Immigrants Reduce Unionization in the United States

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Abstract

Since the 1960s, U.S. union density has consistently dropped as the immigrant share of the population has risen. Using the Naylor and Cripps (1993) model of union formation, we argue that immigrants reduce unionization because they have lower preferences for unionization and increase diversity in the working population that, in turn, decreases solidarity among workers. Empirically, we employ the skill-cell method devised by Borjas (2003) over the 1980-2020 period. We find that immigration reduced union density by 5.7 percentage points between 1980 and 2020, which accounts for 29.7 percent of the overall decline in union density during that period.

Keywords: Unions, Immigrants, Fractionalization

JEL Codes: J5, J15, J61, F22, F66, R23

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1 Introduction

The rise of unionization from the early to mid-20th century and its subsequent decline marked one of the most dramatic changes in the U.S. labor market over its history (Farber and Western, 2001). In 1900, about 3 percent of the employed workforce was unionized. As shown by Figure 1, union density rose to 26 percent in 1960 on the eve of immigration liberalization, and has steadily fallen since to about 11 percent today (Nowrasteh and Powell, 2020).

[Insert Figure 1 about here]

This trend alludes to a negative relationship between immigration and unionization, which bears substantial implications for the United States labor market. Economists have studied this relationship in many parts of the world, including Norway (Finseraas et al., 2020), Austria (Antón et al., 2016), and across OECD countries more broadly (Lee, 2005). In this paper, we seek to bridge the literature on unions and the labor market impact of immigrants to examine how immigrants affected unionization by increasing the ethnic and racial diversity of the American workforce that, in turn, diminished worker solidarity. Our first step is identifying and modifying a theoretical model of union formation that includes variables of how diversity affects solidarity.

We adapt a model of union formation developed by Naylor and Cripps (1993) to explain how immigration affects unionization through its effects on the solidarity between union members and potential union members. In this model, we allow workers to be heterogeneous in their individual solidarity from social customs and examine the extent to which group solidarity changes with immigration. To measure diversity, we adopt a fractionalization index that gauges the cultural differences of the workforce (Alesina and La Ferrara, 2000). Specifically, we measure immigrant-induced fractionalization by measuring the degree of concentration of various foreign-born nationality groups and native racial groups. A perfectly fractionalized country is one where every resident has a different ethnic or racial background.

To empirically estimate the effect of increased immigration and diversity on unionization, we employ the national skill-cell method developed by Harvard economist George J. Borjas (Borjas, 2003). This method requires the creation of different skill categories based on education level and years of experience in the labor market. The national skill-cell approach assumes that workers are mobile within the United States, seek out the highest wages, are perfect substitutes with other workers who have the same levels of education and experience, and imperfect substitutes with workers in other skill-cells. Grouping individuals by education and work experience allows us to more accurately describe the environment in which workers make labor market decisions.

Our paper is unique in three ways. First, we adapt the Naylor and Cripps (1993) model to study how immigration affects union formation through its impact on worker solidarity. Second, our paper is the first to apply the national skill-cell method to measure how immigrants affect union density. The national skill-cell method is appropriate for this analysis because it groups workers that are substitutes and better explains unionization behavior than the spatial approach.[1] Third, we incorporate commonly accepted measures of fractionalization to study union formation.

In our baseline analysis of the effect of immigrants on union density, we find that a 10 percentage point increase in immigrant share corresponds to a roughly 5 percentage point decline in union density. The immigration-induced diversification of the workforce that, in turn, lowers worker solidarity, is the main channel through which union membership declines. In our robustness checks, we find that a mere increase in labor supply due to immigrants is not responsible for the fall in unionization. We also find qualitatively similar results when using a modified immigrant share to account for contemporaneous native supply shocks with immigrant shocks. The rest of this paper is outlined as follows. Section 2 describes the background for this analysis and delves into the relevant literature. Section 3 gives the theoretical basis. Section 4 explains the empirical methods and data. Section 5 shows the empirical results. Section 6 shows the robustness checks. Finally, Section 7 concludes.

[1]More on this in Section 4.2.

2 Background

American unions largely opposed immigration in the early 20$^{\text{th}}$ century because they viewed immigrants as labor substitutes for members of their unions (Briggs, 2018; Briggs Jr, 2010; Burgoon et al., 2010; Critzer, 2003; Watts, 2002). Thus, unions thought that immigrants would weaken their power to bargain with employers that would result in lower wages and contribute to the demise of organized labor (Sinyai, 2006). The American Federation of Labor (AFL), the largest union in the United States, supported immigration restrictions like the literacy test and national origin quotas to reduce labor competition between their members and immigrants in order to raise wages (LeMay, 2006). Later, union organizers like Cesar Chavez complained bitterly about illegal immigrants and lawful migrant workers competing with his unionized workforce and asked the federal government to step up deportations (Briggs Jr, 2010). But anti-immigration opinion was not uniform across all labor unions and many attempted to extend union membership to immigrants through sustained organizing efforts, especially after many accepted the inevitability of relatively pro-immigration public policy after the immigration liberalization of 1965 (Burgoon et al., 2010; Critzer, 2003; Watts, 2002). Beginning in the mid-20$^{\text{th}}$ century, the newly formed AFL-CIO started supporting more liberal legal immigration policies while opposing illegal immigration. In 2000, the AFL-CIO dropped its support for increasing enforcement against illegal immigrants, supported an amnesty for them, and tentatively endorsed increasing legal immigration (Briggs, 2018).

Unions were likely wrong about immigrants reducing worker wages. A massive empirical literature finds that immigrants have a relatively small effect on the wages of native-born American workers that is often positive, especially in the long run (National Academies of Sciences et al., 2017, 201). The most important strand of research in the literature that examines how immigrants affect wages uses Borjas' skill-cell method, which estimates the relative wage impact of immigrants on native-born workers by regressing cell-specific labor market outcomes on the immigrant share in the respective education-experience group (aka. skill-cell) (Borjas, 2003).

Adding a further wrinkle, union membership has been largely divided along racial and ethnic lines because diversity reduces solidarity among members (Ferguson, 2016; Lane et al., 1987; Mink, 2019).

In fact, according to the survey results of Putnam (2007), people in ethnically and racially diverse communities tend to withdraw and trust others less in the short run. This applies to people of both the same and different racial or ethnic backgrounds. In the words of Putnam (2007), "Diversity does not produce 'bad race relations' or ethnically-defined group hostility, our findings suggest. Rather, inhabitants of diverse communities tend to withdraw from collective life, to distrust their neighbours, regardless of the colour of their skin ..." Putnam's findings are controversial, but we suspect that diversity will make union formation more costly by raising transaction costs across a diverse population (Olson, 2012). In recent decades, immigrants have dramatically increased the diversity of the labor force. Hence, immigrants could affect union formation by increasing ethnic and racial diversity.

We consider how immigrants affect union formation by following in the footsteps of several economists who have tested the social customs model of unionization. Visser (2002) uses European population and survey data to see whether social customs affect an individual's decision to join or leave a union, finding that an individual is less likely to leave a union if their parent(s) were union members and that a person's perception of how others view union membership significantly impacts their probability of joining a union. Finseraas et al. (2020) find that immigrants have no effect on union density in Norway's construction sector. The most relevant empirical literature in the American context is a paper by Ferguson (2016) that examines how diversity increases transaction costs and influences peer effects in the various stages of union formation that reduce union density. His work, however, only examines diversity overall and not whether immigration-induced diversity makes the U.S. labor force less likely to unionize.

Other papers also examine the relationship between immigration and unionization within specific contexts. For instance, a cross-country analysis by Brady (2007) finds that immigrants positively impact unionization, but the results are not robust because they did not hold up to a sensitivity check.[2] Antón et al. (2016) look at the relationship between immigration and unionization rates in

[2] In fact, Brady (2007) mentions "... a careful sensitivity analysis of the models suggests that these results are sensitive to including the other country-level variables." Brady (2007) also points out that the descriptive statistics show a null relationship between immigration and unionization. Therefore, although their results show a positive relationship between immigration and unionization, a closer look at the robustness of their models and their descriptive statistics points to an insignificant relationship between these variables.

Austria and find that higher shares of foreign workers decrease union density among natives. This pattern is not due to native workers leaving unions, but to the different separation rates and hiring practices of firms which appear to have adjusted their demand to the increased supply of foreign workers. Lee (2005) analyzes the relationship between international migration and unionization across 16 affluent OECD countries and finds a negative relationship between international migration and union density between 1962 and 1997.

Additionally, Burgoon et al. (2010) examine how immigration affects union density in the United States using a time series analysis. They find that immigration does not affect union density. However, this paper is different from our paper in several ways. First, our analysis groups individuals by their educational attainment and level of experience across time. This more accurately represents how workers affect each other in the labor market than a time series analysis that is only indexed by time. Additionally, we introduce several restrictions on our sample that Burgoon et al. (2010) do not. These include restrictions by gender, age, and labor force characteristics. By implementing these restrictions, we more precisely identify how immigrants could affect unionization.

3 Theory

3.1 Overview of Social Customs Theory in Union Formation

The theoretical literature on how immigration may potentially affect union density is relatively small and relies primarily on what is known as the Social Customs Theory. Akerlof (1980) defines a social custom as "an act whose utility to the agent performing it in some way depends on the beliefs or actions of other members of the community." In the context of unionization, Social Customs Theory refers to the idea that individuals decide whether to join a union based on how others decide to unionize and what beliefs others hold about unionization. Social Customs Theory is important when analyzing how immigrants affect unionization behavior because immigrants are different from natives in their proclivity towards unionization. Therefore, when the share of immigrants in the population changes, so will the diversity of beliefs and actions pertaining to unionization. According to Social Customs Theory, these differences in the population will drive changes in unionization behavior. Booth (1985) develops a social customs model that shows unions can form without compulsory membership, even in the presence of the free rider problem, if reputation is included in each individual's utility function and if all individuals are assumed to be identical. Overcoming the free rider problem is important for unions to survive. If, for instance, all workers free rode on unionization efforts by not paying dues while they received the benefits of unionization, then nobody would pay dues, the unions would disband or fail to form in the first place, and those benefits would not exist. Booth (1985) is a major breakthrough in the theoretical literature on union formation because it addresses the free rider problem, but the conclusion that union membership will only exist at a density of 0 percent or 100 percent does not match empirical reality. The advantage of the Naylor and Cripps (1993) model is that workers can be heterogeneous and the model predicts union density that is between the two extremes.

Here, we will describe the mechanism by which immigrants affect union density and unionization behavior using the Naylor and Cripps (1993) social customs model. To start, we will define union density as follows:

$$u = \frac{M}{L}$$

where M is the number of union members and L is the total number of employed individuals. Here, union density will change when either M or L change.

With that, there are two ways by which immigrants can influence union density. The first is through their effects on the labor supply. Since L is a combination of both native and immigrant workers, if the number of working immigrants increases, then L will also increase, *ceteris paribus*. This will cause the denominator of u to increase, which means u itself will decrease. Note that this will only occur if immigrants unionize less frequently than natives. In the United States, the percentage of immigrants who are unionized is less than the percentage of natives that are unionized, which holds across time. Figure 2 shows that immigrants are 33 percent less likely to unionize than natives in the representative sample of labor force participants from the 1994-2020 CPS-ASEC. Mechanically, we would expect union density to fall as immigration increases for this reason alone.

[Insert Figure 2 about here]

The second way immigrants change union density is through their effects on union behavior. In the presence of free riding, the theoretical literature on union formation and social customs states that there are two reasons why an individual may decide to join a union (Akerlof, 1980; Booth, 1985; Naylor and Cripps, 1993). The first is the direct benefits that workers receive from joining a union. These direct benefits include higher wages and benefits, better working conditions, and better protection against employer misconduct. The second reason workers join unions is because of social customs. When workers join unions, they derive benefits from conforming to group social customs that are produced by the union. For instance, according to the results of Van de Vall and Vall (1970):

> *"Many workers join the union in order to occupy a psychologically safe position among the members of their group, i.e. in order not to be isolated or despised as a 'parasite'. Evidence of this is that 82 percent of blue-collar and 81 percent of white-collar workers mentioned persons in their immediate environment who had influenced their decision to join. Since 32 percent and 38 percent, respectively, gave such influence as their basic motive, it may be concluded that at least one-third join mainly on account of the convictions of others."*

Additionally, workers can derive disutility from transaction costs associated with group heterogeneity. When workers are heterogeneous, individual workers will have different demands, thus making collective action more difficult (Olson, 2012).

With that, we will define the utility functions for union membership as follows:

$$U^J = U(w - d) + \alpha V(u, \epsilon) \tag{1}$$

$$U^{NJ} = U(w) + \alpha V(1 - u, \epsilon) \tag{2}$$

where ϵ represents the individual benefit of conforming to the group, α represents individual sensitivity to social custom, w represents the wages and benefits of the worker, d represents the net pecuniary cost of joining a union, and u is union density. Notice that ϵ considers both individual benefit from peer effects and individual disutility from transaction costs (associated with group conformity). U^J is the utility of joining a union and U^{NJ} is the utility of not joining a union. In this case, $U(\cdot)$ accounts for the utility a worker receives from pecuniary factors and $V(\cdot)$ accounts for the utility a worker receives from social factors. This is consistent with the theoretical literature in that it takes into account the two main reasons why people join unions. With that, we will define $u(\epsilon, \alpha, d, w)$ to be the expression of u that satisfies the following equation:

$$Z = U^J - U^{NJ} = 0$$

When $Z = 0$, a given worker is indifferent between joining and not joining a union. Here, we will assume that workers are individually heterogeneous in their utility derived from solidarity effects. Therefore, we will define a twice continuously differentiable distribution function $F(\epsilon, \theta)$, where θ represents the group's propensity to abide by social customs. In this case, θ will shift the distribution of ϵ. For any given union density, union members will have ϵ values higher than non-members. For instance, if union density is 25 percent, then the union members will have ϵ values in the highest quartile.

Workers will alter their decisions to join when the number of people that have incentive to join the union does not equal the number of people in the union. To illustrate this concept, we will use Figure 3. At point M, people who are currently in a union at union density u_a have $\epsilon_a \leq \epsilon \leq \epsilon_0$. However, the number of people who have incentive to join a union at union density u_a have $\epsilon > \epsilon'_a$. Since more people would like to join the union than are in the union, union membership will increase from point M over time. This applies for any $u \in (u_1^*, u_2^*)$. If, however, $u > u_1^*$ or $u < u_2^*$, then for any given union density, the number of people who have incentive to be union members is less than the number of people who are currently union members. In these cases, union density will fall over time.

Since equilibrium will fall to (ϵ_1^*, u_1^*) for $u > u_1^*$ and rise to (ϵ_1^*, u_1^*) for $u_2^* < u < u_1^*$, we will call this equilibrium point the solidarity equilibrium. Also, since union density will fall to 0 for $u < u_2^*$, we will call (ϵ_2^*, u_2^*) the threshold equilibrium. With that, the equilibrium points at which members and non-members will not change their decisions can be expressed as follows:

$$1 - F(\epsilon^*, \theta) = u(\epsilon^*, \alpha, d, w) = u^* \tag{3}$$

where (ϵ^*, u^*) are the equilibrium values of ϵ and u. Given our assumptions about the concavity of $u(\epsilon, \alpha, d, w)$ and $F(\epsilon, \theta)$, there can be, at most, two equilibrium solutions to (3).

[Insert Figure 3 about here]

When considering how increases in the share of immigrants affect the solidarity equilibrium, we will examine how the group's solidarity value changes with immigration and how that affects the equilibrium union density. By property (1c) in Naylor and Cripps (1993), $\frac{\partial u^*}{\partial \theta}$ is positive at the equilibrium level of union membership and negative at the threshold level of union membership.[3] Graphically, this can be represented by a shift in the distribution from $1 - F(\epsilon, \theta_1)$ to $1 - F(\epsilon, \theta_2)$, where $\theta_1 > \theta_2$ (as shown in Figure 4). When θ_1 decreases to θ_2, the solidarity equilibrium will shift from point P to point P', and the threshold equilibrium will shift from point Q to point Q'.

[Insert Figure 4 about here]

The group's value of solidarity will affect the utility individuals derive from abiding by a social norm. For instance, when a group becomes more homogeneous, the utility an individual derives from solidarity effects will increase. Likewise, when a group becomes less homogeneous, the utility an individual derives from solidarity effects decreases. Since we observe that immigrants exhibit unionization behavior that differs from natives (i.e. immigrants are less likely to unionize than natives), we can define group solidarity effects as a function of cultural heterogeneity (Ager and Brückner, 2013; Ottaviano and Peri, 2006). We will describe cultural heterogeneity as follows:

$$\theta = \sum_{i=1}^{N} \pi_{iext}^2$$

where π is the share of cultural group i in education group e and experience group x for time t

[3] This proof can be found in the appendix of Naylor and Cripps (1993).

and N is the total number of cultural groups in the population. Conceptually, θ represents the probability of selecting two individuals from the same cultural group. Therefore, as the share of immigrants in the population increases, group solidarity effects will decrease and, as a result, cause union density to fall.

3.2 Free Choice Assumption

In the Naylor and Cripps (1993) model, we assume that each worker has free choice in whether to join or not join a union. However, in reality, this is not always the case. For instance, in states that do not have Right-to-Work laws, workers can be required to join a union as a condition of employment. In the cases where workers are not able to freely decide on their union membership status, equation (3) will not hold. Without loss of generality, in the case where workers are not allowed to freely leave unions, the number of workers that join a union will be greater than the number of workers with incentive to join a union. Figure 5 shows this phenomenon in relation to the two curves in Figure 3. Here, the solidarity equilibrium will shift to u_{seq} and the threshold equilibrium will shift to u_{teq}, outside of the intersection points.
[Insert Figure 5 about here]

4 Data and Methodology

This section explains the data and methods used to test how immigrant-induced workforce diversity affects unionization in the United States.

4.1 Data Overview

Given that data on union membership and immigration cannot be aggregated from the same source for our time period (1980-2020), we used several different data sets. We used data from the Decennial Census (1980-2000) and the American Community Survey (ACS, 2010) to measure immigrant shares of the population from 1980 - 2010.[4] For the year 2020, we used immigration data from the

[4] Each year of the Decennial Census used 5% and the ACS used 1% of the population.

Current Population Survey Annual Social and Economic Supplement (CPS-ASEC). Union membership data from 1990-2020 was also retrieved from the CPS-ASEC.(Flood, King, Rodgers, Ruggles, and J.Warren, Flood et al.) Finally, union membership data for 1980 was retrieved from the CPS May Extract on the NBER Website (Gary and Staigler, Gary and Staigler). The main analysis is restricted to males between the ages of 18-64 who are employed in a civilian wage/salary job. From here on, we will refer to the combination of all data as the Final Data Set (1980-2020). We later relax the sex restriction in the results section and when looking at public sector unionization.

We define an immigrant to be anyone who is born outside of the United States (and its territories) that is also either a naturalized citizen or a non-citizen. We structure the data so that we are looking at immigrants and natives with the same level of education and work experience. In this paper, we use share of immigrants in particular education and experience groups rather than geographic regions as we obtain more reliable estimates of immigrants on union density using the national skill-cell group approach.[5] Immigration share is therefore defined as follows:

$$I_{ext} = \frac{imm_{ext}}{imm_{ext} + native_{ext}}$$

Here, the subscript e denotes the highest education level that are divided into four large categories: 1 (less than high school), 2 (high school graduates), 3 (some college), and 4 (college and more). The subscript x denotes experience levels and has 8 categories: 1 (1-5 years), 2 (6-10 years),...,8 (36-40 years). The combination of e and x constitutes a skill-cell, and these cells are repeatedly observed for time t. None of our data sets show the years of work experience, so we followed the Borjas (2003) method of subtracting the assumed age at completion of highest degree from the current age. These skill-cells will be the unit of analysis as immigrant shares differ across these cell groups and across years.

We divided the observations into skill-cells to clearly see the direct effect of incoming immigrants on labor market outcomes of similarly skilled workers. If immigrants do affect existing workers' propensity to unionize, the effect will be strongest among workers with levels of education and work

[5] Section 3.2 explains in detail how the national skill-cell approach is more appropriate than using regional variation of immigrant populations.

experience identical to those of the incoming immigrant workers. For example, a Vietnamese immigrant with a high school degree employed as a construction worker will not have a direct impact on the labor market outcomes of workers with a college degree who work in finance. Similarly, the same immigrant with 0 years of work experience will have little effect on a worker with 30 years of experience even if they had the same level of schooling.

Sampling weights are used in all calculations and regressions. In some cases, different sampling weights may be used for different years/variables. For instance, the Decennial Census and ACS from 1990-2010 use person-level weights.[6] The immigrant share variable (from the CPS-ASEC) for the year 2020 used a person-level weight that was adjusted to account for nonrandom nonresponses from the COVID-19 pandemic. The union membership variable (for the years 1990-2020) uses an Earner Study weight that is different from the person-level CPS-ASEC weight. Finally, for the union membership variable for 1980, we used the CPS May Extract weight. In addition to using weights in our variable calculations, we weighed each observation in our final data set by the size of each skill-cell. Given that we have different weights from different surveys, we chose to use the weight that corresponds to our dependent variable.[7]

Our main outcome variable is union density. It is based on the same skill-cell division as we have used for immigrant share. Union density is therefore defined as follows:

$$u_{ext} = \frac{M_{ext}}{L_{ext}}$$

where M is the number of union members and L is the total number of employed individuals per skill-cell ex for time t. We look at all workers, both immigrants and natives. For this reason, we are looking at how immigrants impact the overall tendency for unionization rather than just the impact on native's propensity to unionize. In fact, one of the channels through which union density is affected by immigrants is the lowering of $\frac{M_{ext}}{L_{ext}}$, as immigrants are less prone to unionize.

[6]The year 1980 was a flat sample, so all individuals had the same weight here.

[7]We conducted the analysis with the weights used to create the immigrant share variable and found no statistically significant difference in our results.

In order to measure diversity, we use the country of origin and race to develop an index of cultural diversity based on a method developed by Ottaviano and Peri (2006) and Ager and Brückner (2013). We call this the index of "fractionalization" following the literature. The equation is given as follows:

$$frac_{ext} = 1 - \sum_{i=1}^{N} \pi_{iext}^2 = 1 - \theta$$

where π_{iext}^2 is the squared value of the share of the population in cultural group i belonging to education and experience group e and x at time t. Since we wanted to consider both diversity in culture and ethnicity, we combined the method employed by Ottaviano and Peri (2006) and Ager and Brückner (2013) in classifying the cultural group. To be specific, Ottaviano and Peri (2006) uses immigrant nationality groups and Ager and Brückner (2013) adds various racial groups who are U.S. born.

Table 1 lists the cultural groups we used in calculating our fractionalization index that account for the largest proportion of our sample.[8] We follow the literature by limiting nationality groups to those that make up more than 0.5 percent of the foreign-born population within a given year. For the native-born, we have divided the population by four main racial categories of white, black, Hispanic, and other. As the fractionalization index approaches zero, one group's share dominates the population and hence there is little diversity. When it approaches one, it indicates that there is a balance in the cultural groups where each group has equal share and hence diversity is high. The fractionalization index is just the solidarity parameter θ in the model subtracted from 1; the more heterogeneous cultural groups are, the lower the θ, and in turn, this decreases the fractionalization index.

[Insert Table 1 about here]

4.2 Strength of the skill-cell Approach Compared to Other Methods

Most research that examines the impact of immigrants on labor market outcomes exploits some exogenous variation of immigrant influx across geographic regions, occupation groups, industries,

[8] In the appendix, we provide the full list of countries used to construct the fractionalization index.

or skill-cells. Peri et al. (2015) use regional variation, Orrenius and Zavodny (2007) use occupational variation, and Finseraas et al. (2020) exploit industry level differences in immigration shocks. In contrast to the standard way of looking at regional variation in immigration, we have taken the same approach as Borjas (2003) and Borjas (2014) as we look at the differing influx of immigrants across skill-cells defined by education and experience. This method is appropriate for the following reasons:

1. The biggest reason for our choice to use skill-cells as opposed to regional variation is that workers move across states regularly. For example, in Figure 6, we have plotted the percentage of people that have changed their state of residence from the previous year. This movement is problematic because it may influence union density, but cannot be explained by our variables. In Table 2, we run estimates for the effect of immigrants on unionization using spatial grouping of workers and find that 1) the explanatory power of the model weakens,[9] and 2) the coefficient estimates become increasingly insignificant when workers are aggregated by smaller geographic units. This suggests either measurement error and/or selection is responsible for the weakening of the model using smaller spatial units.[10]

   [Insert Figure 6 about here]

   [Insert Table 2 here]

2. According to a U.S. Census Bureau article by Schmidley and Robinson (1998), *"[t]he CPS sample frame and stratification levels are based on geography and socioeconomic data from the latest census. Groups such as the foreign born who are not represented in the sample strata and non-randomly distributed across the United States."* Hence, using variation in either regional, education, work experience, or other socioeconomic variables may not perfectly capture a nationally representative change in immigrant share due to small sample sizes in some units. However, using educational-experience as opposed to regional variation has a slight advantage in that there are a fewer number of skill-cells than states or metropolitan areas that vary overtime which allows more samples in each varying unit [11] Also, using the national skill-cell

[9]The adjusted R-squared becomes smaller with smaller geographic units

[10]Please refer to Table 4.2 of Borjas (2014) for more information on the reasons that Borjas lays out for avoiding spatial variation.

[11]Some states such as Alabama, Indiana, Iowa, Kentucky, Main, Mississippi, Missouri, Montana, North Dakota,

as the unit allows us to estimate the fractionalization index; there are severe data limitations in slicing the data by nationality groups when we use states as the varying units. The same argument goes with doing any heterogeneity analysis using occupations or industry.[12]

3. Borjas (2014) criticizes the use of regional variation in immigrant shocks to identify the causal effect of immigrants on the labor market. Immigrants and natives self-select to migrate to certain localities due to underlying labor market characteristics that will bias the result due to underlying omitted variables. For this reason, we have also decided against using the shift-share instrument that utilizes MSA-level or state-level variation in immigrant populations by nationality group. Apart from the data restrictions of using CPS to further slice by U.S. regions and nationality groups, Borjas (2014) argues that the initial economic conditions that attracted immigrants to certain localities is not random and correlated with the economic outcomes of natives.[13]

4. To show that our panel specification is valid, we have tested for both serial correlation and the unit-root. Serial correlation will not necessarily bias our results but it will affect our standard errors to be underestimated. This is resolved by clustering the standard errors by the panel ID which in our case is the education and experience level (Cameron and Trivedi, 2010). Unit-root test ensures that our dependent variable (log(union density)) and independent variable (log(immigrant share)) is stationary, which indicates that an effect of an event that happened at time 't' is not being amplified at a later time. Using the Levin–Lin–Chu test, we accept the alternative hypothesis that all panels are stationary (Levin et al., 2002).

With the national skill-cell method, we may still have selection of immigrants into certain education

South Carolina, South Dakota, Tennessee, West Virginia, Wyoming has less than 10 immigrants in the CPS-ASEC sample in some years.

[12]Further dividing the data by industry sectors is also something we have considered but have not been able to fully develop as the data become severely limited in certain industries and so preclude a robust analysis. In general however, there is no single industrial sector that is solely driving the effect that we find later in the results section.

[13]In other words, national level shift-share instruments do not satisfy the exclusion restriction, which will produce an inconsistent estimator (Goldsmith-Pinkham et al., 2020). Additionally, Borusyak et al. (2018) point out that, if the unobserved shocks affect the outcome variable via the exposure shares, then the shift share estimator will violate the share exogeneity assumption, even if the observed and unobserved shocks are uncorrelated. For instance, Borusyak et al. (2018) use an example where, if the share used is local employment share (with the shock being new import tariffs), then changes in foreign migration (a shock) may be dependent on other industry factors, which is problematic in this context. A skill-cell method on the national level obviates this concern on the regional geographic level.

or experience cells. However, as we aggregate these measures across all U.S. regions, we are able to use the disproportionate and sometimes erratic influx of immigrants who vary by education and experience over time. Table 3 shows the percentage change in union density and immigration between 1980 and 2020 by education level. Where immigrant share generally increased, union density had a proportional decrease. Table 4 shows a similar, albeit less-correlated trend for experience levels. These are suggestive descriptive evidence that there might be a relationship between immigrant shares and union density in each skill-cell. The following sections of the paper will estimate the relationship using the skill-cell method.

[Table 3 and Table 4 go about here]

5 Results

5.1 Immigrants and Union Density

This section explains our baseline regression model and results. The first relationship we explore is how immigration affects the union density of the existing labor force. We are interested in the outcome variable u_{ext}, which is the ratio of workers in a union to all workers in the relevant skill-cell ex as defined as the combination of education and experience. The data are collapsed by the national skill-cells for each year and the variable values are averages in each cell. The regression specification is as follows:

$$u_{ext} = \beta(I_{ext}) + s_e + \sigma_x + \pi_t + \phi_{ex} + \mu_{et} + \delta_{xt} + e_{ext} \tag{4}$$

where I is the immigration share defined as the ratio of immigrants over the total labor force in a skill-cell, s_e is a vector of fixed effects indicating the group's educational attainment, σ_x is a vector of fixed effects indicating the group's work experience, and π_t is a vector of fixed effects indicating year. These first three fixed effects control the different rates of unionization across education, experience, and over time. We also control for how, over time, there are structural changes in how education or experience impact union density. The interaction term μ_{et} accounts for the impact of education groups changing over time such as how having an extra year of schooling may affect union density differently 20 years ago compared to today. Similarly, experience groups δ_{xt} account for how an extra year of experience has had a different effect on union density over time. Finally, ϕ_{ex} accounts for how an extra year of experience has a different effect on union density compared to an extra year of education. Table 5 presents the results for regression (1). Column 1 values are in levels and the standard deviation of union density and immigrant share are in the bottom rows. The coefficient is -0.479 which means that a 10 percentage point increase in immigrant share translates to a 4.8 percentage point decrease in immigrant share. Given that the overall immigrant share of the workforce increased from 6.9 percent in 1980 to 18.8 percent in 2020, this translates to immigrants causing a 5.7 percentage point decrease in union density during the same period. Given that union density went from 30.2 percent to 11 percent during the period, immigrants were responsible for 29.7 percent of the decline in union density from 1980 to 2020.

[Insert Table 5 about here]

5.2 Heterogeneity

5.2.1 By Schooling and Experience

Table 3 shows that the largest increase in immigrant shares has been in the less-than-high-school and high-school education categories, which are also where the largest decreases in union densities have occurred. To test whether the negative relationship between union density and immigrant share is mostly driven by changes in the lower educated skill-cells, we run the benchmark regression where we omit one educational category starting with the less-than-high-school level. This allows us to keep our identifying strategy of using the skill-cell method and to still infer how much each education category contributes to the overall effect.

Column 1 of Table 6 contains our original results from Table 5. With the omission of all individuals who did not finish high school, we see that the coefficient on the immigrant share variable becomes insignificant, which indicates that the biggest decrease in union density is coming from those who have not graduated high school. All other columns remain significant when omitting a given education group. One caution in interpreting the coefficients is that the less economically or statistically significant the coefficient becomes with the omission of an education sub-category, the bigger the share the particular sub-category has in driving the overall effect.

In Table 7, we have similarly omitted each experience level from the benchmark regression. We find that the biggest driver of the effect is coming from those with the lowest experience of 0 to 10 years. This is consistent with other findings that younger workers are much less likely to be unionized than older workers (Milkman, 2020).

[Insert Tables 6 and 7 about here]

5.2.2 By Sector and Sex

So far, we have restricted the sample of analysis to employed, working-age civilian males and have not distinguished private and public sector union members. In this section, we show how union density is affected by the addition of female workers and the separation of private and public sector union membership. Our data does not explicitly have variables for public or private sector unions. For this reason, we have categorized union members who are employed in local, state, or the federal government as belonging to public sector unions, and all other union members as belonging to private sector unions. We combine the heterogeneity analysis of public vs. private sector union membership and sex into one section as the two are closely related because females tend to work in public unions at higher rates than males.

To start, females are often omitted when studying how immigrants affect wages (Borjas, 2003), because their labor market dynamics are slightly different than for males; they are underrepresented in union membership (Finseraas et al., 2020), and frequently change union membership (Haile, 2016). Figures 7 and 8 show evidence of this disproportionately by sex. To be specific, public sector union density is high for both sexes compared to the private sector, but females are much less likely to work in a private sector labor union (Figure 7). Despite low private sector union density, the number of union members in the private sector is larger than the public sector, and males dominate in private sector union membership in total count and density. Figure 8 shows that females who are highly educated have higher union density, because they are more likely to be unionized school teachers and work in other skilled government occupations that are unionized, while less educated males tend to have higher union density. Given that the influx of immigrants happened primarily in the less-than-high-school or high-school educated cells, immigrants would have had a much larger effect on male union members and less of an effect on female union members.

To see if the addition of females changes our main results, we run our benchmark regression separately for male-only, male and female combined, and female-only workers. In addition, we also split between private and public sectors since males and females tend to have higher membership in private sector unions and public sector unions, respectively. Tables 8, 9, and 10 show the differences in results between male/female samples in the public/private sector (you can ignore the "frac" columns until we define it in the next section). In the private sector, the male union density is more affected by immigration than the female union density. However, in the public sector, union density is unaffected by immigration for both males and females.

[Insert Figure 7 and Figure 8 about here]

[Insert Table 8, Table 9, and Table 10 about here]

We chose not to focus our analysis on just the private sector, despite the concentration of male workers, since the addition of the public sector members adds statistical power and richness to the data in terms of education, experience levels, and nationality groups in the calculation of the fractionalization index.

5.3 Diversity and Union Density

The decrease in union density that is correlated with a rise in immigration can be partly explained by the mechanical channel of adding more workers to the labor force who are less prone to unionize. However, we hypothesize that the main channel is through how immigrants affect whether workers choose to unionize. The immigration-induced diversification of the work force is the mechanism by which immigration diminishes worker support for unionization. As we have seen in the theory section, the Naylor and Cripps (1993) model includes the θ parameter, which represents the propensity to abide by social customs; we will also call it the solidarity parameter. As the model suggests, at the solidarity equilibrium level of union membership, the relationship between θ and union membership is negative. In other words, unionism is more likely when people have the same social customs.

Our hypothesis is that the influx of immigrants increases diversity and weakens the solidarity of workers. Solidarity is weakened as cultures, languages, and demands for different work-place amenities differ between cultural groups. Collective action is more costly when there are high transaction costs due to communication difficulties and homophily, especially when it comes to unionization and their role in the work place (Alesina and La Ferrara, 2000; Bacharach and Bamberger, 2004; Bond et al., 2020). As an example showing demands for different workplace amenities, Bond et. al., (2020) find that immigrants prefer night shifts relative to natives while unions tend to support regular working hours for all workers. Since immigrants have different preferences for their work environments relative to other groups of people, more immigrant workers will further weaken the motivation for diverse groups to unionize together.

Labor unions in the United States faced similar barriers to expanding union membership at the beginning of the 20$^{\text{th}}$ century. In order to overcome the free rider problem that bedeviled union formation, unions tried to entice members to join by supplying local excludable goods like insurance (Olson, 2012). Importantly, supplying excludable goods was less costly when the workers were culturally and ethnically homogeneous as they were more likely to demand similar goods like accident insurance or Christmas parties. Local unions were also more likely to be homogeneous than nationwide unions and membership was correlated with meaningful social and recreational commonalities (Olson, 2012). Overcoming the free-rider problem is difficult even when all of the workers are homogeneous and have essentially identical demands, but it becomes even more difficult when they can't even agree on those demands – such as which holidays deserve vacation time, which sabbath should be honored by employers, and what kind of insurance is appropriate (Nowrasteh and Powell, 2020; Olson, 2012).

For these myriad reasons, immigration-induced diversity creates an environment that dis-incentivizes various demographic groups to come together to unionize. Here, we use the fractionalization index as our measure of diversity, which is 1 minus the solidarity parameter θ. The equation is given as follows:

$$frac_{ext} = 1 - \sum_{i=1}^{N} \pi_{iext}^2 = 1 - \theta$$

where π_{iext}^2 is the squared value of the share of the population in cultural group i belonging to education and experience group e and x at time t. Since we wanted to consider both diversity in culture and ethnicity, we combined the method employed by Ottaviano and Peri (2006) and Ager and Brückner (2013) in classifying the cultural group. Note, Ottaviano and Peri (2006) use immigrant nationality groups and Ager and Brückner (2013) adds various racial groups who are U.S. born. We measure diversity of the workforce using an immigrant-induced fractionalization that measures the degree of concentration of various foreign-born nationality groups and native racial groups. A perfectly fractionalized country is one where every resident has a different ethnic or racial background.

We run a regression with the specification that uses the fractionalization index:

$$u_{ext} = \beta(frac_{ext}) + s_e + \sigma_x + \pi_t + \phi_{ex} + \mu_{et} + \delta_{xt} + e_{ext} \quad (5)$$

Table 11 shows the relationship between increasing fractionalization and unionization. We used the same regression specification as in Table 5 but used the fractionalization index as the explanatory variable rather than the immigrant share. Immigration affects union density, but fractionalization has a slightly smaller effect. We believe that both the effects from immigration and diversity (fractionalization) are one and the same. In other words, immigration increases diversity and this lowers the solidarity of workers to unionize. This would not necessarily be the case if an influx of immigrants does not increase diversity, i.e., only a single immigrant nationality group comprises the majority of a skill-cell. However, we believe such instances are rare, and that a given skill-cell contains a diverse groups of immigrants. The variables "imm_share" and "fraction_index" have a correlation coefficient of 0.78 which indicates that high immigrant share in a skill cell generally means high diversity as well. In sum, influx of immigrants increases diversity, and in turn, lessens solidarity among workers that contributes to the demise of unions.

[Insert Table 11 about here]

6 Robustness Checks

6.1 Are Immigrants Just Diluting the Labor Force?

In this section, we want to abstract away from viewing immigrants and natives as different groups and see if the effect on unionization is driven by a sudden increase in the supply of workers in a particular skill-cell rather than an increase in diversity. A sudden influx of workers, be it immigrants or natives, may create some short-term frictional cost on the incoming workers' ability to join unions. We assume that these short-term frictional costs are not driving the decrease in union density, but if our assumption is wrong, we would see an increase in the supply of immigrant workers in a skill-cell have the same qualitative effect as a similar increase in the supply of native workers in the same skill-cell.

To explore whether a sheer increase in the number of workers can explain the decline in union density, we looked to see whether the marginal effect of an additional immigrant on unionization is different from the marginal effect of an additional native-born worker. If immigrants are merely increasing the supply of potential union workers and thereby diluting union density, then the impact of an extra immigrant worker will be similar to that of an additional native-born worker.

To precisely show this channel, we had to use a subset of our main data: the CPS-ASEC (1994-2020) in 1 year increments. We could only modify the dependent variable union density to our preferred specification using the CPS-ASEC because the 1980 survey does not allow us to identify immigrants or natives with their union membership status. Thus, we modify our dependent variable to measure the union density of just natives since we are interested in comparing the marginal effect of immigrants on native union density to the marginal effect of natives on the same native union density. The dependent variables we use then is the log of:

$$u_{ext}^{N} = \frac{M_{ext}^{N}}{L_{ext}^{N}}$$

where M^N is the number of union members who are native-born and L^N is the total number of employed individuals who are native-born per skill-cell ex for time t. We also introduce a slight change to the main independent variable in columns 1 and 2 in Table 12; instead of the usual immigrant share we merely look at the raw count of immigrants for each skill-cell, which we label as "raw imm" in Table 12. Since we are comparing units that are scaled very differently we standardized both the dependent and the independent variable into logs. The interpretation of the coefficient is then that of an elasticity between immigrants and unions; if we change immigrants by one percent, we'd expect union density to change by β_1 percent.

Column 1 of Table 12 shows that adding an extra immigrant to the existing pool of workers has a negative effect on unionization of -0.255. The coefficient's interpretation is that a 10 percent increase in the raw number of immigrant workers, as opposed to immigrant share, corresponds to a 2.5 percent decrease in union density. Compare this to the column 2 result that a 10 percent increase in the raw number of natives increases union density by 4.2 percent. Comparing columns 1 and 2 clearly shows that immigrants and natives differently affect union density, which supports our hypothesis that immigrants reduce union density because they increase cultural diversity.

Decline in unionization could also be driven by a pure increase in the number of immigrants rather than their impact on fractionalization. We have previously discussed two channels through which immigrants affect union density. The first channel is through immigrants diluting the union density due to their lower propensity to unionize, and the second channel is through weakening the solidarity of all workers. Using only natives in calculating the union density has the added benefit of seeing whether the effect is still present after taking away the first channel: immigrants' lower propensity to unionize.

Our prior is that the negative relationship between immigration and unionization is mainly driven by the second channel that weakens worker solidarity, but the first channel could still be driving a substantial part of the effect. In Table 11, we show that the second channel, the indirect effect on worker solidarity, is the main channel. Column 3 of Table 12 shows that even after considering only natives in calculating union density, we still see a big negative effect of immigrants on natives' propensity to unionize. This result is contrasted with column 4, where the effect of an increase in native shares boosts natives' union density. This shows that the decrease in union density is not a result of a mechanical decrease due to inclusion of immigrants but due to immigrants having an effect on natives.

[Insert Table 12 about here]

6.2 Lagged Immigrant Share

Card and Peri (2016) claim that the Borjas (2014) method of calculating the immigrant share is biased as changes in the supply of natives are confounded with the immigrant supply shock in ways that may bias the outcome variable, which in our case is union density. For example, a troublesome correlation can arise if changes in the number of workers in a particular skill-cell is positively correlated with other labor market outcomes such as wages. Although our outcome variable is the share of union membership, the same mechanism that may bias wages may also bias union membership. In essence, Card and Peri (2016) argue that immigrant shock to a particular skill-cell is not exogenous if such correlations arise. [14]

[14]To show this formally, let's go back to how we defined immigrant share.

In Borjas (2014)(and ours), the immigrant share p_{it} is simply the current period's count of immigrants in skill-cell i at time t over the size of the labor force of skill-cell i at time t:

$$p_{it} = \frac{imm_{ext}}{imm_{ext} + native_{ext}}$$

To see how the outcome variable y changes with the immigrant share we specified, for outcome y of natives in skill-cell i at time t:

$$\Delta y_{it} = \text{fixed effects} + \beta^p \Delta p_{it} + \Delta v_{it}$$

This equation is the simplified version of our benchmark regression with first-differencing. The fixed effects here include time, education, experience, and the combinations of the three fixed effects (some of which are accounted for with the first-differencing). According to Card and Peri (2016), the coefficient β^p is biased as we do not know how much of the effect is 1) coming from an exogenous change in immigrant population at time t and 2) how much of it is coming from changes in the base supply of natives in the same time period. They show this conundrum through

Card and Peri (2016) propose a slight modification to the usual immigrant share that Borjas (2003) calculated. Basically, they use the lagged size of the labor force as the base when calculating the current immigrant shock. Hence, with the modification, the changes in immigrant share from $t-j$ to j is now:

$$\Delta p'_{it} = \frac{imm_{it} - imm_{it-j}}{native_{it-j} - imm_{it-j}} = \frac{\Delta imm_{it}}{native_{it-j} - imm_{it-j}}$$

The authors use $j = 10$ due to Borjas' original use of the decennial census that is ten years apart. However, in our framework, j can be a smaller passage of time. Here since we are using the previous period's count of natives in the denominator of $\Delta p'_{it}$, we do not have to worry about confounding the effect of changes with current changes in native labor supply. In short, this correction allows the immigrant shock to be more exogenous than in equation (4).

In Table 13, we incorporate the lagged immigrant share to the CPS-ASEC (1994-2020); as in the previous section, we use the log transformation for ease of interpretation. We vary the number of lags to see how sensitive the outcomes are to the choice of lags. Column 1 is our original result with no lag to the labor force. Each subsequent column represents one additional year of lag. In general, with the longer lags, the effect size is smaller, and the effect size is no longer significant around $t-5$. In column 7, we have used the our final data set from 1980 to see how it compares to the CPS-ASEC; with the 10 year lagged base, we see that the coefficient on the lagged immigrant share is not significant. These results indicate that when we bias-correct the immigrant share variable using the size of the labor force in the previous years, similar negative effects persist. In addition, once we go too far back for our base year, the effect size tapers off as the composition and size of the labor force in the distant past is not reflective of today's labor force.

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estimating the first-order approximation for Δp_{it}:

$$\Delta p_{it} \approx (1 - p_{it-j})\frac{\Delta imm_{it}}{imm_{it-j} + native_{it-j}} - p_{it-j}\frac{\Delta native_{it}}{imm_{it-j} + native_{it-j}}$$

This first term is the weighted average of the immigrant-driven supply shock $\frac{\Delta imm_{it}}{imm_{it-j}+native_{it-j}}$ and the second term is the weighted average of the change in the number of native workers in skill-cell i divided by the lagged size of the skill-cell: $\frac{\Delta native_{it}}{imm_{it-j}+native_{it-j}}$. The takeaway from this equation is that when we are looking at the change in the native outcome Δy_{it}, it is important not to confound the effect coming from the 1) supply shock of immigrants which is the first term and 2) the native supply changes which is the second term.

[Insert Table 13 about here]

7 Conclusion

Even with the decline of unions, few researchers have examined how immigrants affect unionization and most tend to attribute their decline to changes in labor law, deregulation, structural economic changes, or other issues (Farber, 2005; Fisk and Malamud, 2008; Greenhouse, 2020; Kleiner, 2001; Milkman, 2020; Nunn et al., 2019). Most research on how immigrants affect the U.S. labor market focuses on wage and employment effects. Unions, despite being on the wane in the United States, wield sizable influence on wages and employment in different sectors. Government policies are also affected by union density. Furthermore, many politicians today want to increase legal immigration and unionization – two goals that could be in conflict (Greenhouse, 2021). Thus, examining how immigrants affect union density is important insofar as how unions are important in affecting wages, employment, and government policies.

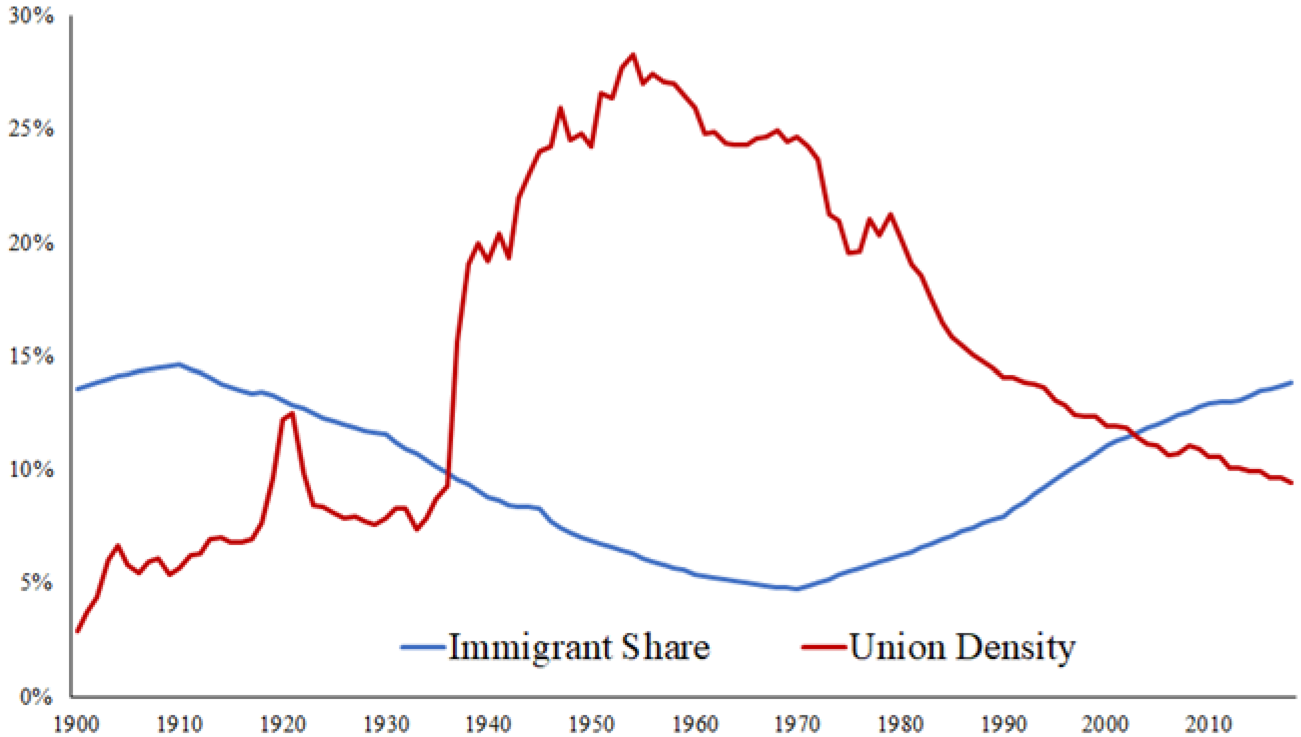
We find that immigration explains a sizable portion of the decline in unionization in the United States. Overall, we find that a 1 percentage point increase in the immigrant share corresponds to a 0.479 percentage point decrease in the union density. Immigration reduced union density by 5.7 percentage points between 1980 and 2020, which accounts for 29.7 percent of the overall decline in union density during that period.

Across education and experience groups, we find that the effect of immigrants on unionization is most pronounced for high school dropouts and people with 1-10 years of experience. Across all sectors, this effect is most substantial for males; however, in the private sector, this effect is significant for both males and females. Immigrants do not have an effect on public sector unionization. Replacing immigrant share with the fractionalization index does not affect the direction or significance of the results compared to the main regression. To see whether immigrants reduced union density through an increase in the labor supply, we compared regressions where the main independent variable was the native population share or the immigrant population share. Here, we found that immigrants and natives both affect unionization differently, which suggests that immigrants decreased union density through the diversification of the population. Finally, we changed our definition of immigrant share to match that of Card and Peri (2016) and found results similar to our original results.

Although we have found sizable and significant negative relationships between the share of the workforce that is foreign-born and union density, the data show only the final union membership of individuals, and hence, it is difficult to sift out how much of the effect is coming from peoples' changing preferences for unionization behavior or high external costs to joining a union. Ferguson (2016) claims that minorities are more prone to unionize but face harsher hurdles from employers and hence end up having lower unionization rates. In this paper, we have assumed that less union membership indicates that individuals choose to not join unions or organizers have a harder time organizing more diverse people. More research and data are required to examine the employer-side. Regardless, from policy viewpoint, our results indicate that there is a clear trade-off between pro-immigration policies and pro-union policies.

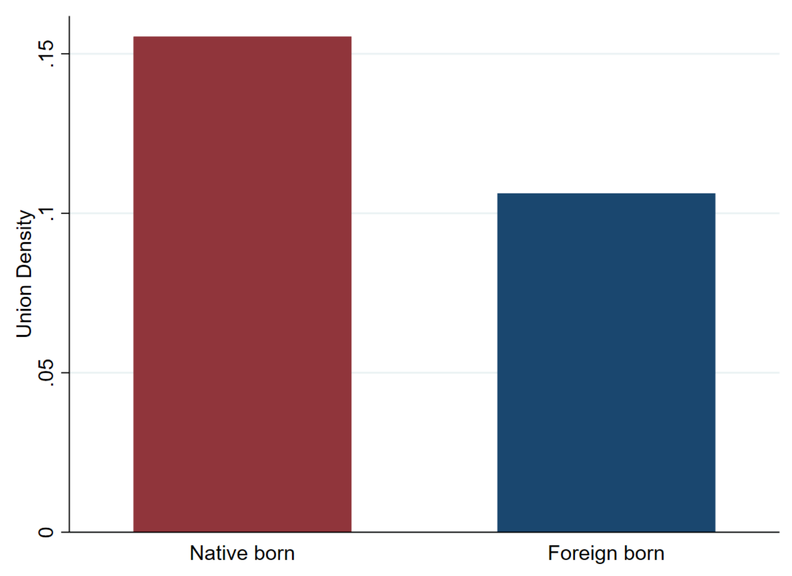
Figures

Figure 1: Union Density v. Immigrant Share



Source: Nowrasteh and Powell 2020, 208.

Figure 2: Preferences for Unionization by Nativity



Generated using CPS-ASEC 1994-2020. This figure shows the share of natives and immigrants who are part of a union averaged over 1994-2020. Used sampling weights.

Figure 3: Union Density and Individual Solidarity Distributions

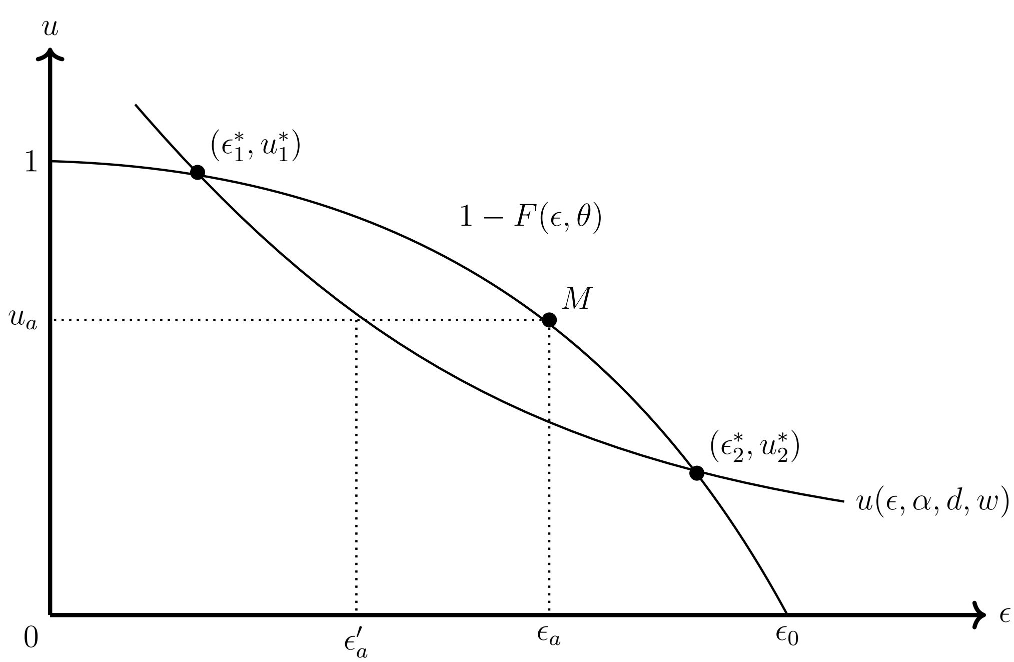


Figure 4: Shift in ϵ Distribution from an Decrease in θ

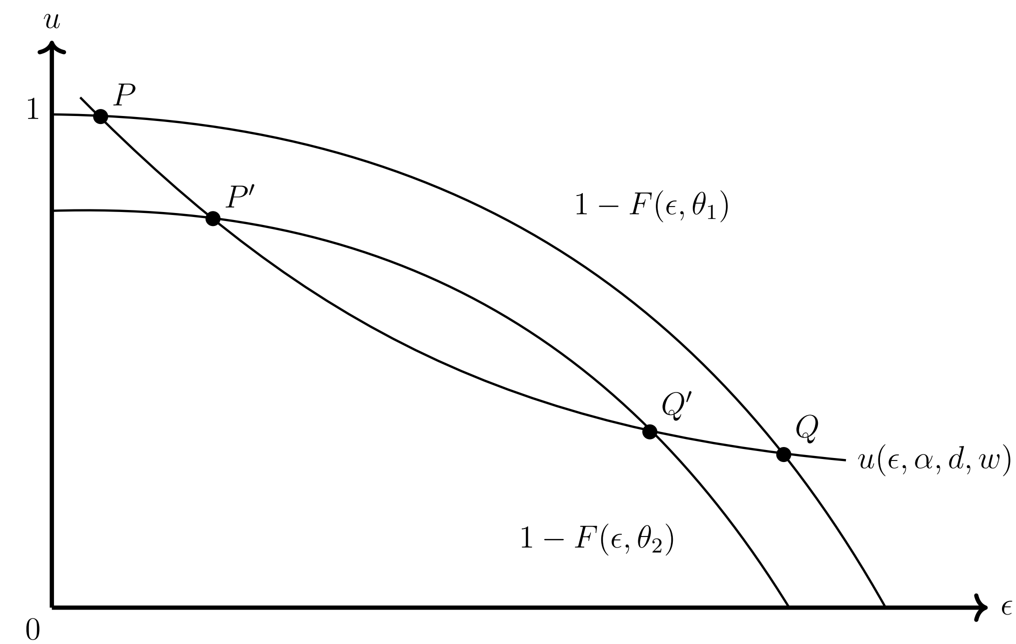


Figure 5: Equilibria When Free Choice Assumption Does Not Hold

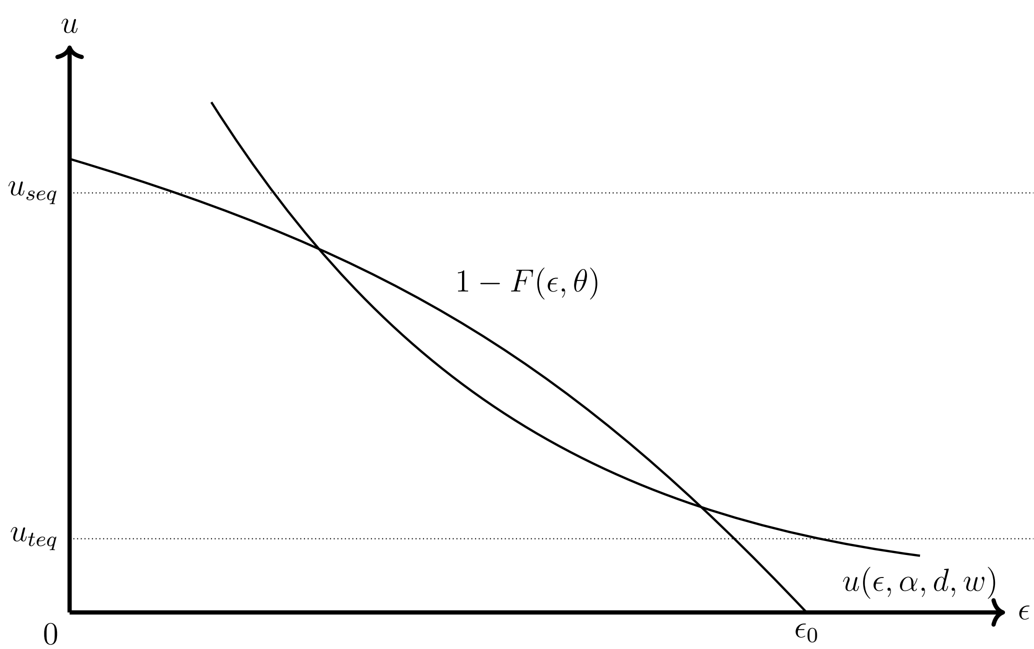
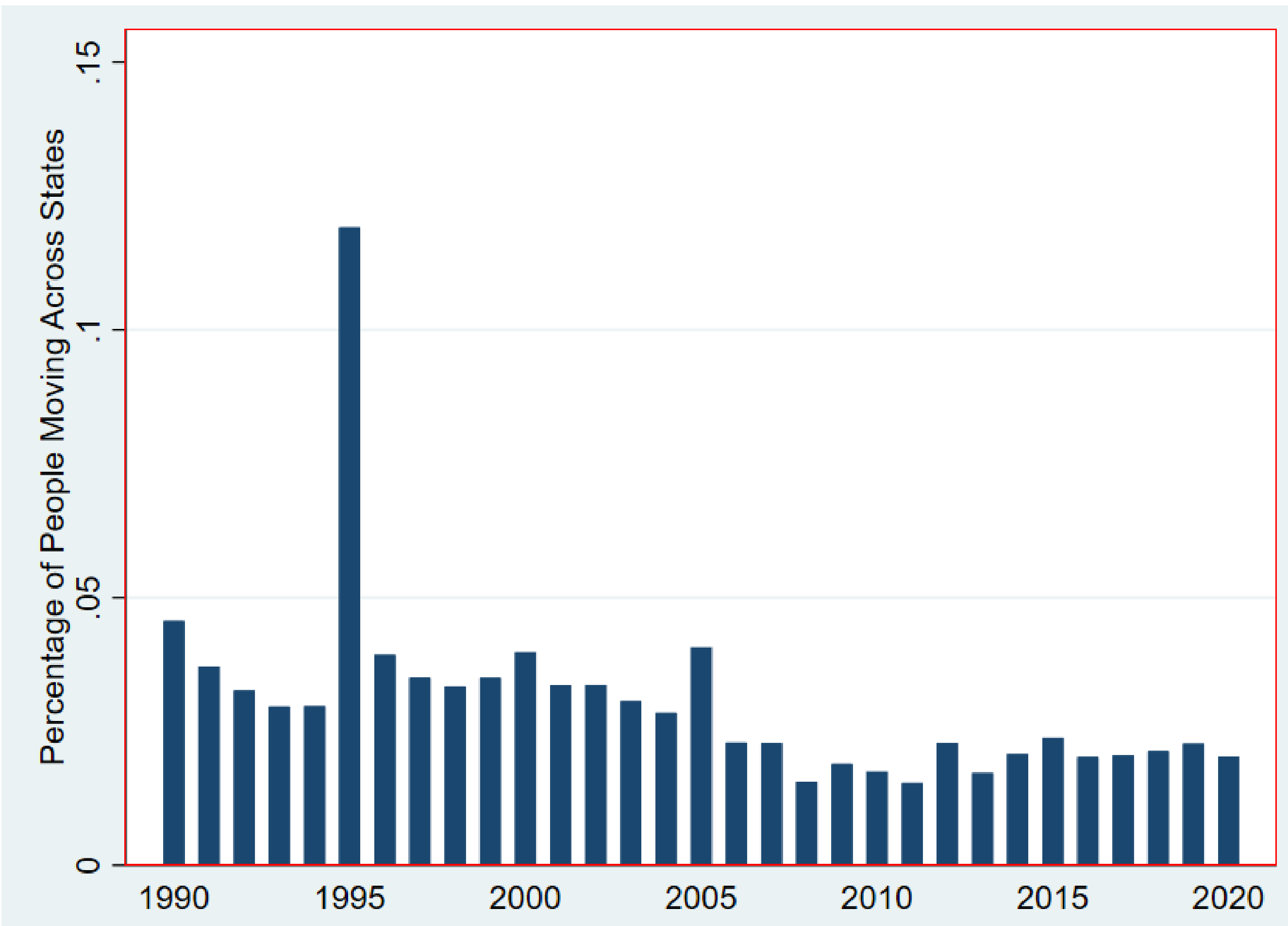
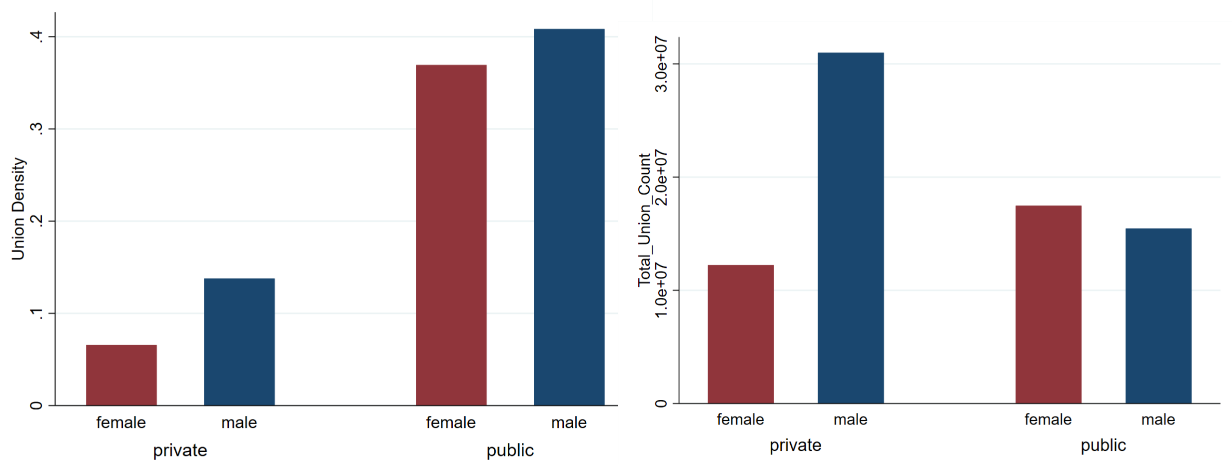


Figure 6: Interstate Migration for Workers



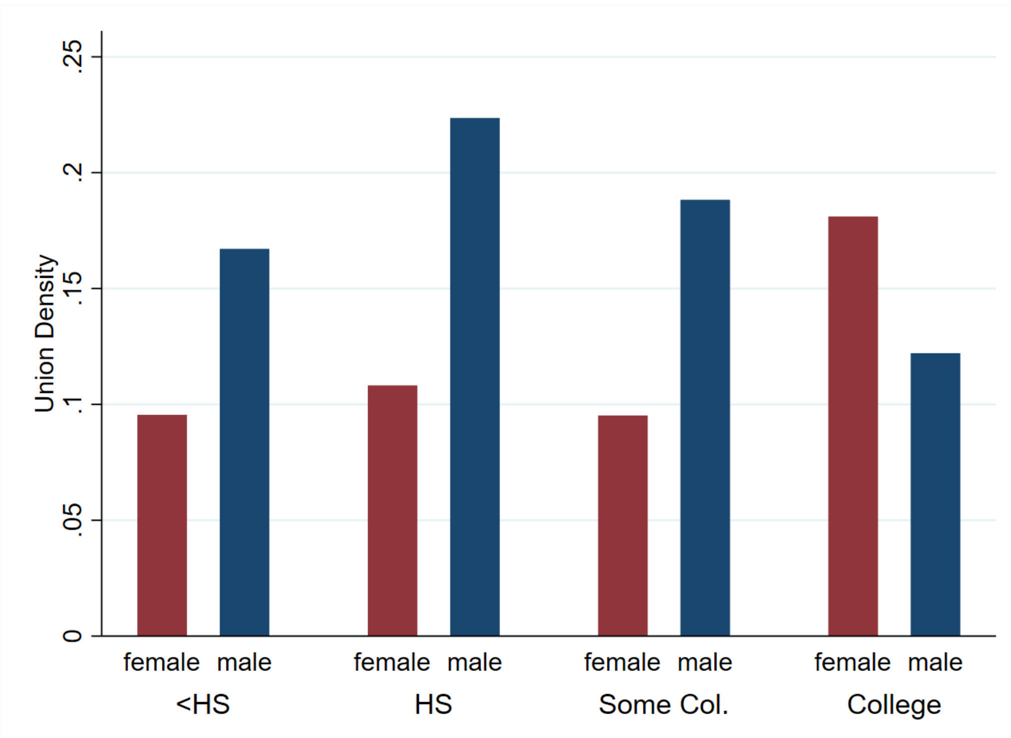
Generated using CPS-ASEC 1990-2020. Sample of employed, working-age males. This figure shows the percentage of people that moved to another state from the previous year. The IPUMS recommends using caution when interpreting migration data from 1995.

Figure 7: Union Density and Count by Sex and Sector



Generated using the final data set (1980-2020). This figure compares union density by sector and sex between 1980 and 2020 by education levels of all employed, working-age adults.

Figure 8: Union Density by Sex and Education



Generated using the final data set (1980-2020). This figure compares union density by education and sex between 1980 and 2020 by education levels of all employed, working-age adults.

Tables

Table 1: List of Largest Cultural Groups

Nativity	Cultural Groups (1980)	Percentage	Nativity	Cultural Groups (1990)	Percentage
Native	White	79.42	Native	White	75.58
Native	Black	8.71	Native	Black	8.58
Native	Hispanic	3.84	Native	Hispanic	4.31
Native	Other Race	1.09	Native	Other Race	1.28
Immigrant	Mexico	1.53	Immigrant	Mexico	2.94
Immigrant	Cuba	0.34	Immigrant	Philippines	0.45
Immigrant	Canada	0.32	Immigrant	Cuba	0.35
Immigrant	Italy	0.32	Immigrant	India	0.33
Immigrant	Germany	0.32	Immigrant	El Salvador	0.30
Immigrant	Philippines	0.25	Immigrant	Vietnam	0.28

Nativity	Cultural Groups (2000)	Percentage	Nativity	Cultural Groups (2010)	Percentage
Native	White	69.96	Native	White	62.93
Native	Black	8.28	Native	Black	8.28
Native	Hispanic	5.03	Native	Hispanic	7.11
Native	Other Race	2.38	Native	Other Race	2.84
Immigrant	Mexico	4.95	Immigrant	Mexico	6.90
Immigrant	India	0.63	Immigrant	India	1.06
Immigrant	Philippines	0.55	Immigrant	El Salvador	0.73
Immigrant	Vietnam	0.47	Immigrant	Philippines	0.69
Immigrant	El Salvador	0.44	Immigrant	China	0.60
Immigrant	China	0.42	Immigrant	Guatemala	0.55

Nativity	Cultural Groups (2020)	Percentage
Native	White	57.90
Native	Hispanic	10.27
Native	Black	8.55
Native	Other Race	4.49
Immigrant	Mexico	5.55
Immigrant	India	1.97
Immigrant	El Salvador	0.75
Immigrant	China	0.66
Immigrant	Guatemala	0.60
Immigrant	Philippines	0.55

Generated using the final data set (1980-2020).Following Ottaviano and Peri (2006), we include immigrant nationality groups that make up more than 0.5% of the foreign-born population and classify all other immigrant nationality groups into "miscellaneous." For native groups, we divide the sample by non-white Hispanic, black, Hispanic, and all other races that include mixed races and other lesser represented minorities. Given that Germany and Korea are classified differently across time, we treated East/West Germany as Germany and North/South Korea as Korea. All categories are mutually exclusive.

Table 2: Regional Analysis

	(1) metarea	(2) statefip	(3) region
log_imm	-0.0602**	-0.121***	-0.250***
	(0.0235)	(0.0387)	(0.0706)
Observations	4,114	1,372	243
R-squared	0.629	0.802	0.937

Generated using CPS-ASEC 1994-2020. Regression of Log of union denstiy on log of immigrants share with year and region fixed effects. The regional unit varies by column. The effect is dramatically different for level-level and this is due to the presence of heteroscedasticity (tested it using the Breusch-Pagan test). The log transformation resolves this issue. Used Earner Study weight for union density and the CPS-ASEC weight for immigrant share. $(***p < 0.01, **p < 0.05, *p < 0.1)$

Table 3: Changes in Union Density and Immigrant Share by Education

Education		(1) Immigrant Share	(2) Union Density
< HS			
	1980	0.116	0.345
	2020	0.500	0.030
	%Δ	331.03	-91.30
HS			
	1980	0.042	0.377
	2020	0.168	0.118
	%Δ	300.00	-68.70
Some College			
	1980	0.056	0.270
	2020	0.116	0.123
	%Δ	107.14	-54.44
College			
	1980	0.075	0.168
	2020	0.189	0.110
	%Δ	152.00	-34.52

Generated using the final data set (1980-2020). This Table shows the percentage change in Union Density and Immigrant Share between 1980 and 2020 by education levels of all employed, working-age civilian males.

Table 4: Changes in Union Density and Immigrant Share by Experience

Years of Experience		(1) Immigrant Share	(2) Union Density
1-5 Years			
	1980	0.054	0.203
	2020	0.129	0.057
	%Δ	138.89	-71.92
6-10 years			
	1980	0.068	0.287
	2020	0.147	0.109
	%Δ	116.18	-62.02
11-15 Years			
	1980	0.078	0.330
	2020	0.190	0.105
	%Δ	143.59	-68.18
16-20 years			
	1980	0.079	0.318
	2020	0.207	0.127
	%Δ	162.03	-60.06
21-25 Years			
	1980	0.077	0.332
	2020	0.219	0.132
	%Δ	184.42	-60.24
26-30 Years			
	1980	0.073	0.358
	2020	0.225	0.135
	%Δ	208.22	-62.29
31-35 Years			
	1980	0.068	0.348
	2020	0.220	0.100
	%Δ	223.53	-71.26
36-40 Years			
	1980	0.069	0.358
	2020	0.193	0.125
	%Δ	179.71	-65.08

Generated using the final data set (1980-2020). This Table shows the percentage change in Union Density and Immigrant Share between 1980 and 2020 by experience levels of all employed, working-age civilian males.

Table 5: Immigrants and Union Density

	(1) Levels
Immigrant Share (Level)	-0.479***
	(0.083)
Observations	160
SD(imm)	0.144
SD(u)	0.107
Mean(u)	0.181

Generated using the final data set (1980-2020). The dependent variable is union density (col1). The regression includes education, experience and year fixed effects, and their combinations. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. There are 4 education, 8 experience, and 5 different years amounting to 160 cells. Regression weighted using sample size for each collapsed bin (education-experience-year combo). Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 6: Heterogeneity by Education

			Omitted Categories		
	(1) Original	(2) < HS	(3) HS	(4) Some College	(5) College
imm_share	-0.479***	-0.684	-0.440***	-0.504***	-0.420***
	(0.083)	(0.424)	(0.093)	(0.106)	(0.085)
Observations	160	120	120	120	120
Adjusted R-Squared	0.8642	0.8635	0.8076	0.8924	0.8606

Generated using the final data set (1980-2020). Running the benchmark regression but omitting each education category. All other specification is the same as Table 1. The regression includes education, experience and year fixed effects, and their combinations. Each column starting with column 2, omits the education level in the column heading. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. Due to the omission of certain education levels, the observations are less than 160 which is the original number of cells. Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 7: Heterogeneity by Experience

			Ommited Categories		
	(1) Original	(2) 1-10	(3) 11-20	(4) 21-30	(5) 31-40
imm_share	-0.479***	-0.311*	-0.493***	-0.558***	-0.432***
	(0.083)	(0.164)	(0.074)	(0.092)	(0.114)
Observations	160	120	120	120	120
Adjusted R-squared	0.8642	0.8854	0.8452	0.8822	0.8519

Generated using the final data set (1980-2020). Running the benchmark regression but omitting each experience category. All other specification is the same as Table 1. The regression includes, education, experience and year fixed effects, and their combinations. Each columns starting with column 2, omits the experience level in the column heading (i.e. col 2 excludes those who have 1 to 10 years of experience). Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 8: Heterogeneity Analysis (All Sectors)

Public and Private	Male imm	Male frac	M&F imm	M&F frac	Female imm	Female frac
imm_share	-0.479***		-0.363***		-0.142	
	(0.083)		(0.075)		(0.115)	
fraction_index		-0.409***		-0.404**		-0.162
		(0.149)		(0.150)		(0.212)
Observations	160	160	160	160	160	160
Adjusted R-squared	0.8642	0.8518	0.8815	0.8715	0.7723	0.7706

Generated using the final data set (1980-2020). Running the benchmark regression for imm_share and fraction_index separately for all sectors. Run separately by males only, males and females, and female only. The regression includes education, experience, year fixed effects, and their combinations. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. There are 4 education, 8 experience, and 5 different years, amounting to 160 cells. Regression weighted using sample size for each collapsed bin (education-experience-year combo). Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 9: Heterogeneity Analysis (Private)

Private	Male imm	Male frac	M&F imm	M&F frac	Female imm	Female frac
imm_share	-0.466***		-0.414***		-0.276***	
	(0.080)		(0.064)		(0.083)	
fraction_index		-0.409**		-0.452***		-0.269**
		(0.154)		(0.130)		(0.129)
Observations	160	160	160	160	160	160
Adjusted R-squared	0.8856	0.8748	0.9162	0.9021	0.6976	0.6696

Generated using the final data set (1980-2020). Running the benchmark regression for imm_share and fraction_index separately for the Private sector. Run separately by males only, males and females, and female only. The regression includes education, experience, year fixed effects, and their combinations. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. There are 4 education, 8 experience, and 5 different years, amounting to 160 cells. Regression weighted using sample size for each collapsed bin (education-experience-year combo). Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 10: Heterogeneity Analysis (Public)

Public	Male imm	Male frac	M&F imm	M&F frac	Female imm	Female frac
imm_share	-0.892		0.184		0.250	
	(1.325)		(0.450)		(0.416)	
fraction_index		0.196		0.107		0.246
		(0.581)		(0.474)		(0.384)
Observations	156	156	157	157	155	155
Adjusted R-squared	0.2783	0.2704	0.3974	0.3972	0.5729	0.5739

Generated using the final data set (1980-2020). Running the benchmark regression for imm_share and fraction_share separately for the Public sector. Run separately by males only, males and females, and female only. The regression includes education, experience, year fixed effects, and their combinations. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. There are normally 4 education, 8 experience, and 5 different years, amounting to 160 cells. However, given the small size of the public sector, some categories did not have any workers in them. This explains why these regressions have less than 160 observations. Regression weighted using sample size for each collapsed bin (education-experience-year combo). Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 11: Fractionalization and Unionization

	(1) Frac.	(2) Imm.
fraction_index	-0.409**	
	(0.149)	
imm_share		-0.479***
		(0.083)
Observations	160	160

Generated using the final data set (1980-2020). The Fractionalization index is created using immigrant nationality groups and 4 broad categorizations of native-born: whites, blacks, Hispanics, other minorities. All columns include education, experience, year fixed effects, and their combinations. Col 1 only includes frac. Index, Col2 only uses Immigrant share (I) which is the same as that of Table 1. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. There are 4 education, 8 experience, and 5 different years amounting to 160 cells. Regression weighted using sample size for each collapsed bin (education-experience-year combo). Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 12: Raw Count of Immigrants and Natives

	(1) Immigrant Raw	(2) Native Raw	(3) Immigrant (Share)	(4) Native (Share)
log(raw imm)	-0.255*			
	(0.147)			
log(raw nat)		0.424**		
		(0.197)		
log(ImmShare)			-0.311***	
			(0.197)	
log(NativeShare)				1.089*
				(0.621)
Observations	848	848	848	848

Columns 1 and 2 have the log of raw number of immigrant and natives as the main independent variable. Columns 3 and 4 have the log of shares of immigrants and natives. Dependent variable is union density of just natives as opposed both natives and immigrants. The regression includes education, experience and year fixed effects, and their combinations. Observation number indicates the number of cells; each cell representing a unique combination of education and experience for a given year. There are 4 education, 8 experience, and 27 years amounting to 864 cells. When using logs, zero union densities are dropped. Regression weighted using sample size for each collapsed bin (education-experience-year combo). Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

Table 13: Using Immigrant Share with Lagged-size of Labor Force

	CPS-ASEC (1994-2020)						**(1980-2020)**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged Base	t	t-1	t-2	t-3	t-4	t-5	t-10
log(I)	-0.311***						
	(0.109)						
log(I-1)		-0.256**					
		(0.101)					
log(I-2)			-0.321***				
			(0.0968)				
log(I-3)				-0.196*			
				(0.111)			
log(I-4)					-0.249*		
					(0.137)		
log(I-5)						-0.215	
						(0.152)	
log(I-10)							-0.052*
							(0.027)
Observations	848	816	721	753	721	753	128

CPS-ASEC (1994-2020) is used for col1 to col6, each column represents an additional lag to the base labor supply of the main explanatory variable, log of immigrant share. Column 1 is the original result from Table 1, and column 6 is using the modified immigrant share where the base labor supply is lagged 5 periods. Column 7 is uses the final data set (1980-2020) as the main results section and the lag is 10 years. Standard errors are clustered at the education-experience level. Robust standard errors in parentheses ($***p < 0.01, **p < 0.05, *p < 0.1$)

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Appendix

Countries Used for Fractionalization Index

To construct the fractionalization index, we classified the cultural group of each foreign-born person by their birth country if immigrants from that country made up more than 0.5% of the foreign-born population in a given year in our sample. All other immigrant groups were classified as a "miscellaneous" cultural group. Here, we will enumerate the countries used to construct the fractionalization index for each year.

In 1980, the countries used were as follows: Canada, Mexico, El Salvador, Guatemala, Cuba, Dominican Republic, Haiti, Jamaica, Trinidad and Tobago, Argentina, Colombia, Ecuador, Peru, England, Scotland, Ireland, France, Netherlands, Greece, Italy, Portugal, Czechoslovakia, Germany, Poland, Yugoslavia, USSR/Russia, China, Hong Kong, Japan, Korea, Philippines, Vietnam, India, Israel/Palestine, Iran, and Taiwan.

In 1990, the countries used were as follows: Canada, Mexico, El Salvador, Guatemala, Nicaragua, Cuba, Dominican Republic, Haiti, Jamaica, Trinidad and Tobago, Argentina, Colombia, Ecuador, Guyana, Peru, England, UK (other), Ireland, Greece, Italy, Portugal, Germany, Poland, Yugoslavia, USSR/Russia, China, Hong Kong, Taiwan, Japan, Korea, Laos, Philippines, Vietnam, India, Pakistan, Iran, Lebanon, and Nigeria.

In 2000, the countries used were as follows: Canada, Mexico, El Salvador, Guatemala, Honduras, Nicaragua, Cuba, Dominican Republic, Haiti, Jamaica, Trinidad and Tobago, Brazil, Colombia, Ecuador, Guyana, Peru, England, Italy, Portugal, Germany, Poland, USSR/Russia, Ukraine, China, Hong Kong, Taiwan, Japan, Korea, Laos, Philippines, Vietnam, India, Pakistan, Iran, Nigeria, and Africa (other).

In 2010, the countries used were as follows: Canada, Mexico, El Salvador, Guatemala, Honduras, Nicaragua, Cuba, Dominican Republic, Haiti, Jamaica, Brazil, Colombia, Ecuador, Guyana, Peru, Poland, USSR/Russia, China, Philippines, Vietnam, India, Pakistan, Germany, Japan, Korea, Laos, Iran, England, Ukraine, Hong Kong, Taiwan, UK (other), and Nigeria

In 2020, the countries used were as follows: Canada, Mexico, El Salvador, Guatemala, Honduras, Cuba, Dominican Republic, Haiti, Jamaica, Brazil, Colombia, Ecuador, Peru, Venezuela, England, UK (other), USSR/Russia, Ukraine, China, Taiwan, Korea, Philippines, Thailand, Vietnam, India, Bangladesh, Pakistan, Nepal, Iran, Nigeria, and Africa (other).