless frameworks, recent papers have attempted to model the responses of migrants and natives to immigration by introducing specific types of labor market frictions. For example, Moreno-Galbis and Tritah (2016) and Battisti, Felbermayr, Poutvaara and Peri (2018) introduce search and matching frictions into a model of immigration and find that immigration can attenuate search frictions. Relatedly, the literature on internal migration has introduced different types of frictions – moving cost that depends on location, distance, climate and location size – as in Kennan and Walker (2011) and search frictions as in Schmutz and Sidibé (2018) to explain internal migration patterns. We don't take a stand on the particular type of mobility friction that matters most. Instead, our approach captures mobility frictions in a general way and uses those measurements to perform aggregate counterfactuals. In this sense, our approach is closest to Bryan and Morten (2019), who study the gains from re-

moving internal migration costs in Indonesia and the US but abstract from immigration.

Methodologically, our paper is closest to those that use Fréchet distributions to reduce large amounts of heterogeneity to a tractable problem: Burstein, Hanson, Tian and Vogel (2020), Hsieh, Hurst, Jones and Klenow (2019), Bryan and Morten (2019), Redding and Rossi-Hansberg (2017), Lagakos and Waugh (2013), Eaton and Kortum (2002).

Our approach of measuring mobility frictions as wedges is similar to that of the literature on spatial misallocation (e.g. Desmet and Rossi-Hansberg, 2013; Fajgelbaum, Morales, Zidar and Suárez Serrato, 2018; Hsieh and Moretti, 2019; Herkenhoff, Ohanian and Prescott, 2018). This literature typically finds non-trivial gains from ameliorating spatial misallocation in the US. We contribute to this literature by pointing out the role played by immigrants in ameliorating spatial misallocation.

Finally, our paper is also related to a literature that finds an important role of new entrants in labor reallocation. Hobijn, Schoellman and Vindas Q. (2018) and Porzio and Santangelo (2019) show evidence that new cohorts account for a substantial portion of the reallocation of labor across sectors in the US and across countries. Kim and Topel (1995) show similar evidence for Korea and Pérez (2018) for Argentina.

2 Motivating facts

Data description. We begin by providing a brief description of the data. We use Census data collected from the IPUMS-USA project. We use the 1% State Census of Population for 1970 and 2000, the 5% Census for 1950, 1960, 1980, and 1990 and the American Community Survey (ACS) for the years 2001 to 2018. We complement Census data with data from the Annual Social and Economic (ASEC) survey for the years 1982 to 2019. Census data contains information that allows construction of measures of nativity status, migration, wages, education, occupation, and sector. The nativity status of a person can be either native or foreign-born, where foreign-born is defined as persons residing in the United States who were born outside the United States (or one of its outlying areas such as Guam or Puerto Rico). The foreign-born population includes legally-admitted immigrants, refugees, temporary residents such as students and temporary workers, and undocumented immigrants. We use the terms foreign-born and immigrants interchangeably throughout the paper. Our measure of migration is lifetime migration and refers to residing in a state different than the state of birth. The construction of the remaining categories is standard and the details are relegated to the Data Appendix A.

The role of labor earnings in location decisions of immigrants. We next determine the importance of labor market earnings in the location choices of foreign-born vs native work-

ers. For each year of Census data, we run the following regression

$$\log(\text{wages})_{n\ell gt} = \beta_0 + \beta_n \times \text{nativity} + \sum_{\ell} \beta_\ell \times \text{location} + \sum_{g} \beta_g \times \text{worker controls} + \varepsilon_{n\ell gt} \quad (1)$$

where the dependent variable is the log-real-wage-per-hour, which is indexed by n for nativity status, ℓ for location, g for worker characteristics, and t for the Census year. The nativity dummy is equal to 0 for natives and 1 for foreign-born workers. The location of workers is given by their state of residence in the respective Census year. In addition to location controls, we control for worker characteristics such as age, sex, education, industry and occupation.

Table 1 presents our findings from the regression analysis for each Census year from 1950-2018. The table reports the value of β_n for each Census year. Because natives are our baseline group, β_n captures the log-wage difference between foreign-born and natives. Stating wages in logs allows for the coefficient to be interpreted as approximate percentage differences. A positive value of the coefficient β_n shows that foreign-born workers earn a premium over natives, while a negative value indicates there is a wage gap between foreign-born workers and natives. The table reports four different specifications, which show how the β_n coefficient changes as we include controls for location and worker characteristics.

The first specification shows the coefficient β_n for aggregate data for each Census year. The aggregate data exhibit a mixed pattern. Foreign-born workers earn a premium over natives in the 1950, 1960, 1970 and 2018 Census years, while there is a wage gap between foreign-born and natives for the 1980, 1990, 2000 and 2010 Census years. The inclusion of location controls in the second specification provides us with our main result: location controls have a stronger effect on wages of foreign-born workers than on the wages of natives. For years in which the foreign-born earn a wage premium, the inclusion of location controls either lowers the wage premium or reverses the sign of the coefficient. For years in which there is a wage gap between foreign-born workers and natives, the inclusion of location control further widens the gap further reinforcing the importance of location. For example, in 1950, the 11.4% foreign-born wage premium shrinks to 2.1% after including location controls. In 1980, the 2.4% foreign-born wage gap nearly triples in size to a 6.9% wage gap after controlling for location. In 2018, the statistically insignificant 0.2% foreign-born wage premium becomes a statistically significant 4.4% foreign-born wage gap after controlling for location of residence. This suggests that the high wages of the foreign-born in aggregate data were driven by their "better" location choices. For all years, the results suggest that wages play a more important role in the location decisions of foreign-born workers than in the location decisions of natives.

The third and fourth specification show that this result is robust to the inclusion of

Table 1: Regression of log-wages per hour on nativity status

	(1)	(2)	(3)	(4)
1950:				
Foreign-born wage premium	0.114***	0.021***	0.105***	0.021***
	(0.007)	(0.007)	(0.006)	(0.006)
Observations	118,660	118,660	118,660	118,660
R^2	0.002	0.066	0.248	0.286
1960:				
Foreign-born wage premium	0.038***	−0.065***	0.074***	−0.017***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	2,478,673	2,478,673	2,478,673	2,478,673
R^2	0.000	0.064	0.261	0.299
1970:				
Foreign-born wage premium	0.029***	−0.052***	0.053***	−0.019***
	(0.004)	(0.004)	(0.003)	(0.003)
Observations	622,917	622,917	622,917	622,917
R^2	0.000	0.036	0.234	0.258
1980:				
Foreign-born wage premium	−0.024***	−0.069***	−0.010	−0.047***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	2,443,993	2,443,993	2,443,993	2,443,993
R^2	0.000	0.016	0.255	0.266
1990:				
Foreign-born wage premium	−0.052***	−0.135***	−0.007**	−0.078***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	5,599,793	5,599,793	5,599,793	5,599,793
R^2	0.001	0.034	0.309	0.332
2000:				
Foreign-born wage premium	−0.079***	−0.135***	−0.028	−0.074***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	6,301,767	6,301,767	6,301,767	6,301,767
R^2	0.002	0.023	0.297	0.309
2010:				
Foreign-born wage premium	−0.077***	−0.130***	−0.029***	−0.076***
	(0.002)	(0.002)	(0.001)	(0.002)
Observations	1,313,346	1,313,346	1,313,346	1,313,346
R^2	0.001	0.023	0.333	0.345
2018:				
Foreign-born wage premium	0.002	−0.044***	−0.007***	−0.047***
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	1,382,510	1,382,510	1,382,510	1,382,510
R^2	0.000	0.021	0.329	0.341
LOCATION CONTROL		YES		YES
WORKER CONTROLS			YES	YES

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Notes. The table reports the value of β_n in regression (1) for each Census year. The regression is weighted least squares with weights equal to Census population weights. The location control is the state of residence. Worker controls include age, sex, education, industry and occupation.

other worker characteristics. The third specification reports the foreign-born wage gap or premium after controlling for worker characteristics such as age, sex, education, industry and occupation but excluding a location control. As in the first specification, the results in this specification are mixed: foreign-born workers earn a premium over natives in 1950, 1960, 1970 and 2018, while there is a wage gap between foreign-born workers and natives in 1980, 1990, 2000 and 2010. The fourth specification reports the value of β_n with the inclusion of controls for both worker characteristics and location. As in the second specification, for years in which the foreign-born earn a wage premium, the wage premium vanishes with the inclusion of location controls. For years in which there is a wage gap between foreign-born workers and natives, the inclusion of location controls further widens the gap. Therefore, the fourth specification reiterates our main empirical result: with respect to wages, foreign-born workers tend to locate themselves better than native workers.[1]

Figure 2 provides an alternative perspective on the importance of wages in the location choices of foreign-born workers. This figure shows the population share of natives and foreign-born workers in the top ten states by the real hourly wage. The population share of foreign-born workers in the top 10 states is greater than that of natives over the entire sample. From 1950 to 1990, the share of foreign-born workers in the top ten states is almost twice that of natives, 60% vs 32%. In recent years, the share of foreign-born in the top-ten states has declined but there is still a substantial difference between the share of foreign-born and the share of native workers in 2018, 50% vs 30% respectively. This pattern holds in spite of massive shifts in the location of economic activity over time, which reinforces our result that the foreign-born are consistently more highly concentrated in higher wage states.

Decomposition of inter-state labor flows. Next, we measure the contribution of immigrants to the reallocation of labor across locations in the US. To do so, we decompose the change in the working-age population in a state into demographic changes arising from within the state and net migration into the state. US Census data allows us to conduct this exercise separately for natives and foreign-born (see Appendix A.2). Our decomposition first shows that the contribution of net migration to labor reallocation across states in the US is significant. Figure 3a plots this contribution between 1930 and 2016: it ranges from a a minimum of about 40% in 1940 to a maximum of more than 80% in the 1990s and 2000s. Second, our decomposition reveals that the contribution of immigrants to net migration is disproportionately high relative to their contribution to the working-age population.

[1] An open question is why there is a consistent foreign-born wage gap since 1960 after controlling for all observables. One of the leading explanations is that lower level of English proficiency of the foreign-born, either self-reported (Borjas, 2015) or as perceived by potential employers (Oreopoulos, 2011), hurts their labor market prospects.

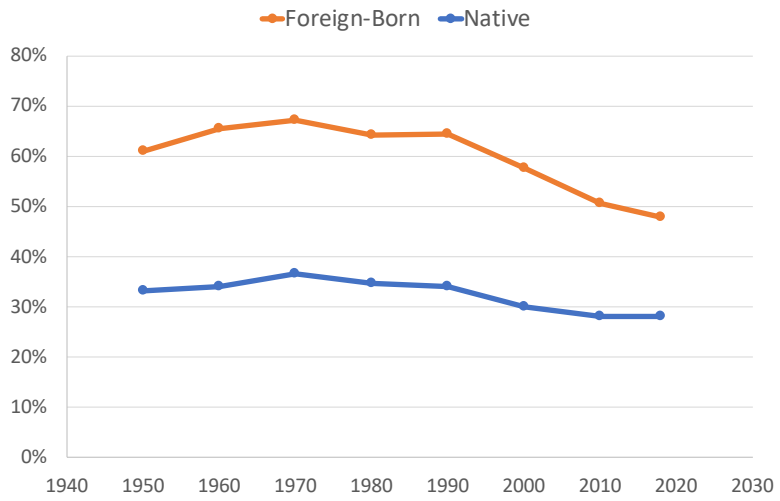


Figure 2: Share of US Foreign-Born and Native Population in Top 10 States by Real Wage per Hour

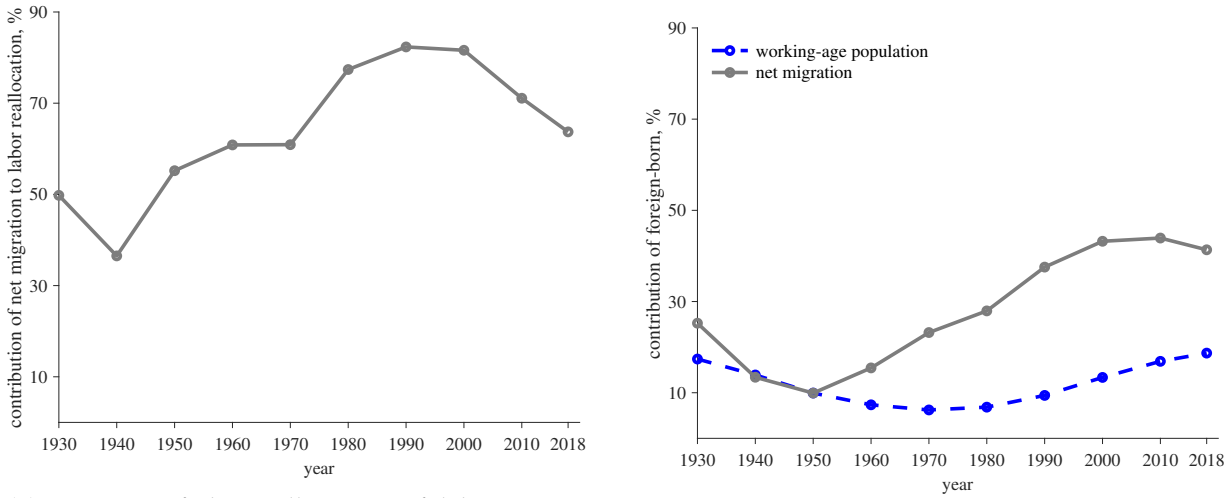
Source. IPUMS-USA and own computations
Notes. Population is working-age population. The top 10 states by real wage per hour in 2018 were New Jersey, Connecticut, Massachusets, Maryland, New York, Washington, California, Virginia, Alaska, and New Hampshire.

As shown in Figure 3b, immigrants account for only 12% of the working-age population, but they account for 28% of the labor reallocation across states, on average between 1930 and 2018. The contribution of immigrants to labor reallocation within the US ranges from a maximum of 4 times their presence in the population to a minimum of a 1-to-1 contribution relative to their presence in the population.[2]

We further dig into the contribution of immigrants to the reallocation of labor by focusing on labor of different skill (age and schooling) or on labor performing different tasks (occupations and sectors) – see Table C-2 in the Appendix. We find that immigrants contributed relatively more to the reallocation of labor with less than a college degree, both in levels and relative to their presence in the schooling group. immigrants contributed the most to the reallocation of older workers (50- to 65-year old) in levels and to that of younger workers (15- to 29-year old) in relative terms to their presence. immigrants mostly contributed to the reallocation of agricultural labor in levels, but relative to their presence, their highest contribution is to low-skill services before 2000 and high-skill services after 2000. A similar pattern emerges when looking at occupations: the contribution is highest in farming occupations in levels and in technicians and sales occupation when scaling to their presence in the occupation.[3]

[2]In the Appendix, we extend the analysis to consider flows of labor across counties, rather than states. Even though the magnitude of labor reallocation is slightly smaller when considering counties, the resulting patterns are similar to those reported for cross-state flows (see Table C-1 in the Appendix).

[3]An alternative way to conduct a systematic evaluation of the importance of immigrants in the reallocation



(a) Fraction of the reallocation of labor across states accounted for by net inter-state migration

(b) Contribution of foreign-born

Figure 3

Source. IPUMS-USA and own computations
Notes. Panel (a) plots the fraction of the reallocation of labor across states accounted for by net inter-state migration. The reallocation of labor is measured by changes in the share of working-age individuals assigned to each US-state between two years. Details on the computation are in Appendix A. Panel (b) plots the contribution of immigrants to the working-age population (in blue, dashed line) and to net migration across states (in grey, solid line).

3 An illustrative example

In this section, we use a simple example with two labor markets to illustrate how dispersion in the wedges determine the extent to which immigrants can ameliorate or worsen the misallocation of labor in the host country.

Suppose that there are two domestic locations indexed by $\ell \in \{1, 2\}$ and one foreign location with index f. Workers initially located in those three locations can work in exactly one of the two domestic locations. Worker i from home location $h \in \{1, 2, f\}$ has exogenous productivity $z_i(\ell|h) > 0$ in location $\ell \in \{1, 2\}$. This productivity determines the efficiency units of labor worker i supplies when working in location ℓ. Each efficiency unit of labor supplied in location ℓ earns the prevailing wage rate $w(\ell) > 0$. In this example, workers from location h face a wedge $\Delta(\ell|h) > 0$ associated with working in location ℓ. This wedge may capture utility costs that dampen the utility from consuming one's earnings such as home bias. It may also capture utility benefits that amplify the utility from consuming

of labor within the US is a variance-covariance decomposition. We run such decomposition and arrive to similar conclusions (details in Appendix A.2). In particular, despite immigrants are only 1/10 of the working age population, they account for about 1/3 of labor reallocation across states and counties, on average between 1960 and 2018. In addition, this decomposition exercise also reveals that immigrants are most important for the reallocation of labor of different schooling and occupations across counties, with a contribution share higher than 50% (see Table C-3 in the Appendix).

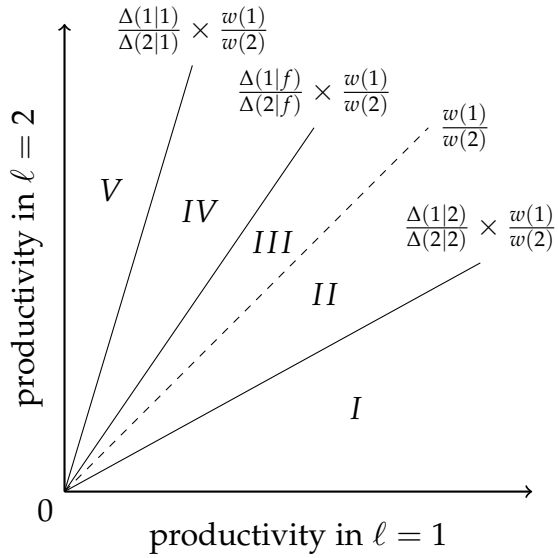


Figure 4: Location choice of native and foreign-born workers.

one's earnings such as the experience of amenities. Suppose that native workers experience a higher wedge when working in their home location than when working away from home, $\Delta(1|1) > \Delta(2|1)$ and $\Delta(2|2) > \Delta(1|2)$. These relative wedge sizes might describe a situation in which native workers experience home bias that outweighs any differences in their experience of amenities at home and away. Suppose further that foreign-born workers experience a higher wedge when working in location 1 than when working in location 2, $\Delta(1|f) > \Delta(2|f)$. These relative wedge sizes might describe a situation in which location 1 offers better amenities than location 2. However, relative to their respective wedge in location 2, foreign-born workers experience a smaller wedge in location 1 than native workers for whom location 1 is home, $\Delta(1|1)/\Delta(2|1) > \Delta(1|f)/\Delta(2|f)$. This higher dispersion in the wedges for native workers from home location 1 than for foreign-born workers might capture that foreign-born workers do not experience home bias towards either domestic location, while native workers from home location 1 are biased towards it. The indirect utility of worker i from home location h when working in location ℓ is

$$u_i(\ell|h) = \Delta(\ell|h)w(\ell)z_i(\ell|h).$$

Each worker i chooses to work in the location that promises them greater utility. Figure 4 depicts this choice in the space of productivities in locations 1 and 2. Four lines with labels indicating their slopes divide the space into five areas. Workers from home location 1 stay in location 1 if their pair of productivities lies in one of the areas I, II, III, or IV. They only move to location 2 if their productivity pair lies in area V. If they chose their location purely

based on their productivity in the two locations, then a productivity pair in areas III or IV would lead them to move to location 2. This discrepancy arises because native workers incur a relative utility cost when moving away from their home location as captured by the relative size of their wedges. For workers from home location 1 to move to location 2, their productivity in location 2 must be sufficiently high compared to their productivity in location 1 to overcome the relative utility cost of moving. The situation of workers from home location 2 is similar. They stay in location 2 if their pair of productivities lies in one of the areas V, IV, III, or II. A comparison of productivities alone would dictate for them to move to location 1 if their productivity pair lies in area II. The location choices of native workers are thus distorted by the relative size, or the dispersion, of their wedges. The more dispersed the wedges are, the more distorted are the location choices.

The location choice of foreign-born workers is distorted as well. They move to location 1 if their productivity pair lies in areas I, II, or III and to location 2 otherwise. Based on a comparison of productivities alone, foreign-born workers with a productivity pair in area III would move to location 2. The higher the wedge foreign-born workers experience in location 1 is relative to the wedge they experience in location 2, the more distorted is their location choice. However, their location choice is less distorted than that of native workers from home location 1. With a pair of productivities in area IV, foreign-born workers do move to location 2, while native workers from home location 1 do not. This difference in location choices arises because the wedges facing native workers from home location 1 are more dispersed than those facing foreign-born workers. The comparison of location choices of foreign-born workers with those of native workers from home location 2 is less clearcut. With a pair of productivities in area II, foreign-born workers do move to location 1, while native workers from home location 2 do not. At the same time, with a pair of productivities in area III, native workers from home location 2 do work in location 2, while foreign-born workers do not. The location choices of which of the two groups is more distorted depends on the dispersion in both groups' wedges.

Overall, the location choices of foreign-born workers can be less distorted than those of native workers. Of course, the location choices of foreign-born workers can also be more distorted than those of native workers. A stark example is the case in which foreign-born workers are not willing to live in location 2 at all, $\Delta(2|f) \to 0$. In this case, they move to location 1 irrespective of their productivity pair. The extent to which a higher fraction of foreign-born workers in the population improves the allocation of labor therefore depends on the frictions captured by the dispersion of the wedges facing foreign-born and native workers. The effect on aggregate productivity further depends on whether and how the productivity of foreign-born workers is systematically different from that of natives. In the next section, we present a strategy to measure frictions and productivity in the data.

4 Frictions to labor allocation

In Section 4.1, we first describe the framework and identification we use for our measurement. Then, we document frictions to labor mobility across states in the US over the last half century.

4.1 Identification

The role of the foreign-born in US labor productivity growth broadly depends on two aspects. First, it depends on the extent to which internal migration reflects changing location productivities or changing location-specific utility components such as amenities (including housing). Second, it depends on the extent to which foreign-born workers differ from native workers in these two dimensions. The general idea of the identification strategy consists of two steps. We first exploit information on earnings in and migration rates into labor markets to infer productivities. We then exploit earnings differences across labor markets to infer a compound location-specific utility component.

Workers are indexed by $i \in [0, 1]$. Each worker inelastically supplies one unit of labor. The endowment of worker i consists of a vector of characteristics g and a home location h. The vector of characteristics includes the worker's age, education, etc. The home location h represents a physical location. For native workers, h corresponds to a geographical unit in the native country such as US states or counties. The set of all such geographic units in the native country is denoted L. Foreign-born workers are assigned a generic home location f, which indicates their foreign status without distinguishing them based on their country of origin. Therefore, for native workers we have $h \in L$, while for foreign-born workers we have $h = f$. A worker's home location is the sole identifier of their nativity status.

Productive activity in the native country occurs across space, so workers are required across locations $\ell \in L$. In each location ℓ, production occurs in multiple occupations indexed by o. The set of all such occupations is denoted O. A combination of a location ℓ and an occupation o is a labor market (ℓ, o). Let $y_i(\ell, o|g, h)$ denote the nominal earnings of worker i with endowment (g, h) in labor market (ℓ, o). We have

$$y_i(\ell, o|g, h) = \underbrace{w(\ell, o)}_{\text{wage rate}} \times \underbrace{A(\ell, o|g, h)\epsilon_i(\ell, o)}_{\text{worker productivity}},$$

where $w(\ell, o)$ is the prevailing wage rate and $A(\ell, o|g, h)\epsilon_i(\ell, o)$ is worker i's productivity in labor market (ℓ, o). The wage rate $w(\ell, o)$ captures the price of an efficiency unit of labor across locations and occupations. For example, the term would capture the fact that, regardless of other worker characteristics, one efficiency unit of labor supplied as

a computer programmer in San Francisco is paid more than one efficiency unit of labor supplied as a barista in Kansas City.

The productivity term shows how many efficiency units of labor worker i supplies to a labor market (ℓ, o). This term determines the differential comparative advantages of workers in various locations. The factor $A(\ell, o|g, h)$ is a productivity shifter that scales the average productivity that workers with a given endowment (g, h) have in labor market (ℓ, o). The dependence of this shifter on the home location can be interpreted as capturing differences in, for instance, the quality of schooling across locations. The dependence of the shifter on group characteristics captures productivity differences that arise due to, for instance, age or education. For example, it would capture earnings differences, if any, between computer programmers in San Francisco who have different educational backgrounds. The dependence of the productivity shifter on the labor market captures how labor-market-specific earnings premia depend on the endowment of the worker. For example, it would capture differences in those earnings differences between computer programmers who have different educational backgrounds in San Francisco and Tulsa.

In addition to the shifter $A(\ell, o|g, h)$, the productivity of each worker i has a labor-market-specific idiosyncratic component $\epsilon_i(\ell, o)$. This term can be interpreted as workers drawing various job offers in different labor markets. The idiosyncratic component is drawn from a univariate Fréchet distribution with cumulative distribution function $F(\epsilon_i) = \exp(-\epsilon_i^{-\theta})$. The productivity draws of worker i are *iid* across labor markets and independent of their endowment. The productivity draws are also *iid* across workers. The *iid* property across workers and labor markets implies that the law of large numbers applies, and there is no aggregate uncertainty.

After drawing the idiosyncratic productivity component in each labor market, workers sort themselves across labor markets. The indirect utility function of worker i is

$$u_i(\ell, o|g, h) = \underbrace{\Delta(\ell, o|g, h)}_{\text{wedge}} \times \underbrace{y_i(\ell, o|g, h)}_{\text{earnings}} = \widetilde{u}(\ell, o|g, h)\epsilon_i(\ell, o).$$

The term $\Delta(\ell, o|g, h)$ denotes a wedge a worker with endowment (g, h) experiences when working in labor market (ℓ, o). This wedge depends on home location and destination labor market and may vary by group characteristics such as age or education. It captures, for example, a utility cost of moving to a labor market facing workers. It also captures utility from amenities workers experience when working in a labor market that may be associated with cost of living and other location-specific benefits. Later on, we will breakdown this wedge to distinguish between these components. We define a function $\widetilde{u}(\ell, o|g, h) \equiv \Delta(\ell, o|g, h) \times w(\ell, o) \times A(\ell, o|g, h)$ that contains all the systematic components

of utility, including the components that determine earnings. The utility of worker i with endowment (g, h) working in labor market (ℓ, o) then is the product of the systematic component $\widetilde{u}(\ell, o|g, h)$ and the idiosyncratic shock $\epsilon_i(\ell, o)$.

Workers choose labor markets to maximize their utility given their endowment and their productivity draws. They take the wedge associated with moving to each labor market as given. The implied migration rates $\pi(\ell, o|g, h)$ can be derived from well-known properties of the Fréchet distribution.

Lemma 1 (Migration rates)**.** *The rate at which workers with endowment (g, h) move into labor market (ℓ, o) is*

$$\pi(\ell, o|g, h) = \frac{\widetilde{u}(\ell, o|g, h)^{\theta}}{\sum_{(\ell', o')} \widetilde{u}(\ell', o'|g, h)^{\theta}}.$$

The migration rate determines how workers sort themselves based on their comparative advantage. The comparative static properties of the migration rate $\pi(\ell, o|g, h)$ are intuitive. Given an endowment (g, h), workers migrate at higher rates to labor markets that result in a higher systematic component of utility. These include markets with higher wage rates $w(\ell, o)$, a higher productivity shifter $A(\ell, o|g, h)$, and a higher wedge $\Delta(\ell, o|g, h)$. Due to the properties of the Fréchet distribution, higher migration rates for workers into a labor market decrease the average productivity of those workers and therefore their average earnings in that market. The following relationship between migration rates of workers with endowment (g, h) into labor market (ℓ, o) and their average earnings $\overline{y}(\ell, o|g, h)$ arises.

Proposition 1 (Average earnings)**.** *The average earnings of workers with endowment (g, h) in labor market (ℓ, o) are*

$$\overline{y}(\ell, o|g, h) = w(\ell, o)A(\ell, o|g, h)\pi(\ell, o|g, h)^{-1/\theta} \times \Gamma\left(1 - 1/\theta\right). \tag{2}$$

All else equal, average earnings are higher in markets with higher wage rates. Average earnings in the market are higher for groups with a higher productivity shifter $A(\ell, o|g, h)$. Average earnings in a market are declining in the migration rate $\pi(\ell, o|g, h)$. Workers move into the labor market until the decrease in average earnings balances out the higher systematic component. Therefore, workers' moving decisions equalize average utility $\overline{u}(\ell, o|g, h)$ across all labor markets for every endowment.

Proposition 2 (Average utility)**.** *The average utility of workers with endowment (g, h) in labor market (ℓ, o) is*

$$u^*(g, h) = \overline{u}(\ell, o|g, h) = \Delta(\ell, o|g, h)\overline{y}(\ell, o|g, h). \tag{3}$$

While the average earnings of workers after the migration decisions are not equal in general, their average utility is equalized across labor markets. The wedge $\Delta(\ell, o|g, h)$ serves

the role of a compensating differential. We use this role to back out this wedge from variations in average earnings.

We want to back out the systematic components of earnings, $w(\ell, o)A(\ell, o|g, h)$, and the wedge, $\Delta(\ell, o|g, h)$. We have data on average earnings and migration rates for each labor market and each endowment type, $\overline{y}(\ell, o|g, h)$ and $\pi(\ell, o|g, h)$, respectively. We use this data, along with (2) and (3) and an estimate of θ that we discuss below, to back out the model unknowns in two steps. First, we use (2) to back out $w(\ell, o)A(\ell, o|g, h)$. Second, we use (3) and a normalization to back out $\Delta(\ell, o|g, h)$. We discuss each step in detail.

Step 1: Exploit information on earnings in and migration rates into labor markets to identify productivities. We identify the systematic component of earnings in a given labor market with a given endowment, $w(\ell, o)A(\ell, o|g, h)$, from average earnings in and migration rates into the labor market. In particular, given θ, we use (2) to get:

$$w(\ell, o)A(\ell, o|g, h) = \overline{y}(\ell, o|g, h)\pi(\ell, o|g, h)^{1/\theta}\Gamma(1 - 1/\theta)^{-1}. \tag{4}$$

Step 2: Exploit earnings variation across labor markets to identify wedges. We identify the wedge associated with a given labor market facing a worker with a given endowment, $\Delta(\ell, o|g, h)$, from average earnings in the labor market compared to average earnings in some baseline labor market. The labor market choices of workers equalize the average utility of workers across all labor markets for every endowment. They are compensated for variations in their average income across labor markets by the wedge they experience in the destination labor market. We can rewrite (3) to identify all wedges relative to that in some baseline labor market (ℓ_b, o_b) as

$$\frac{\Delta(\ell, o|g, h)}{\Delta(\ell_b, o_b|g, h)} = \frac{\overline{y}(\ell_b, o_b|g, h)}{\overline{y}(\ell, o|g, h)}. \tag{5}$$

Without loss of generality, we can normalize the wedge in the baseline labor market, which determines the scale of the wedges but makes no difference otherwise.

Normalization 1. *The wedge facing workers with all endowments (g, h) in the baseline labor market (ℓ_b, o_b) is*

$$\Delta(\ell_b, o_b|g, h) = 1.$$

Using Normalization 1 in (5), the wedge can then be backed out from the variation in average income of workers relative to the baseline labor market:

$$\Delta(\ell, o|g, h) = \frac{\overline{y}(\ell_b, o_b|g, h)}{\overline{y}(\ell, o|g, h)}. \tag{6}$$

Table 2: Measurement

	Mean		*Standard deviation*	
	1960	2018	1960	2018
Utility:				
$\log \Delta(\ell\|h)$ natives			0.077	0.100
$\log \Delta(\ell\|h)$ foreign-born			0.020	0.023
Productivity:				
$w(\ell)A(\ell\|h)$ natives	7.541	11.162	2.304	5.662
$w(\ell)A(\ell\|h)$ foreign-born	5.329	7.771	2.137	5.129
$w(\ell)A(\ell\|h)E(\epsilon)$ natives	14.227	22.702	5.488	8.898
$w(\ell)A(\ell\|h)E(\epsilon)$ foreign-born	14.606	23.219	1.980	3.370

Notes. The table shows the weighted average and the standard deviation of the inferred wedge, $\Delta(\ell|h)$, and of productivity-related parameters (value-weighted shift parameters, $A(\ell|h)w(\ell)$, and value-weighted labor productivity, $A(\ell|h)w(\ell)E(\epsilon)$), separately for natives and foreign-born.

4.2 Measurement

We use our identification strategy to measure productivity, amenities, and movings costs in the US, between 1960 and 2018. We focus on how these parameters vary by nativity status across states. That is, we abstract away from occupations and group characteristics at this point, but plan to introduce these dimensions in future versions of the paper.

To implement our identification strategy, we need to first assign a value to the parameter that governs the shape of the Fréchet distribution, θ. This parameter is linked to the price elasticity of labor supply, which, for fixed average earnings across labor groups, equals exactly $\theta - 1$ (see, for example, Caunedo, Jaume and Keller, 2020). We use the long-run estimate of this supply elasticity in Hornbeck and Moretti (2018) and set $\theta = 3.3$, consistent with Hsieh and Moretti (2019).[4]

Table 2 summarizes the outcome of our measurement, separately for the utility-related parameters and for the productivity-related parameters. Starting from the first set of parameters, the table reports the standard deviation of the wedge of moving across states, $\Delta(\ell|h)$, natives and foreign-born face, given their home location. In 2018, the standard deviation of the wedge facing natives is more than a fourfold that of the wedge facing foreign-born. Hence, the dispersion in state-related utilities is much higher for natives than for foreign-born. In 2018, South Dakota is the state with the highest wedge facing foreign borns, while New Hampshire is the one with the lowest wedge. The wedge facing foreign

[4]Alternatively, the shape parameter of the Fréchet distribution can be parameterized to fit the dispersion in the wage residuals predicted from a Mincerian regression that controls for demographic characteristics included in the identification framework. Using this method in a model of immigration, Burstein et al. (2020) estimate θ to be 2.

born does not depend on initial location and may largely reflect the cost of living. The correlation between the wage rate, which determines the price of output in a state, and the wedge facing foreign-born across states is -0.48. Natives face the lowest wedge when relocating to Oklahoma and the highest one when relocating to New Hampshire, on average. Individuals initially located in South Dakota face the lowest average wedge of leaving the state while those initially located in Washington face the highest wedge.

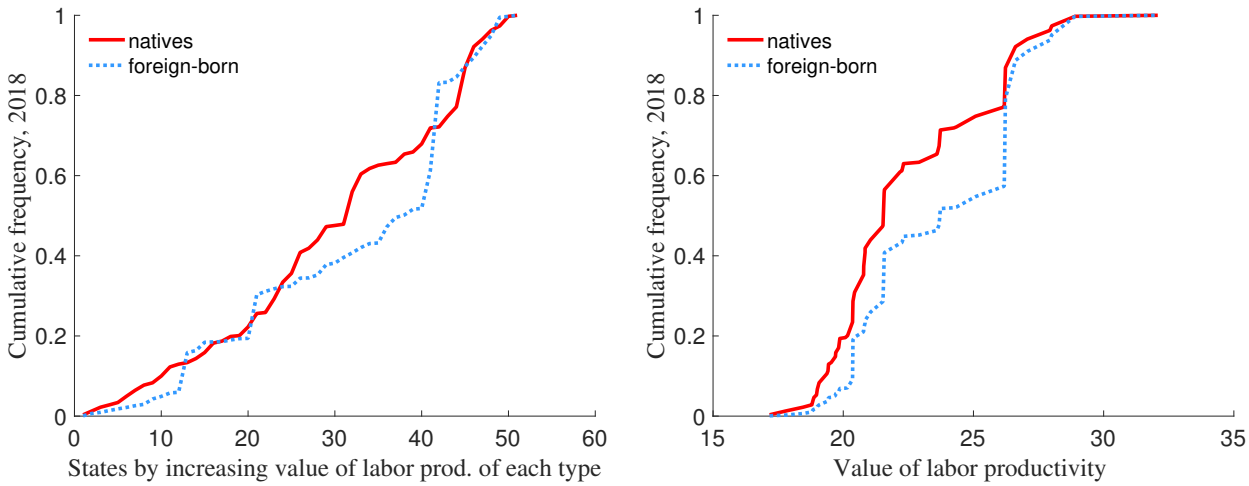


Figure 5: Allocation of natives and foreign-born across locations

Notes. The left panel shows the cumulative distribution function of natives and foreign-born across states ranked by their respective value-weighted labor productivity. The right panel shows the cumulative distribution function of natives and foreign-born across states of increasing value-weighted labor productivity.

Turning to productivity, Table 2 shows that the value-weighted average of the shift parameters of the Fréchet distribution, $w(h)A(\ell|h)$, is 44% higher for natives than for foreign-born. The value-weighted average productivity (that is, the value of labor productivity) is instead 2.3% higher for foreign-born than for natives. We conclude that, despite the foreign-born being less productive than natives in the same state, they allocate more efficiently across states and so measure a higher average labor productivity. Indeed, Figure 5 shows that, compared to natives, foreign-born tend to allocate more frequently in states where their value of labor productivity is higher (Figure 5a) and in states of higher value of labor productivity (Figure 5b). This conclusion is the mirror image of the fact we reported in Section 2 that the positive earnings premium received my immigrants turns to a negative one when controlling for location choice. Last, notice that the dispersion in the value-weighted productivity parameters is much higher for natives than for foreign borns. This indicates that the elasticity of labor productivity to labor allocation may be higher for natives than for foreign-born.

Figure C-2, in the appendix, shows the distribution of amenities, moving costs, value-

weight scale parameters, and selection effects across all states in 2018.

5 The role of immigration for labor allocation

With the measurement at hand, we now turn to counterfactual experiments. In order to make these counterfactuals meaningful, we specify a production structure for the economy, which determines the precise way in which prices, and therefore migration flows, respond to changes in immigration policy.

5.1 A spatial equilibrium of the labor market

Consider a modification of the framework described in Section 4, with only one occupation and one worker characteristic – that is, labor markets are indexed by their location and individuals by their home location, only. We combine this framework with a production structure and define a spatial labor market equilibrium.

Output for the economy, Y, is produced by a representative firm that combines the outputs (efficiency units) across locations:

$$Y = \left(\sum_{\ell} \mu(\ell)^{\frac{1}{\sigma}} n(\ell)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

where $n(\ell)$ is the output of location ℓ and $\mu(\ell)$ is the productivity of output in location ℓ, or a demand shifter. The representative firm maximizes profits as follows:

$$\max_{\{n^d(\ell)\geq 0\}_{\ell\in L}} \quad \left(\sum_{\ell\in L} \mu(\ell)^{\frac{1}{\sigma}} n^d(\ell)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} - \sum_{\ell\in L} w(\ell) n^d(\ell). \tag{7}$$

The solution of the firm problem implies that prices for the output produced in each location equal their marginal products,

$$\frac{w(\ell)}{w(\ell')} = \left(\frac{\mu(\ell)}{\mu(\ell')} \frac{n(\ell')}{n(\ell)} \right)^{\frac{1}{\sigma}}. \tag{8}$$

The equilibrium output of a location ℓ is:

$$n(\ell) = \sum_{h} A(\ell|h) \underbrace{\pi(\ell|h)^{-1/\theta}\Gamma(1-1/\theta)}_{\mathbb{E}[\epsilon_i(\ell)|i \text{ from } h \text{ chooses } \ell]} \underbrace{\pi(\ell|h)q(h)}_{\%\text{ of workers of type } h \text{ in location } \ell}. \tag{9}$$

where $q(h)$ is the frequency of workers with home location h. This equation sums total output produced in location ℓ by natives of different initial locations and foreign-born.

Definition 1. *An equilibrium is an allocation $\{n(\ell)\}_{\ell \in L}$ and wages $\{w(\ell)\}_{\ell \in L}$ such that:*

1. *given $\{w(\ell)\}_{\ell \in L}$, for all i and h, worker i from location h works in location ℓ iff*

$$u_i(\ell|h) > u_i(\ell'|h) \quad \forall \ell' \in L, \ell' \neq \ell;$$

2. *given $\{w(\ell)\}_{\ell \in L}$, $\{n(\ell)\}_{\ell \in L}$ solves the firm's problem in equation (7);*

3. *all labor markets clear – that is, equation (9) holds and $\pi(\ell|h)$ is consistent with utility maximization;*

4. *the final goods market clears*

$$Y = \sum_{\ell \in L} w(\ell) n(\ell).$$

5.2 Quantitative exercise

Our first step in evaluating the equilibrium effects of immigration is to parameterize the production structure just described. We map a home location to a state in the US and a foreign location to any location outside the US. The parameterization of the production structure requires values for the demand shifters, $\mu(\ell)$, and for the elasticity of substitution across state outputs, σ. Estimates of the latter parameter are hard to come by. We set $\sigma = 3$ and run a sensitivity analysis on the results. To measure the demand shifters, we combine the measurement in Section 4 with the cost minimization of the final output producer, equations (8) and (9). These equations define a link between the demand shifter, the wage rate, and observable location choices. We infer the wage rates from our previous inference of the value-weighted shifters of the Fréchet distribution across states and worker types, $w(\ell)A(\ell|h)$. This step amount to a choice of units. We set the wage rate in each state to be the average of $w(\ell)A(\ell|h)$ across all workers in the state and then infer $A(\ell|h)$ residually.

Our main exercise assesses the quantitative importance of immigration for labor productivity via a counterfactual. We take the equilibrium economy in 2018 and progressively increase the fraction of immigrants from zero to one – that is, we set the fraction of foreign-born $q(f) = x$ for $x \in [0, 1]$ and rescale $1 - q(f)$ so that the measure of workers is fixed at

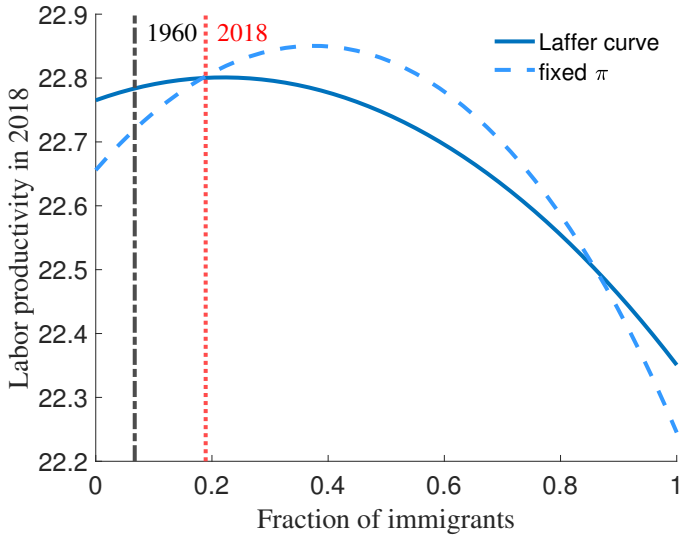


Figure 6: Laffer curve of immigration.

Notes. The solid line plots labor productivity computed for each fraction of immigrants via counterfactual exercises (details in the text) – that is, the Laffer curve of immigrations. The dashed line plots the solid line under constant location choice, set at the 2018 level – that is, when the fraction of immigrants in the economy is set at 18.9%. The vertical lines highlight the fraction of immigrants in 1960 and in 2018.

one. Figure 6, solid line, plots the evolution of labor productivity in 2018 against the fraction of immigrants. Labor productivity first increases with immigration and then decreases, generating an inverted-U pattern, which we refer to as the *Laffer curve of immigration*. Our computations indicate that labor productivity in 2018 is maximized with a fraction of immigrants at 22.45%. Between 1960 and 2018, the fraction of immigrants in the data increased from 6.7% (black-dashed line in Figure 6) to 18.9% (red-dotted line in Figure 6). As a consequence, labor productivity increased by 0.077%. Further increasing the fraction of immigrants to the labor productivity maximizing one, would increase labor productivity by 0.004 pp.

The Laffer curve of immigration reflects evolving equilibrium state prices and location choices along the immigration spectrum. Recall first that average earnings of foreign-born are 2.3% higher than those of natives, in 2018. As a consequence, in a partial equilibrium exercise where prices of state outputs and location choices are held fixed, labor productivity monotonically increases with the fraction of immigrants. Figure 6, "*fixed-π*" line, plots labor productivity computed by considering equilibrium prices but by holding the location choice of workers of all types at the one observed in the data in 2018 – that is, when the fraction of immigrants in the economy is set at 18.9%.[5] The "*fixed-π*" line increases at first, but then decreases, showing an inverted-U. This shape in comparison to the increasing one implied

[5]In other words, following the notation in our paper, we set $\pi(\ell|h)\ \forall\ h$ to the one observed in the US in 2018.

under fixed prices and location choices reflects the equilibrium effect of changing prices of state outputs that adjust in relation to the structure of production, as determined by the elasticity of substitution across these state outputs, σ, and the profile of productivity across states by nativity status, $\gamma(\ell|h) \equiv A(\ell|h)\mu(\ell)^{\frac{1}{\sigma-1}}$.[6]

Then, consider the implications for labor productivity of the evolving location choice along the immigration spectrum. This is the vertical distance between the solid line and "*fixed-π*" line in Figure 6. The response of the location choice is labor productivity enhancing at high and low fractions of immigrants but is labor productivity reducing for fractions of immigrants between 18.4% and 85.7%. This is a consequence of the fact that foreign-born also face wedges that distort their location choice, part of which probably reflect state amenities common to natives and foreign-borns. Importantly, the response of the location choice to the fraction of immigrants is quantitatively relevant for studying the effect of immigration on labor productivity. If we were to ignore it, we would wrongly infer a productivity maximizing fraction of immigrants of 36.7% instead of the 22.4%, with a related increase in labor productivity from the 2018 fraction of immigration of 0.23 p.p. instead of 0.004p.p.

How does immigration influence the allocation of labor across states? We find that rising the fraction of immigrants decreases the misallocation of labor in the 2018 US economy. To document this, we compute the labor allocation across states that maximizes labor productivity, at each level of immigration, by shutting down heterogeneity in the wedge– that is, by setting $\Delta(\ell|h) = 1$. Figure 7 plots the absolute distance of the labor allocation to the labor productivity maximizing one at each level of immigration, our misallocation index. As the fraction of immigrants increases, the misallocation index decreases (continuous line). This reflects both a composition effect, as foreign-born are better allocated than natives on average, and a within-group effect as the misallocation index for both natives and foreign-born decreases with the fraction of immigrants. What are the labor productivity implications of this reduced misallocation?

To answer this question, we isolate the two channels via which immigration influences labor productivity: the reduction in the dispersion of the wedge, $\Delta(\ell|h)$, and the change in the structure of productivity, $\gamma(\ell|h)$, across states in the economy. We design two alternative experiments: first, we equalize the structure of productivity between natives and foreign-born by assigning to natives the profile of $\gamma(\ell|h)$ of foreign-born (Common γ); second, we equalize the structure of the wedge by assigning to natives the profile of foreign-born and so remove the dependency of initial location (Common Δ). We quantify the importance of

[6]Note that, in our framework, the demand shifters are not separately identified from the location component of the Fréchet scale parameters.

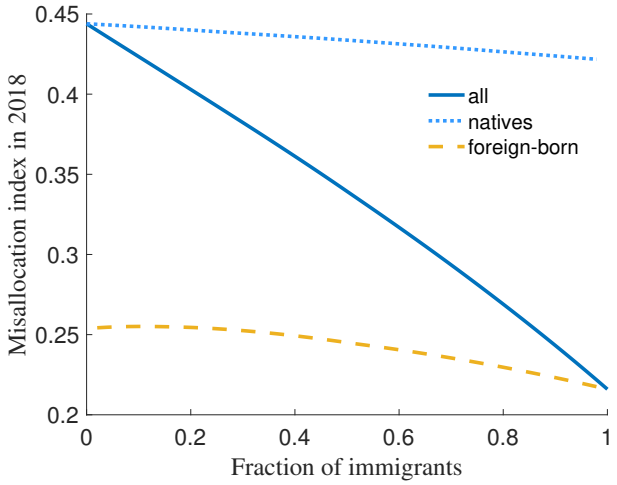


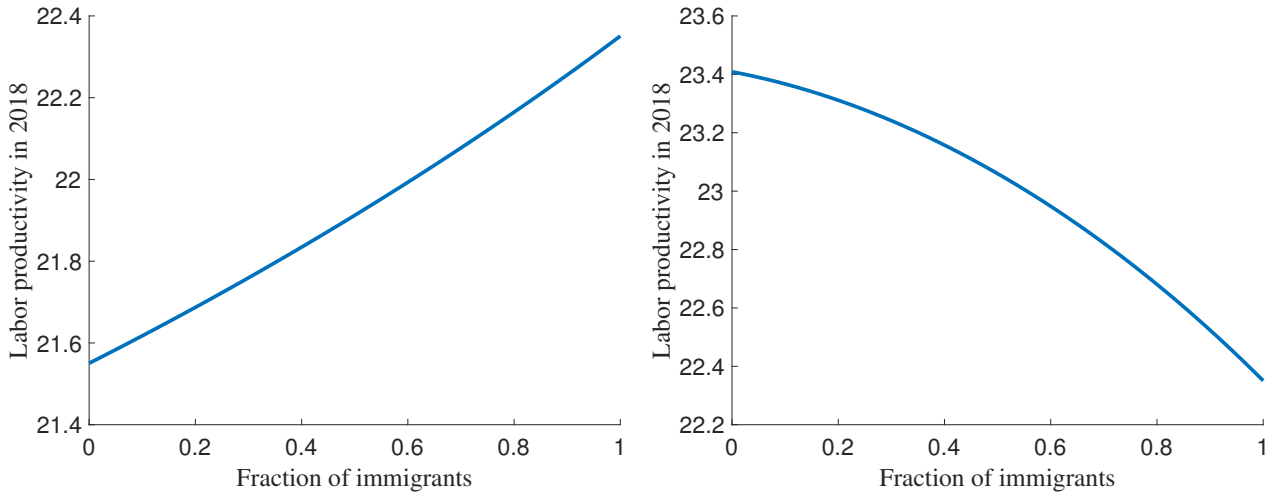
Figure 7: Misallocation and immigration.

Notes. The figure plots the absolute distance of the labor allocation to the labor productivity maximizing one at each level of immigration for natives (dotted line), foreign-born (dashed line), and for the entire economy (solid line).

immigration in each of these two alternative experiments by again changing the fraction of immigrants and analyzing the response of labor productivity in 2018. The results are shown in Figure 8.

Consider first panel (a) of Figure 8. This plot shows that if natives and foreign-born only differ by their wedges, then increasing the fraction of immigrants would monotonically increase labor productivity. Foreign-born alleviate the misallocation of natives' labor as foreign-born have no state asymmetry in their wedges. Via this channel, the increase in the fraction of immigrants the US witnessed between 1960 and 2018 increased labor productivity of 0.57pp. To benchmark the quantitative relevance of this increase, we compare it to the increase in labor productivity that follows from altogether eliminating heterogeneity in the wedge of natives across states in this counterfactual economy of identical productivity of natives and foreign-born. We then conclude that the increase in immigration we witnessed in the US between 1960 and 2018 alleviated the misallocation of natives' labor and generated 12% of the gains achievable from shuffling native labor to their labor productivity-maximizing level. Alternatively, comparing labor productivity in 1960 and 2018, the increase in immigration generates 23% of the gains achievable from shuffling native labor.

Turning, to the productivity channel, Figure 8 panel (b) shows that if natives and foreign-born only differed by their productivity profile, then increasing the fraction of immigrants would monotonically decrease labor productivity. First note that in this counterfactual economy, natives earn on average 1.14% more than foreign-born in 2018. This is a



(a) common productivity γ (b) common wedge Δ

Figure 8: Improvements in the allocation of labor and productivity.

Notes. The left panel plots the relation between the fraction of immigrants and labor productivity in an economy where natives and foreign-born have identical productivity $\gamma(\ell|h)$. The right panel plots in the solid line the relation between the fraction of immigrants and labor productivity in an economy where natives and foreign-born have identical wedges, $\Delta(\ell|h)$.

consequence of the fact that the higher earnings of foreign-born we documented in 2018 only reflect a more efficient allocation of foreign compared to native labor (see Section 2). This feature is abstracted away in this alternative exercise as the moving costs of natives are set to zero, and therefore the earnings premium shifts in favor of the natives. Under this earnings premium, increasing the fraction of immigrants with fixed prices of state outputs and location choices would therefore linearly decrease labor productivity. The path shown in the figure has a concave shape. This shape is a result of the location choice shifting the productivity profile $\gamma(\ell|h)$ across states and the average productivity ϵ via selection effects as well as of the changing state prices.

Overall, we measure that, increasing immigration in the 2018 US economy alleviates the costs of the misallocation of native labor, on the one hand, and decreases average productivity, on the other hand. These two effects have opposite impact on labor productivity and generate a Laffer curve of immigration.

6 Conclusion

[To be completed]

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Appendices

Appendix A Data

A.1 Data sources and description

Sample. We use the 1% State Census of Population for 1970, and the 5% Census for 1950, 1960, 1980, 1990 and 2000 and the American Community Survey (ACS) for the years 2001 to 2018 (Ruggles et al., 2019). We complement Census data with data from the Annual Social and Economic (ASEC) survey for the years 1982 to 2019 (Flood et al., 2019). Observations are weighted by sampling weights. We restrict the sample to individuals in the labor force, between the age of 16 and 65. We exclude self-employed workers, unpaid family workers and institutional group quarters. In exercises where the information is needed, we disregard workers with missing information on hours worked, weeks worked, earnings, current location and location 5-year prior.

Lifetime migration. We measure lifetime migration across locations in the USA by comparing current location and location at birth. We measure location at birth from BPL. We measure current state location from STATEFIP and current county location from COUNTYFIP.

Migration. We measure short-term migration across states in the USA by comparing current location (as measured by STATEFIP and location 5-year prior (as measured by MIGPLACE5 and, more generally, by MIGSTATUS). An alternative way to measure cross-location migration is to follow the method proposed by Molloy, Smith and Wozniak (2011). They determine migration based on children aged 4-5 years living in the household that have a different birth state than state of current residence. When using this method, we restrict the sample to households with children between the age of 4 and 5. The final sample size however significantly decreases and does not allow enough observations to compute average wages across current and initial location. For example, in 1970 we go from a full sample of 800,000 to a sample of slightly more than 80,000 observations.

Schooling. Our measure of schooling attainment is the IPUMS variable EDUC. It indicates the highest year of school or degree completed by the respondent. We focus on four main education groups: *less than high school* (up to 11th grade of high school), *high school* (12th grade of high school, with or without graduation), *college* (bachelor degree or more).

Occupation. We use the occupational classification of Acemoglu and Autor (2011), based on the IPUMS variable OCC1990. We grouped occupations in six groups: managerial and professional occupations (professionals), technicians, sales and administrative occupations (clerical occupations), low-skill services occupations (low-skill services), farming, forestry

and fishing occupations (agricultural occupations), production, craft and repair occupations (craftsman), operators, fabricators and laborers occupations (operators).

Sector. We use the industry classification based on the IPUMS variable IND1990. We grouped sectors in four groups: the agricultural sector (agriculture), the mining, construction and manufacturing sector (manufacturing), the transportation, communication, wholesale trade, entertainment, business repair services and personal services sector (low-skill services), and the finance, insurance, real estate, recreation, retail trade, and professional services sector (high-skill services).

Wages. Our measure of wages is the IPUMS variable INCWAGE. It reports total pre-tax wage and salary income, i.e. money received as an employee for the previous calendar year, as midpoints of intervals (instead of exact dollar amounts). We deflate our wage series to 2008 US dollars using the Personal Consumption Expenditure Deflator produced by the US Bureau of Economic Analysis. To compute hourly wages, we measure annual working hours by combining information on weekly working hours and number of week worked in a year. We use the variable HRSWORK2 and UHRSWORK for weekly working hours. HRSWORK2 reports the total number of hours the respondent was at work during the previous week. UHRSWORK reports the total number of hours that the respondent usually worked during the previous year. Our measure of the annual weeks worked is the IPUMS variable WKSWORK2. WKSWORK2 reports the number of weeks that the respondent worked for profit, pay, or as an unpaid family worker during the previous year. Finally, we follow Acemoglu and Autor (2011) in cleaning top and bottom-coded salaries. For 1950 to 2000, top-coded wages are multiplied by 1.5. For the years 2010 and 2018, top-coded wages are replaced by the mean hourly wage of those above the 99.5th percentile. For all years, bottom-coded wages are set to the first percentile of the hourly salaries of the whole country for the respective year.

Age. Age groups are 17 to 25 year olds, 26 to 40 year olds, 41 to 55 year olds, and 56 to 65 year olds.

Nativity. Foreign-born are persons residing in the United States who were born outside the United States (or one of its outlying areas such as Guam or Puerto Rico). The foreign-born population includes legally-admitted immigrants, refugees, temporary residents such as students and temporary workers, and undocumented immigrants.

A.2 Accounting for changes in the geographical allocation of labor

We measure the contribution of immigrants to changes in the allocation of labor across locations in the US. We use two methods, one based on the decomposition of net migration flows and another one based on a variance-covariance decomposition.

Decomposition of net migration flows. Indicate by $n_t(\ell)$ the number of individuals of working age in location ℓ in year t. The change in the fraction of individuals allocated to location ℓ between year t and year $t+10$ is:

$$a_{t+10}(\ell) = \frac{n_{t+10}(\ell)}{n_{t+10}} - \frac{n_t(\ell)}{n_t},$$

where $n_t \equiv \sum_\ell n_t(\ell)$. We decompose each of the $a_t(\ell)$'s in two components: one that relates to demographics specific to the location and one that relates to net-migration in or out of the location. We measure the demographic component by using the age distribution in year t to compute the number of individuals of working-age that we should have observed in year $t+10$ had there been zero net-migration to the location. We then measure the net-migration component residually, from the change in the fraction of individuals allocated to location net of the demographic component.

Indicate by $\tilde{n}_{t+10}(\ell)$ the number of individuals of working age in location ℓ at time $t+10$ had there been zero net-migration to the location between t and $t+10$. The net-migration component for location ℓ between year t and year $t+10$, $m_{t+10}(\ell)$, is:

$$m_{t+10}(\ell) = a_{t+10}(\ell) - \underbrace{\left(\frac{\tilde{n}_{t+10}(\ell)}{\tilde{n}_{t+10}} - \frac{n_t(\ell)}{n_t}\right)}_{\text{demographic comp.: } d_{t+10}(\ell)}.$$

Similarly, we decompose the change in the fraction of individuals allocated to each location, separately for each labor group, g:

$$m_{t+10}(\ell|g) = \underbrace{\frac{n_{t+10}(\ell|g)}{n_{t+10}} - \frac{n_t(\ell|g)}{n_t}}_{\text{total change: } a_{t+10}(\ell|g)} - \underbrace{\left(\frac{\tilde{n}_{t+10}(\ell|g)}{\tilde{n}_{t+10}} - \frac{n_t(\ell|g)}{n_t}\right)}_{\text{demographic comp.: } d_{t+10}(\ell|g)}.$$

Finally, and with the above definitions at hand, we decompose the change in the fraction of individuals allocated to a location in four components:

$$a_{t+10}(\ell) = \underbrace{d_{t+10}(\ell|b) + d_{t+10}(\ell|f)}_{\text{demographic comp.}} + \underbrace{m_{t+10}(\ell|b) + m_{st+10}(\ell|f)}_{\text{net migration comp.}}. \tag{A-1}$$

A labor group g contributes to the changing share of individuals of working age allocated to a location with its demographics, $d(\ell|g)$, and with its net migration, $m(\ell|g)$. To summarize the various forces that contribute to changes in the allocation of labor across locations, we use the absolute value sum.

In particular, define the contribution of net migration to the change in allocation of

individuals of working across locations to between year t and $t+10$ to be:

$$cont_m = \frac{\sum_g \sum_\ell |m_{t+10}(\ell|g)|}{\sum_\ell |a_{t+10}(\ell)|}.$$

Further, define the contribution of group g net migration to the change in allocation of individuals of working age across locations between year t and $t+10$ to be:

$$cont_m(g) = \frac{\sum_\ell |m_{t+10}(\ell|g)|}{\sum_\ell |a_{t+10}(\ell)|}.$$

Last, define the total contribution of group g to changes in the labor allocation to be:

$$cont(g) = \frac{\sum_\ell |m_{t+10}(\ell|g)| + \sum_{s\in S} |d_{t+10}(\ell|g)|}{\sum_\ell |a_{t+10}(\ell)|}.$$

With these definitions at hand, we compute the contribution of immigrants to the reallocation of individuals of working age across locations in the US. We define a location to be either a state or a county. We consider two labor groups, based on nativity: natives b and immigrants f– that is, $g \in \{b, f\}$. The results for the decomposition are reported in Figure 3a and Table C-1.

For robustness, we extend our baseline analysis to consider other individuals' characteristics that may influence labor market outcomes in their relation to the skill of the worker or to the task the worker performs in his/her job. Indicate by p this additional characteristic. To proceed with the decomposition, we need to take a stand on the counterfactual distribution of individuals of working age by the additional characteristic p had there be zero net migration across locations. We take two assumptions:

1. In each location, the distribution of individuals of working age in year t by the additional characteristic p does not change between year t and year $t+10$ – for example, if an individual is a college graduate in year t, we take he/she is a college graduate in year $t+10$ as well;

2. In each location, the distribution of individuals of age 5 to 14 in year t by the additional characteristic p at time $t+10$ is identical to that of individuals of age 15 to 24 in year t.

Then, indicate by $\tilde{n}_{t+10}(\ell|g,p)$ the number of individuals of working age in group g and of characteristic p in location ℓ at time $t+10$ had there been zero net-migration to the location of that labor group of that characteristic between t and $t+10$. This is:

$$\tilde{n}_{t+10}(\ell|g,p) = n_t(\ell|g,p,age \in (14,56)) + n_t(\ell|g,p,age \in (4,15)) \frac{n_{t+10}(\ell|g,p,age \in (14,25))}{\sum_p p_{t+10}(\ell|g,p,age \in (14,25))}$$

We map the characteristic p to, separately: age, schooling, occupation, and sector. The results for the decomposition are reported in Table C-2.

Variance-covariance decomposition. Indicate a labor market by ℓ, foreign-born individuals in the working age by f, and native-born individuals in the working age by b. Indicate by $n_t(\ell|g)$ the number of individuals of working age in group $g \in \{f, b\}$ in labor market ℓ at time t. Indicate by $e_t(\ell)$ the labor market ℓ's employment share at time t:

$$e_t(\ell) = \frac{\sum_g n_t(\ell, g)}{\sum_{g,\ell} n_t(\ell, g)},$$

and by $e_t(\ell|g)$ the labor market ℓ's employment share of group g at time t:

$$e_t(\ell|g) = \frac{n_t(\ell|g)}{\sum_\ell n_t(\ell|g)}.$$

Indicate by $s_t(g)$ the fraction of individuals of working age of type g:

$$s_t(g) = \frac{\sum_\ell n_t(\ell|g)}{\sum_{g,\ell} n_t(\ell|g)}.$$

Denote a change in variable x between time t and $t+1$ by Δx. We can write the change in the employment share of labor market ℓ between t and $t+1$ as:

$$\begin{aligned}
\Delta e_t(\ell) &= \sum_g \left(s_{t+1}(g)e_{t+1}(\ell|g) - s_t(g)e_t(\ell|g)\right) \\
&= \sum_g \left(s_{t+1}(g)e_{t+1}(\ell|g) - s_t(g)e_t(\ell|g) + s_t(g)e_{t+1}(\ell|g) - s_t(g)e_{t+1}(\ell|g)\right) \\
&= \sum_g \left(s_{t+1}(g)e_{t+1}(\ell|g) - s_t(g)e_{t+1}(\ell|g) + s_t(g)e_{t+1}(\ell|g) - s_t(g)e_t(\ell|g)\right) \\
&= \sum_g \left(\Delta s_t(g)e_{t+1}(\ell|g) + s_t(g)\Delta e_t(\ell|g)\right).
\end{aligned}$$

The first term in the equation above is the between-group component and the second term is the within-group component. We measure the contribution of foreign-born to the reallocation of labor across labor markets by summing up the between and within group terms for the group – that is, $\Delta s_t(f)e_{t+1}(\ell|f) + s_t(f)\Delta e_t(\ell|f)$.

We first define a labor market based on location, a state or a county in the US. Then we extend this definition to include characteristics that relate to the skill of the worker or to the task the worker performs in his/her job. In particular, we consider, one at at time: age, schooling, sector and occupation. We use variance-covariance accounting to perform the

decomposition. We regress the change in the employment share of a labor market to group dummy (for immigrants vs natives). The results are reported in Table C-3.

A.3 Geographic mobility of natives and foreign-born

We compare the geographic mobility of immigrants to that of natives by looking at migration rates and the elasticity of labor allocation to local labor market conditions.

We compute short-run migration rates (cross-state, within-state, and international) by comparing the current location of an individual and his/her location 5- and 1-year prior. These migration rates are reported in Table C-4 based on location 5-year prior and in Table C-5 based on location 1-year prior. The tables report overall migration rates, by nativity and schooling, along with within- and cross-state migration rates.

The migration rates of immigrants are overall higher than those of natives, and the difference increases with schooling. The fraction of immigrants who report to currently reside in a different location than 5 years ago is 57.8%, 7pp above the fraction reported by natives, on average between 1940 and 2000. This difference is higher for college-educated individuals (8.8pp) than that for individuals without a college degree (4.8pp). Similarly, the fraction of foreign-born that reported to currently reside in a different location than one year ago is 17.7%, 3.4pp above the fraction reported by natives, on average between 1995 and 2018. This difference is higher for college-educated individuals (4.7pp) than that for individuals without a college degree (2.7pp).

Most of the difference in migration rates between natives and immigrants is due to immigration rates (migration from abroad). The difference in internal migration rates (within- and across-state migration rates) by nativity is substantially smaller. Focusing on cross-states migration rates, Table C-4 reports that 6.7% of the immigrants reside in a state different from 5-year prior, compared to 9.1% of natives, on average between 1940 and 2000. Similarly, C-5 reports that 2.2% of immigrants reside in a state different from 1-year prior, compared to 2.4% of natives, on average between 1995 and 2018.

The higher cross-state migration rates of natives may reflect self-selection of workers across locations at entry. Indeed, Cadena and Kovak (2016) show that foreign-born who are not new immigrants play an important role in smoothing regional economic fluctuations. We compute the elasticity of labor allocation to local labor market conditions by nativity using data on the working-age population and employment between 1930 and 2018.

Define $n_t(\ell|g)$ to be the number of individuals of working age of group g in location ℓ at time t. Further, define $emp_t(\ell)$ the number of individuals of working-age employed in

location ℓ. We regress:

$$\ln n_{t+1}(\ell|g) - \log n_t(\ell|g) = \beta_0 + \beta_1[\log emp_{t+1}(\ell) - \log emp_t(\ell)] + \nu(\ell|g), \tag{A-2}$$

where $\ln(\cdot)$ indicates the natural logarithm operator and ν is an i.i.d. error term, normally distributed with mean zero. The regressor proxies the condition of the labor market in location ℓ. As demographic groups may differ by their sectoral distribution and sectors may be growing or shrinking at different rates over time, to have a more sensible measure of the labor market conditions group g faces, adjust the regressor to:

$$\log emp_{t+1}(\ell|g) - \log emp_t(\ell|g) = \sum_i \frac{emp_t(\ell, i|g)}{\sum_i emp_t(\ell, i|g)}[\log emp_{t+1}(\ell, i) - \log emp_t(\ell, i)],$$

where i indicates a sector.[7]

We map a demographic group to the nativity and the schooling (college education) of the individual. We use two alternative definitions of location: states and counties. We regress equation A-2 using 10-year data between 1930 and 2018 and using yearly data between 2000 and 2018. We use weights in our regression and add year fixed effects. Results are in table C-6.

The elasticity of labor allocation to local labor market conditions is higher for immigrants than for natives. Between 1960 and 2018, immigrants measure an elasticity of more than 1.2 across states and counties, compared to an elasticity of less than 0.9 for natives. The difference between the two groups decreases with the education of the individuals. immigrants without a college degree measure an elasticity of 0.56 points higher than that of natives across states (0.39 points higher across counties), compared to 0.13 points higher for college graduates (0.09 points higher across counties) .

Appendix B Proofs

Since the draws are i.i.d. across workers and labor markets and $\epsilon_i(\ell, o)$ follows a Fréchet distribution with cdf $F(x) = \exp\left(-x^{-\theta}\right)$ if $x > 0$ for all i and (ℓ, o),

1. $u_i(\ell, o|g, h) = \widetilde{u}(\ell, o|g, h)\epsilon_i(\ell, o)$ follows a Fréchet distribution with cdf $F(x) = \exp\left(-[\widetilde{u}(\ell, o|g, h)]^{\theta}\right.$ if $x > 0$;

[7] Cadena and Kovak (2016) first use the regression model outlined in the text to estimate the causal effects of changes in local labor demand to the reallocation of workers across location. We instead use the regression to describe the elasticity of the allocation of labor across locations to local labor market conditions.

2. $\max_{(\ell',o')\neq(\ell,o)}\{u_i(\ell',o'|g,h)\} = \max_{(\ell',o')\neq(\ell,o)}\{\widetilde{u}(\ell',o'|g,h)\epsilon_i(\ell',o')\}$ follows a Fréchet distribution with cdf $F(x) = \exp\left(-\left(\sum_{(\ell',o')\neq(\ell,o)}[\widetilde{u}(\ell',o'|g,h)]^\theta\right)x^{-\theta}\right)$ if $x > 0$;

3. $\max_{(\ell',o')}\{u_i(\ell',o'|g,h)\} = \max_{(\ell',o')}\{\widetilde{u}(\ell',o'|g,h)\epsilon_i(\ell',o')\}$ follows a Fréchet distribution with cdf $F(x) = \exp\left(-\left(\sum_{(\ell',o')}[\widetilde{u}(\ell',o'|g,h)]^\theta\right)x^{-\theta}\right)$ if $x > 0$.

Lemma 1

Proof. From Observations B.1–2 follows that

$$\begin{aligned}
\pi(\ell,o|g,h) &= \mathbb{P}\left(\max_{(\ell',o')\neq(\ell,o)}\{u_i(\ell',o'|g,h)\} < u_i(\ell,o|g,h)\right) \\
&= \frac{[\widetilde{u}(\ell,o|g,h)]^\theta}{\sum_{(\ell',o')\neq(\ell,o)}[\widetilde{u}(\ell',o'|g,h)]^\theta + [\widetilde{u}(\ell,o|g,h)]^\theta} \\
&= \frac{[\widetilde{u}(\ell,o|g,h)]^\theta}{\sum_{(\ell',o')}[\widetilde{u}(\ell',o'|g,h)]^\theta},
\end{aligned}$$

as was to be shown. ■

Proposition 1

Proof. Let ϵ_i^* satisfy $\widetilde{u}(\ell^*,o^*|g,h)\epsilon_i^* = \max_{(\ell',o')}\{\widetilde{u}(\ell',o'|g,h)\epsilon_i(\ell',o')\}$. By Observation B.3,

$$\begin{aligned}
\mathbb{P}(\epsilon_i^* < x) &= \mathbb{P}(\widetilde{u}(\ell^*,o^*|g,h)\epsilon_i^* < \widetilde{u}(\ell^*,o^*|g,h)x) \\
&= \mathbb{P}\left(\max_{(\ell',o')}\{\widetilde{u}(\ell',o'|g,h)\epsilon_i(\ell',o')\} < \widetilde{u}(\ell^*,o^*|g,h)x\right) \\
&= \exp\left(-\left(\sum_{(\ell',o')}[\widetilde{u}(\ell',o'|g,h)]^\theta\right)(\widetilde{u}(\ell^*,o^*|g,h)x)^{-\theta}\right) \\
&= \exp\left(-\frac{\left(\sum_{(\ell',o')}[\widetilde{u}(\ell',o'|g,h)]^\theta\right)}{[\widetilde{u}(\ell^*,o^*|g,h)]^\theta}x^{-\theta}\right).
\end{aligned}$$

That is, ϵ_i^* follows a Fréchet distribution with cdf $F(x) = \exp\left(-\left(\left(\sum_{(\ell',o')}[\widetilde{u}(\ell',o'|g,h)]^\theta\right)/[\widetilde{u}(\ell^*,o^*|g,h)]^\theta\right)x^{-\theta}\right)$ if $x > 0$. So, $y_i(\ell^*,o^*|g,h) = w(\ell^*,o^*)A(\ell^*,o^*|g,h)\epsilon_i^*$ follows a Fréchet distribution with cdf $F(x) = \exp\left(-\left(w(\ell^*,o^*)^\theta A(\ell^*,o^*|g,h)^\theta\left(\sum_{(\ell',o')}[\widetilde{u}(\ell',o'|g,h)]^\theta\right)/[\widetilde{u}(\ell^*,o^*|g,h)]^\theta\right)x^{-\theta}\right)$ if $x > 0$. Thus, for

all (ℓ, o), as $\pi(\ell, o|g, h) = [\widetilde{u}(\ell, o|g, h)]^\theta / \left(\sum_{(\ell', o')} [\widetilde{u}(\ell', o'|g, h)]^\theta\right)$ by Lemma 1,

$$\begin{aligned}
\overline{y}(\ell, o|g, h) &= \mathbb{E}\left(y_i(\ell^*, o^*|g, h) \mid (\ell^*, o^*) = (\ell, o)\right) \\
&= \left(w(\ell, o)^\theta A(\ell, o|g, h)^\theta \frac{\sum_{(\ell', o')} [\widetilde{u}(\ell', o'|g, h)]^\theta}{[\widetilde{u}(\ell, o|g, h)]^\theta}\right)^{1/\theta} \Gamma\left(1 - 1/\theta\right) \\
&= w(\ell, o) A(\ell, o|g, h) \pi(\ell, o|g, h)^{-1/\theta} \Gamma\left(1 - 1/\theta\right),
\end{aligned}$$

as was to be shown. ■

Proposition 2

Proof. Let (ℓ^*, o^*) satisfy $u_i(\ell^*, o^*|g, h) = \max_{(\ell', o')} \{u_i(\ell', o'|g, h)\}$. From Observation B.3 follows that, for all (ℓ, o),

$$\begin{aligned}
\overline{u}(\ell, o|g, h) &= \mathbb{E}\left(u_i(\ell^*, o^*|g, h) \mid (\ell^*, o^*) = (\ell, o)\right) \\
&= \mathbb{E}\left(\max_{(\ell', o')} \left\{u_i(\ell', o'|g, h)\right\}\right) \\
&= \left(\sum_{(\ell', o')} [\widetilde{u}(\ell', o'|g, h)]^\theta\right)^{1/\theta} \Gamma\left(1 - 1/\theta\right) \\
&= u^*(g, h).
\end{aligned}$$

Since $\pi(\ell, o|g, h) = [\widetilde{u}(\ell, o|g, h)]^\theta / \left(\sum_{(\ell', o')} [\widetilde{u}(\ell', o'|g, h)]^\theta\right)$ by Lemma 1,

$$u^*(g, h) = \overline{u}(\ell, o|g, h) = \widetilde{u}(\ell, o|g, h) \pi(\ell, o|g, h)^{-1/\theta} \Gamma\left(1 - 1/\theta\right) \quad \forall (\ell, o).$$

Using (2) and $\widetilde{u}(\ell, o|g, h) = \Delta(\ell, o|g, h) w(\ell, o) A(\ell, o|g, h)$,

$$u^*(g, h) = \overline{u}(\ell, o|g, h) = \Delta(\ell, o|g, h) \overline{y}(\ell, o|g, h) \quad \forall (\ell, o),$$

as was to be shown. ■

Appendix C Tables and Figures

Table C-1: The contribution of foreign labor to net migration across counties and states (i).

	states			counties		
	(a)	(b)	(c)	(a)	(b)	(c)
1930	50	25	17			
1940	37	13	14			
1950	55	10	10			
1960	61	15	7			
1970	61	23	6			
1980	77	28	7			
1990	82	38	9			
2000	82	43	13	79	41	18
2010	71	44	17	59	38	22
2018	64	41	19	50	40	24

Source. IPUMS-USA and own computations
Notes. Columns (a) show the fraction of the reallocation of labor across states or counties accounted for by net migration; Columns (b) show the contribution of foreign-borns to net migration; Columns (c) show the fraction of foreign-borns in the working age population. Entires are in percent.

Table C-2: The contribution of foreign labor to net migration across counties and states (ii).

	Schooling:						Age:								
	less than college			college or more			15 to 29			30 to 49			50 to 65		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
1960	52	21	7	62	15	6	67	14	3	59	17	6	46	38	15
1970	58	24	6	71	18	6	68	19	4	65	26	6	47	37	10
1980	76	27	7	80	23	7	73	29	6	76	28	8	73	18	7
1990	81	36	9	78	31	10	77	38	9	73	36	10	72	27	9
2000	79	43	13	87	35	13	70	44	14	79	42	14	71	27	11
2010	68	43	16	78	37	16	48	35	16	63	45	19	65	32	14
2018	56	39	18	74	27	19	43	30	14	53	43	23	58	40	17

	Sectors:											
	agriculture			manufacturing			low-skill services			high-skill services		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
1960	65	10	4	57	16	9	54	13	7	62	16	6
1970	68	14	4	55	21	7	58	24	6	62	22	6
1980	51	35	6	69	25	8	73	26	6	77	21	6
1990	69	48	12	76	34	10	80	38	9	80	31	8
2000	82	50	20	81	44	14	80	45	14	82	36	11
2010	73	50	29	80	39	19	73	45	18	75	39	13
2018	59	31	30	78	35	21	65	38	20	79	36	15

	Occupations:																	
	managers and professionals			technicians and sales			service occupation			farming occupations			craftsmen			laborers		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
1960	67	12	8	66	13	5	43	18	9	66	11	4	59	19	9	51	17	8
1970	63	14	6	68	18	5	47	26	7	64	15	4	55	14	7	46	33	7
1980	80	20	6	79	17	5	62	34	8	52	33	6	72	23	7	69	33	8
1990	83	25	8	81	31	7	77	41	11	70	47	12	83	34	9	75	42	11
2000	89	33	11	80	35	10	74	47	16	79	49	21	82	44	13	81	49	17
2010	83	34	13	73	36	13	66	49	21	68	50	29	81	46	18	73	45	22
2018	78	33	15	72	35	14	60	41	23	56	29	31	78	41	21	69	35	23

Source. IPUMS-USA and own computations

Notes. Columns (a) show the fraction of the reallocation of labor across states or counties accounted for by net migration; Columns (b) show the contribution of foreign-borns to net migration; Columns (c) show the fraction of foreign-borns in the working age population. Entires are in percent.

Table C-3: Variance-covariance decomposition.

		States					Counties			
		age	schooling	sector	occupation		age	schooling	sector	occupation
1960 to 2018	31	19	10	16	18	16	23	64	10	54
1960 to 2000	31	19	10	15	18	15	19	66	9	48
2000 to 2018	28	19	28	25	23	34	37	58	19	57

Source. IPUMS-USA and own computations
Notes. The table shows the contribution of foreign-borns to the reallocation of labor across labor markets between 1960 and 2018. A labor market is defined by location (county or state) alone or by location along with age, schooling, sector, or occupation. Entires are in percent.

Table C-4: Migration rates: foreign-borns vs natives (i).

	All		Between states		Within state	
	native	foreign	native	foreign	native	foreign
All						
1940	61.5	55.7	5.8	3.1	55.0	49.1
1960	51.8	51.7	9.2	5.5	40.0	32.6
1970	48.3	57.8	9.6	7.8	34.4	30.1
1980	48.3	61.5	10.2	8.2	37.5	33.7
1990	48.3	61.1	10.1	7.8	37.6	35.4
2000	47.0	59.2	9.5	8.1	36.8	33.9
2015^C	36.5	41.1		0.0		
Less than college						
1940	61.3	56.2	5.5	3.2	55.1	49.4
1960	51.2	51.3	8.4	5.1	40.2	32.7
1970	47.0	56.4	8.3	6.9	34.4	30.7
1980	46.3	59.7	8.8	7.0	37.0	34.0
1990	46.9	59.7	8.7	6.7	37.7	35.9
2000	47.7	45.9	8.0	7.0	37.3	35.0
2015^C	36.4	40.1		0.0		
College or more						
1940	64.0	66.8	12.2	8.3	51.0	48.9
1960	60.3	66.0	18.8	13.3	38.3	32.2
1970	59.4	69.8	20.4	15.5	34.9	26.8
1980	59.8	70.3	18.3	14.8	40.5	32.7
1990	54.3	66.0	16.0	12.8	37.5	33.1
2000	50.8	62.7	14.5	12.3	35.5	30.0

Source. IPUMS-USA, with exception of entries highlighted with "C", for which we use IPUMS-CPS.
Notes. The table shows migration rates based on comparing current location and location 5-year prior. Entires are in percent.

Table C-5: Migration rates: foreign-borns vs natives (ii).

	All		Between states		Within state	
	native	foreign	native	foreign	native	foreign
All						
1995	18.0	23.4	3.0	2.5	14.9	17.5
2000	16.8	22.7	3.4	3.5	13.2	15.4
2005	14.4	18.6	2.8	2.7	11.4	12.6
2010	13.3	15.2	1.6	1.5	11.5	12.1
2015	12.7	13.6	1.9	1.4	10.6	9.9
2018	11.0	12.8	1.7	1.8	9.2	9.4
Less than college						
1995	18.3	23.8	2.7	2.3	15.5	18.2
2000	17.0	22.7	3.2	3.1	13.7	16.1
2005	14.8	18.9	2.6	2.5	12.0	13.1
2010	14.0	15.2	1.4	1.1	12.4	12.8
2015	13.0	12.9	1.6	1.0	11.2	10.2
2018	11.1	11.2	1.5	1.5	9.5	8.8
College or more						
1995	16.9	21.8	3.9	3.6	12.8	14.6
2000	16.3	22.8	4.1	4.5	11.8	13.2
2005	13.2	17.8	3.4	3.5	9.7	10.9
2010	11.5	15.4	2.2	2.6	9.2	10.1
2015	12.1	15.1	2.5	2.3	9.3	9.1
2018	10.9	16.0	2.1	2.4	8.5	10.7

Source. IPUMS-USA and own computations
Notes. The table shows migration rates based on comparing current location and location 1-year prior. Entires are in percent.

Table C-6: Elasticity of labor allocation to local labor market conditions.

	All		Less than college		College or more	
	native	foreign	native	foreign	native	foreign
States:						
1930 to 2018	0.787***	1.388***	0.772***	1.299***	0.899***	1.054***
	(0.018)	(0.018)	(0.023)	(0.023)	(0.022)	(0.027)
1960 to 2018	0.760***	1.407***	0.753***	1.318***	0.896***	1.008***
	(0.021)	(0.021)	(0.023)	(0.023)	(0.021)	(0.031)
1960 to 2000	0.795***	1.547***	0.794***	1.481***	0.918***	1.045***
	(0.022)	(0.022)	(0.023)	(0.023)	(0.021)	(0.051)
2000 to 2018^{Y}	0.478***	0.472***	0.479***	0.698***	0.759***	1.226***
	(0.021)	(0.132)	(0.021)	(0.113)	(0.016)	(0.021)
Counties:						
1930 to 2018	0.841***	1.277***	0.833***	1.206***	0.914***	1.054***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.027)
1960 to 2018	0.837***	1.296***	0.833***	1.221***	0.922***	1.008***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.031)
1960 to 2000	0.852***	1.353***	0.854***	1.319***	0.944***	1.045***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.051)
2000 to 2018^{Y}	0.447***	0.478***	0.497***	0.377***	0.724***	1.226***
	(0.009)	(0.045)	(0.009)	(0.042)	(0.007)	(0.021)

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Source. IPUMS-USA and own computations

Notes. The table reports the estimates of coefficient β_1 in regression A-2 in the text. Standard errors are in parenthesis. All elasticities are reported on a ten-year time span, with the exception of the observations highlighted with "Y", for which we use yearly data. Data at the county level are not available pre-1950 and for the year 1970.

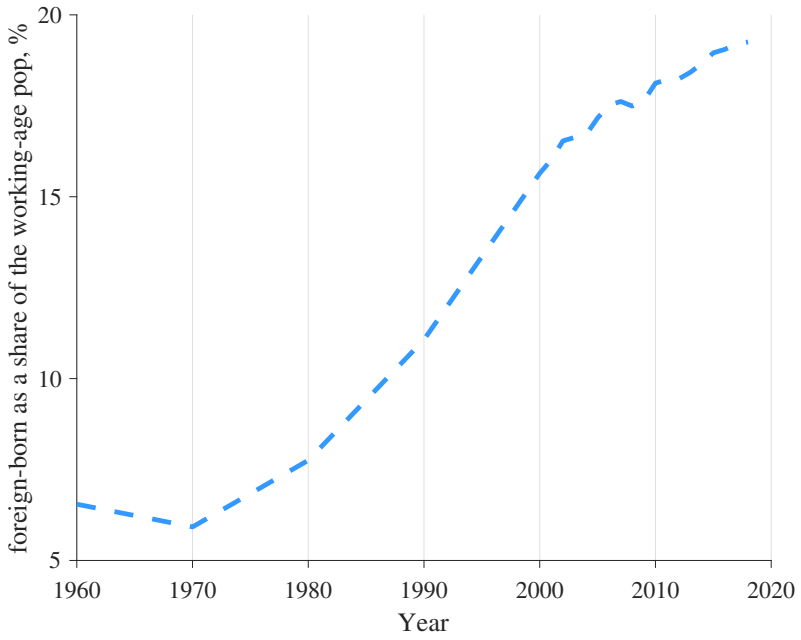
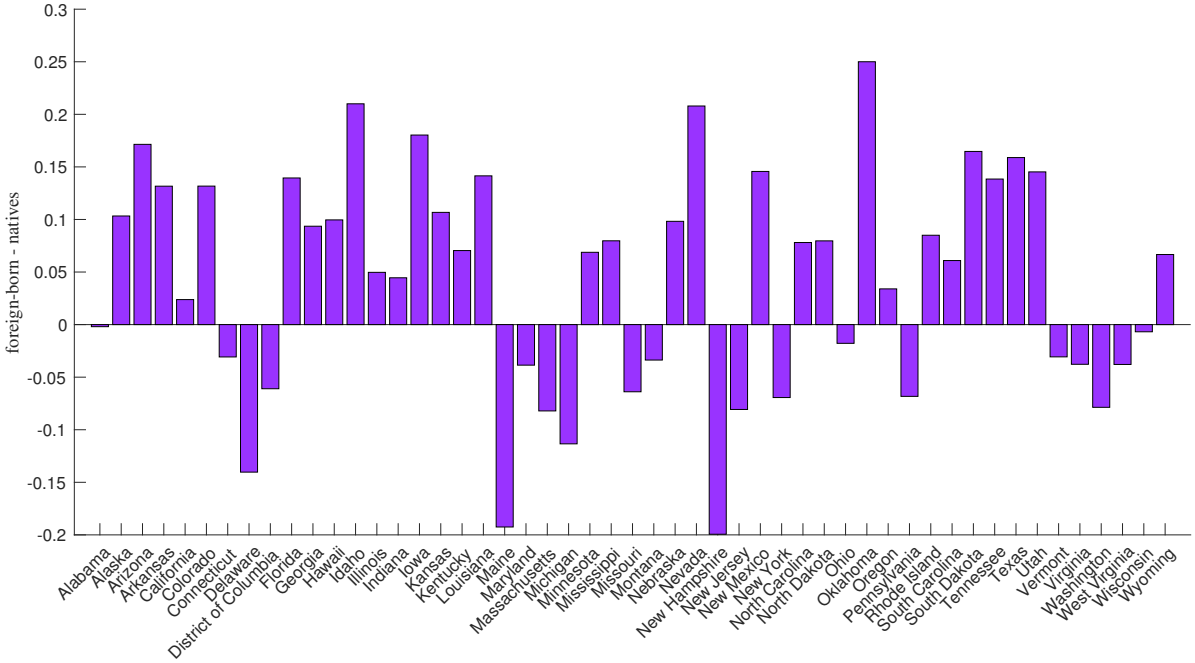
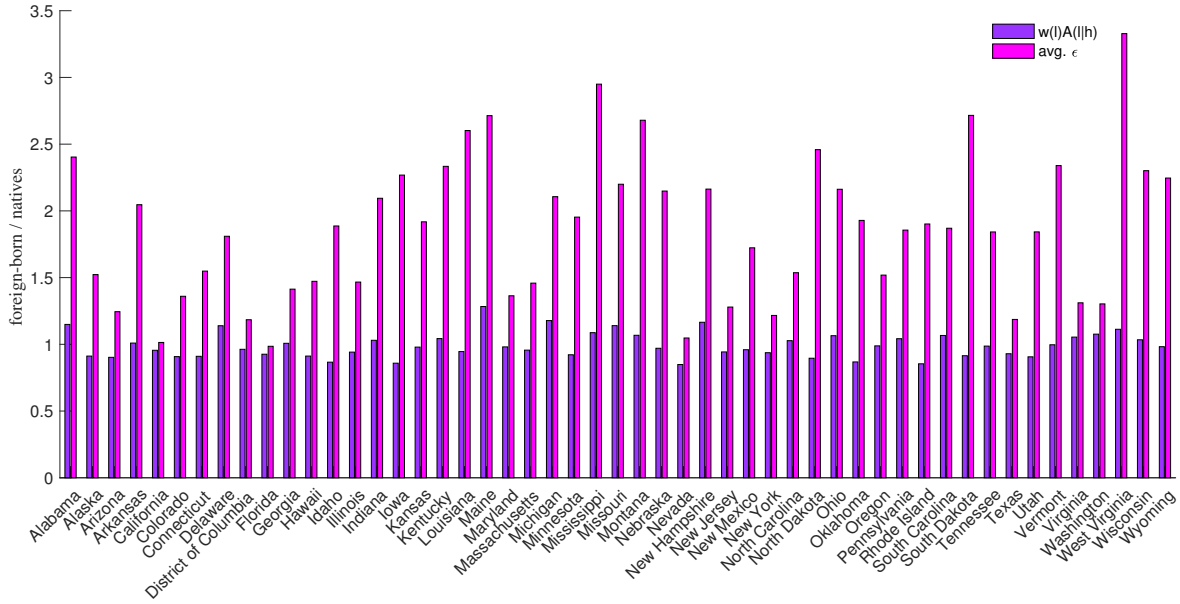


Figure C-1: Composition of the working-age population by nativity.

Source. IPUMS-USA and own computations
Notes. The figure shows the share of foreign-born in the US working-age population.



(a) wedge, $\log \Delta(\ell|h)$



(b) productivity

Figure C-2: Calibration outcomes, by state.

Notes. The figure presents the outcomes of the calibration exercise for the year 2018. Panel (a) shows the utility-wedge of foreign-born vs natives for each state. Panel (b) shows workers' labor productivity by plotting the value-weighted scale parameters of the Fréchet distribution, $A(\ell|h)w(\ell)$, and the average ϵ.