Immigration and Local Business Dynamics: Evidence from U.S. Firms

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Abstract

This paper argues that firm entry and exit play critical roles in determining how immigrant workers are absorbed into and affect local industries. Using a comprehensive collection of survey and administrative data from the U.S. Census Bureau, it documents a positive relationship between immigrant workers and business presence, with inflows driving entry by small-to-medium sized firms and preventing exit by older, large firms. These extensive margin responses play a dominant role in immigrant worker absorption, accounting for more than two-thirds of immigrant-induced job creation. Observed proxies for productivity further reveal an important heterogeneity: immigrant inflows increase the probability of exit by lower-productivity firms and decrease the probability of exit by higher-productivity firms, with the latter effect driving the overall reduction in firm exit. A general equilibrium model proposes a mechanism that ties immigrant workers to high-productivity firms and shows how accounting for heterogeneous firm entry and exit can yield substantially larger estimates of immigrant-generated economic surplus than canonical models of labor demand.

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1 Introduction

The Census Bureau estimates that by 2030, immigration will overtake natural increase (births minus deaths) as the primary driver of population growth in the United States.[1] A workforce that will increasingly rely on foreign-born workers requires a comprehensive understanding of how they are absorbed into and ultimately shape local economies.[2] Recent advances to data and theory have dramatically expanded our insight into how this process occurs on the firm side of the labor market, with a particular focus on the form and choice of production technique.[3] Nonetheless, most of this literature has either implicitly or explicitly restricted its attention to representative firm models of production that, by definition, do not feature differences across firms in input use or total factor productivity. Moreover, the empirical work that has studied individual firm responses to immigration has largely centered on existing firms in non-U.S. settings.[4]

In contrast, broader study of the U.S. economy—the largest immigrant destination in the world—finds that firm entry and exit dynamics are crucial drivers of job creation and productivity growth, particularly when firm entry is accompanied by the exit of less productive firms.[5] Furthermore, immigrant workers appear to be especially active in changing firm entry and shut down decisions: immigrants have a higher propensity to start businesses than natives[6], are relatively more likely to work for new businesses[7], and have been found to increase establishment presence in particular contexts.[8] When viewed through this lens, the question of how local economies generate enough jobs to absorb immigrant inflows naturally leads us to consider firm entry and firm exit. When we accordingly open the door to differences in productivity and input use across firms, such entry and exit introduces a new channel through which immigrants alter a local economy: by changing its firm composition.

In this paper, I thus argue that immigrant absorption into local labor markets and the subsequent effects immigrant workers have on local economies are predicated on firm entry and firm exit. I conduct several empirical analyses using administrative data from the U.S. Census Bureau's Longitudinal Business Database (LBD), the universe of survey responses to the Decennial Census Long Form, and the American Community Survey (ACS) to illustrate this proposition. The first set of analyses quantifies and characterizes the effect of immigrant worker inflows on firm presence in U.S. local industries, defined as commuting zone-industry pairings. To resolve endogeneity concerns, I develop a new shift-share instrument for immigrant inflows into a local industry that exploits data on bilateral stocks of emigrants in non-U.S. OECD member nations to isolate exogenous migration pushes from over 150 sending countries. These exogenous pushes are distributed

[1] See Vespa and Armstrong (2018).

[2] This paper will use the term workers to encompass both the self-employed and employees.

[3] See, e.g., Lewis (2005, 2012); Clemens et al. (2018); Dustmann and Glitz (2015); Peri (2012); Mitaritonna et al. (2017); Lewis (2011); D'Amuri et al. (2010); Peri and Sparber (2009); Gonzalez and Ortega (2011).

[4] See, e.g., Mitaritonna et al. (2017); Malchow-Moller et al. (2012).

[5] See, e.g., Foster et al., 2008; Bartelsman and Doms, 2000; Baldwin, 1995.

[6] See, e.g., Borjas (1986); Fairlie and Lofstrom (2015); Kerr and Kerr (2018); Hunt (2011); Azoulay et al. (2020).

[7] See, e.g., Kerr and Kerr (2016).

[8] See, e.g., Olney (2013) and Orrenius et al. (2020).

into specific commuting zones using previous compatriot locational choices and into specific industries by compatriot industry choices in other Census Regions. I find a robust, positive effect of immigrant inflows on firm presence within local industries. Each immigrant added roughly 0.05 additional firms to the commuting zone and industry in which they worked in the decades spanning 1980 through 2010, driven by the entry of small-to-medium sized firms and the prevention of exit among large, older firms.

These extensive margin effects are at the crux of two novel empirical results on immigrant absorption. First, firm entry and the prevention of firm exit account for more than two-thirds of immigrant-induced job creation, while the expansion of continuing firms plays a minimal role over the span of a decade. In U.S. local industries, immigrant absorption is a phenomenon driven by firm entry and exit. Second, firm productivity is a key moderator of how immigration impacts firm shut down decisions. Using a set of productivity proxies and a panel of nearly all U.S. firms in operation as of 2000, I find that immigrant inflows into local industries increase the probability of exit by lower-productivity firms while decreasing the probability of exit by higher-productivity firms, with the latter effect driving the overall reduction in firm exit. These results suggest a productive reallocation through creative destruction. A second panel that follows a representative sample of firms covered by the 2007 Survey of Business Owners (SBO) through 2012 adds nuance to this primary finding: native-owned, lower-productivity firms are subtantially more likely to shut down in response to immigrant inflows than are immigrant-owned, lower-productivity firms. The results from this second panel are suggestive of ties between immigrant entrepreneurs and employees.

The empirical results in this paper have important implications for how economists and policymakers evaluate immigration in general equilibrium. In order to elucidate this point, I develop a theoretical framework that incorporates firm heterogeneity into the analysis of immigration by combining workhorse labor and trade models (e.g., Melitz, 2003; Ottaviano and Peri, 2008). In the spirit of Bustos (2011), I propose a mechanism that ties high-productivity firms to immigrant workers: some firms pay additional fixed costs to access a technology that allows them to better utilize immigrant employees. Because these firms must pay an additional cost, they are positively selected on productivity. When immigrant exposure increases, these higher-productivity, high-immigrant-use firms see larger reductions in labor costs than their lower-productivity counterparts, and competitive forces drive the lowest-productivity firms out of the market. The effect of immigration on native welfare—the "immigration surplus"—in this framework hinges on the effect of immigration on firm entry and firm reallocation. Immigrant-induced changes to the productivity composition and mass of firms generate first-order welfare benefits. In comparison, second-order effects that also arise in canonical, representative firm models of production are relatively muted.

The rest of this paper is organized as follows: Section 2 provides a brief literature review. Section 3 describes the comprehensive U.S. Census Bureau data and shift-share identification approach used in subsequent analyses. Section 4 quantifies and characterizes the positive relationship between immigrant worker inflows and increased business presence and culminates by showing how this relationship drives immigrant absorption. Section 5 analyzes firm shut down decisions in

response to immigrant worker inflows, stratified by correlates of initial firm productivity. Section 6 synthesizes the results from Sections 4 and 5 and discusses welfare implications using a theoretical model. Section 7 concludes.

2 Related Literature

The empirical analyses presented in this paper add to a growing literature that utilizes advances in data availability to study firm-level responses to immigration. Three important, related papers contain results regarding the effect of immigration or foreign-born workers on the number of establishments in local labor markets. Olney (2013) presents evidence that low-skilled immigrants generate increased establishment presence in the 30 largest U.S. metropolitan areas using a yearly panel that covers 1998 through 2008. These findings are consistent with those presented in Section 3, and help motivate the expanded set of empirical analyses I present below. Unlike Olney (2013), who finds no effect of immigrant workers on establishment presence in non-tradable industries, Section 4 documents a relationship between immigrant workers and net firm entry that is broad-based across tradability of industry. Beerli and Peri (2015) and Ruffner and Siegenthaler (2016) both find that the abolition of restrictions on cross-border commuters in Switzerland led to increased establishment presence in areas most affected by the policy. Unlike this study, the workers they analyze are not immigrants since they continue to live in foreign countries and were mostly high-skilled. Nonetheless, their results illuminate another context in which the effect of foreign workers on establishment creation is not likely due to consumer demand, given that they still live abroad. This paper makes a similar argument regarding inflows of immigrants into the U.S. that are relatively low-skilled.

Two important studies relate to the first benchmark result in this paper, presented in Section 4.2. Hong and McLaren (2015) find that immigrant inflows lead to spillover job creation—specifically, that each immigrant generates 1.2 jobs in local labor markets that they arrive in. They also find that effects are primarily driven by the nontradable industries, which leads them to conclude that immigrant consumer demand is responsible for local spillover job creation. In contrast to their motivation (but not their results), my empirical specification attempts to control for the effect of immigrant-specific consumer demand, instead focusing on adjustments to immigration that are made on the supply side of the product market. Dustmann and Glitz (2015) use employer-employee linked data from Germany to test the importance of alternative immigrant absorption mechanisms. As in this paper, they focus on adjustment mechanisms other than wage changes. They find that 15 percent of immigrant absorption in the tradable sector can be accounted for by net firm creation. This result provides important motivation for the decomposition exercise presented in Section 4.2, though results are not directly comparable because my analysis includes nontradable industries, is conducted fully within-sector, and takes place in the U.S.

A growing body of work relates to the findings in Section 5 and its implications for immigrant-induced changes to local productivity. Mitaritonna et al. (2017) study the effect of immigration

on existing firm productivity in France. They find that exposure to immigrants increases firm productivity and decreases the probability of firm exit, the latter of which is also found in Section 5 here. However, Mitaritonna et al. (2017) do not find that exit prevention is stratified by firm productivity. Once again, this discrepancy may be caused by their focus on the manufacturing sector, differences between the French and U.S. economies as a whole, the fact that immigrant inflows were skill-intensive in their setting, or differences in how initial firm productivity is measured. Future work reconciling these differences will help clarify the external validity of the results contained in this paper. Peri (2012) analyzes a state-decade panel and finds that immigrant inflows into the workforce generate increases in total factor productivity, resulting in an immigration surplus that is augmented by endogenous technological change. He finds that at least half of this technological change is mediated by task reallocation and increased specialization by native workers in response to immigrant inflows. In conjunction with the aforementioned literature on the importance of firm entry and exit to productivity gains, the empirical results presented in this paper suggest that some of this task specialization may occur through reallocations that are enabled by firm entry. Burchardi et al. (2020) analyze U.S. counties during the same study period as this paper and find that immigration leads to increased innovation (as measured by patents), job creation, job destruction, job growth skewness, and local wages. That job destruction increases in tandem with job creation—indicating an increase in dynamism—comports with the increased creative destruction at the firm level found in Section 5. Further evidence consistent with these dynamics comes from recent work on immigration enforcement. Ayromloo et al. (2020) find that state enforcement of e-Verify laws—which have previously been shown to lead to declines in the presence of undocumented workers (Bohn et al., 2014)—lead to exits by *larger* firms. All told, this paper contributes advances a growing literature on the link between immigration and economic dynamism and productivity by providing evidence that firm entry and exit are key mechanisms underlying this link.

In general, my results also suggest that taking entrepreneurship into account is crucial to the economic analysis of immigration. This notion is broadly in line with Beaudry et al. (2018), who reintroduce the importance of entrepreneurship to labor demand using a search theoretic framework. It also relates to recent work by Karahan et al. (2019) and Hopenhayn et al. (2018), who model and test for the importance of population growth declines in explaining declining entrepreneurship in the U.S. economy. The results contained in Section 4.1 imply that immigration can help alleviate the declining start-up rate simply by replenishing population growth. However, this paper's focus is on the unique extensive margin labor demand responses to immigration shocks, motivated by unique features that immigrants bring to local economies. For example, results in Section 4.1 indicate that immigrant inflows increase firm presence, even when controlling for overall employment growth. Additionally, results in Section 5 imply that immigrant-owned firms benefit the most from access to immigrant employees, consistent with previous evidence that immigrant employees disproportionately work at immigrant-owned firms (Garcia-Perez, 2009).

This paper is thus also related to a budding literature on immigrant entrepreneurship in gen-

eral (Kerr and Kerr, 2016, 2018; Fairlie and Lofstrom, 2015), which has recently broadened its previous focus from only the high-tech sector and the sciences (e.g., Kerr 2013; Hunt 2011; Hunt and Gauthier-Loiselle 2010; Peri et al. 2015; Kerr et al. 2016). Of particular note is new work by Azoulay et al. (2020), who use some of the same data sources as this paper to show that immigrants tend to generate more employee-hiring firms than natives as entrepreneurs; and, most importantly, that this effect is present throughout the firm size distribution. I find that immigrant workers in general—employees and entrepreneurs—have a similar effect throughout the firm size distribution. However, as discussed in Section 4, the magnitude of the effect of immigrant presence on firm presence means that immigrant entrepreneurship alone cannot be the only mechanism. Thus, this paper also relates to literature on how the presence of immigrant workers can spur native entrepreneurship (e.g., Duleep et al., 2012).

Section 6 develops a theoretical model in which heterogeneous firms distinguish between immigrant and native workers. Simply allowing for these heterogeneities clarifies the large role individual firms play in determining the effects immigrant workers have on local economies. In particular, increased firm presence benefits native consumers by increasing product variety, and reallocation from less to more productive firms (through culling of the former and entry by the latter) reduces prices. Seminal work by George Borjas (see, e.g., Chapter 7 in Borjas, 2014) motivated these "immigrant surplus" calculations—where immigrant surplus is defined as the effect of immigration on native welfare. As in his calculations, immigrants in my model generate increases in average native welfare when they arrive with a different skill mix than the incumbent population. Ottaviano and Peri (2012), meanwhile, show that immigrants can further increase native welfare when they are imperfect substitutes in production for native workers of the same skill and experience. I show that both of these results are amplified when we account for heterogeneous firm responses. Waugh (2017) also studies firm dynamics in response to immigration in a model with monopolistic competition. While his focus is high-skilled immigration and the H1-B visa program, he similarly finds that immigrant inflows result in net firm creation. However, the mechanisms through which this occurs are increased scale and an endogenous relationship between productivity and high-skilled labor. Motivated by Bustos (2011)—who introduces endogenous technological change to the Melitz framework by allowing a subset of firms to pay a higher fixed cost to access a better production technology—and Blaum et al. (2018)—who show how heterogeneity in imported input use can dramatically alter the effect of shocks on firm prices—I instead allow for heterogeneity in the ability of firms to utilize immigrant labor. This introduces an alternate channel through which immigrants spur net firm creation and increase productivity. Resulting price decreases that increase consumer welfare have been studied by Cortes (2008) (through a wage reduction channel) and di Giovanni et al. (2014) (through an increased variety channel). The productive reallocation channel is a novel addition to this theoretical literature.

3 Data and Identification

3.1 Data and Sample Restrictions

The analyses presented in Sections 4 and 5 are facilitated by access to confidential data from the U.S. Census Bureau's Longitudinal Business Database (LBD), which contains survey responses that are mandated by law from each U.S. non-farm, employee-hiring, private-sector establishment. Establishments are assigned unique, consistent identifiers that can be linked over time to create a true panel. Crucially, the LBD also contains unique firm identifiers, which allows me to aggregate establishments to their owning firms. The focus on firms is distinct from a focus on establishments because it carries the possibility of a new "variety" from the perspective of the consumer and an additional outside option from the perspective of a worker.[9] Fort and Klimek (2018) provide consistent North American Industrial Classification System (NAICS) codes over time for these firms which I then map to industry groups described below. This facilitates within-industry analyses that more credibly isolate the effect of immigrant workers on firm entry and exit decisions.

The LBD allows me to go beyond the publicly-available, overall counts of establishments in a given geography by allowing for firm counts within geography *and* industry group *by* various firm characteristics. The most important of these characteristics is firm age. Haltiwanger et al. (2013) find that much of the public attention paid to small businesses and their role in job creation should be transferred to young businesses, which are generally but incidentally small. Furthermore, as documented in Decker et al. (2014), new firm creation also appears to play a particularly crucial role in both job creation and productivity. That the longitudinal linkages in the LBD facilitate the construction of within sector-geography firm counts by age bin allows me to understand whether immigrant inflows are preventing continuing firm deaths, spawning new firm activity, or both. In addition, the LBD also allows for within industry group-geography firm counts in size-by-age bins. These splits facilitate a more complete characterization of the increased firm presence that arises with immigrant inflows and lead to specific hypotheses regarding its consequences that are tested in Sections 4.2 and 5. A firm is counted in a given commuting zone and industry if it owns at least one operating establishment in that commuting zone and industry. This means the same firm can be counted multiple times, if it operates in multiple locations and/or industries.

In order to study the effect of immigrant presence on these outcomes, I also exploit restricted-access U.S. Census Bureau demographic data from the 1980, 1990, and 2000 Long-Form Decennial Censuses and the 2005 through 2012 American Community Surveys. These data allow for unusually precise measures of immigrant inflows, not just into geographies, but into relatively detailed industry groups within U.S. county and by country of origin. These elements are crucial to the identification strategy presented in Section 3.2. Because industry classifications differ between the Census and NAICS, I construct aggregated industry groups using the 1990 Decennial Census industry codes as a bridge between Census industry codes in other years and 3-digit NAICS codes

[9] For additional reasons to favor the study of firms over establishments in a similar context, see Haltiwanger (2015).

contained in the LBD.[10] In some cases, the 1990 industry classification corresponds to more than one 3-digit NAICS code, and in some cases a 3-digit NAICS code corresponds to more than one 1990 industry classification. The industry groups I use therefore generally represent the smallest possible mutually-exclusive sets of industry classifications.[11] Some additional aggregations are made to ensure that industry groups do not vary excessively in size. The agriculture, mining, and public sectors are dropped from the analysis due to relatively less reliable coverage in the LBD. The final set of industry groups can be seen in Table A1.

The analyses presented in Section 4 and Section 5 are thus based on immigrant exposure in commuting zone-industry group pairings—local industries—over time. Commuting zones are groupings of counties meant to mimic local labor markets. Crosswalks from counties to commuting zones are downloaded from David Dorn, as used in Autor and Dorn (2013). In order to limit the impact of measurement error and take full advantage of the precision allowed for by the restricted-access demographic data, I make two sample restrictions: I keep local industries with at least 100 workers in all time periods and local industries whose worker counts are underlay by at least 10 Census respondents in all time periods.

3.2 Identification Strategy

The primary specification for the analyses in Section 4 is

$$\Delta y_{gkt} = \alpha + \beta \left(\Delta I_{gkt} \right) + \Gamma X_{gkt} + \alpha_{gt} + \alpha_{kt} + \varepsilon_{gkt} \tag{3.1}$$

where g indexes a commuting zone, k indexes an industry group, t indexes a year, and the Δ operator represents a ten-year change within a local industry (change within gk). For example, in Columns 2 and 3 of Table 2, Δy_{gkt} is the change in firm presence in commuting zone g and industry group k during a given decade, divided by the start-of-decade workforce in gk. The independent variable of interest, ΔI_{gkt}, is the change in immigrant worker stock in gk between year $t-10$ and t, divided by the start-of-decade workforce in gk. In that specification, the coefficient of interest β measures the number of additional firms in operation per immigrant. X_{gkt} is a vector of control variables that can include 1980 commuting zone-industry characteristics interacted with year dummy variables and a region-industry-year fixed effect.[12] These analyses span three decades in which there were large immigrant inflows to the U.S. (1980–2010) and cover nearly all of the contiguous U.S. in geography (more than 700 commuting zones, excluding Alaska and Hawaii).

Even with the rich fixed effect structure contained in Equation (3.1), endogeneity concerns re-

[10] Crosswalks provided by IPUMS-USA between the 1990 and other Census year classifications, as well as between the 1990 Census industry classifications and NAICS codes, were crucial to this process.

[11] For example, 1990 Census Industry classification code 132 is "Knitting mills" and corresponds to NAICS Codes 315 and 313. However, NAICS code 313 also covers "Yarn, thread, and fabric mills," which is 1990 Census Industry classifiction code 142. Additionally, NAICS code 315 also includes manufacturing of "Apparel and accessories other than knitting." Manufacturing of apparel and accessories, knitting mills, and yarn, thread, and fabric mills are therefore all covered in the same industry grouping in my analysis.

[12] Region refers to a Census Region: East, West, South, or Midwest.

garding immigrant industry choices within geographies and geographical choices within industry remain. Immigrant employees, for example, may choose to work in booming industries, generating biased estimates of β. Immigrant employees may also be more adept than native workers at locating to areas that are booming, as found in Cadena and Kovak (2016), even if they work in the same industry. Meanwhile, if immigrant entrepreneurs are attracted to geographies where they face less competition or if immigrant employees are linked to large firms in more concentrated markets, ordinary least squares (OLS) estimates of β with firm presence as an outcome may contain a downward bias. Attenuation bias from measurement error may also bias estimates, given that immigrant inflows can be small (and thus estimated from relatively few unweighted sample observations) within commuting zone-industry group and that Equation (3.1) is in changes. In short, even in a relatively saturated model, isolating exogenous variation that pushes immigrants into local industries substantially strengthens our case for a causal interpretation of β.

3.2.1 Emigrants IV

A standard shift-share instrument for immigrant stock I_{gkt} takes the following form:

$$z_{gkt}^{\text{Standard}} \equiv \frac{1}{E_{gk,1980}} \sum_{o} \pi_{og,1980} \times I_{okt}$$

where $\pi_{go,1980}$ is the share of origin country o's stock of 1980 U.S. immigrants that was located in commuting zone g, I_{okt} is the stock of year t U.S. immigrants from origin country o working in industry group , and $E_{gk,1980}$ is the 1980 workforce in local industry gk. In this standard setup, Δz_{gkt} would serve as an instrument for ΔI_{gkt} in Equation (3.1), with shift component ΔI_{okt} representing net immigration into industry group k from origin country o.

Previous literature has implicitly recognized the value of an exogenous shift in a shift-share instrument. In a famous, recent example Autor et al. (2013), instrument for Chinese import exposure in U.S. local labor markets by interacting measures of initial industry concentration in commuting zones (shares) with Chinese, industry-level *export* growth to eight advanced, *non-U.S.* economies (shifts). Non-U.S. export growth takes the place of industry-level Chinese import growth in the U.S. in an effort to purge the instrument of supply and demand dynamics in specific U.S. local labor markets. Similar efforts to replace aggregate immigrant inflows from origin countries with exogenous, origin-specific migration push factors have been made in the immigration literature.[13] A particular motivating example is Llull (2017), who uses conflict, natural disasters, changes in per capita income, and changes to political regimes as origin-country-level shifts. He interacts these plausibly exogenous shifts with flexible education-experience-cell fixed effects to distribute them into the specific experience-education cells that he studies in destination areas.

Recent work by Borusyak et al. (2020) and Jaeger et al. (2018) provide some explicit theoretical backing for the use of plausibly exogenous shifts. Borusyak et al. (2020) show that when shifts represent a set of relatively disbursed and uncorrelated shocks across origin countries, their quasi-

[13] See, e.g., Angrist and Kugler (2003), Monras (2015), and Llull (2017).

random assignment conditional on shares can overcome endogeneity in the share component of the instrument.[14] In particular relevance for the immigration shift-share instrument, Jaeger et al. (2018) show that aggregate immigrant inflows into the U.S. are highly serially correlated in their origin country composition. This generates a potentially severe bias in which panel regressions can confound short- and long-run responses to immigration: $\Delta z_{gkt}^{\text{Standard}}$ can often be just as—if not more—correlated with $\Delta I_{gk,t-10}$ than it is with ΔI_{gkt}. Thus, to the extent that they are more plausibly exogenous and less serially correlated at the origin-country-level than aggregate inflows, push factors that replace ΔI_{okt} are also less likely to generate bias estimated β coefficients from Equation (3.1).

In this paper, I construct a shift-share instrument that borrows in spirit from Llull (2017) and Autor et al. (2013). First, I note that

$$I_{okt} \equiv \rho_{okt} \times I_{ot}$$

where ρ_{okt} is the share of origin country o's stock of year t U.S. immigrants that are working in industry group k, and I_{ot} is origin country o's stock of year t U.S. immigrants. Thus[15],

$$z_{gkt}^{\text{Standard}} = \frac{1}{E_{gk,1980}} \sum_{o} \pi_{og,1980} \times \rho_{okt} \times I_{ot} \tag{3.2}$$

Next, utilizing the German Institute for Employment Research's (IAB) Brain-Drain Data—a unique data set that contains counts of bilateral emigrant stocks from more than 150 sending countries worldwide residing in OECD member nations (Brücker et al., 2013)—I am able to replace I_{ot} in (3.2) with

$$M_{ot}^{\text{non-U.S.}} = \sum_{d \in \{\text{OECD}\} \setminus \text{U.S.}} \text{Emigrants}_{odt}$$

where Emigrants_{odt} is the stock of emigrants from origin country o living in destination country d at time t. $M_{ot}^{\text{non-U.S.}}$ is therefore a count of emigrants from origin country o living in all OECD member nations *other than* the United States.[16] The idea behind replacing I_{ot} with $M_{ot}^{\text{non-U.S.}}$ is to retain the full suite of factors that are *pushing* individuals in origin country o to emigrate—both to the U.S. and to other destinations—while discarding any factors that are specifically *pulling* immigrants into the U.S.—including and most importantly, gk-specific labor demand. Just as Autor et al. (2013) claim that Chinese exports to non-U.S. countries reflect increases in Chinese export productivity rather than product demand in the U.S., I claim that non-U.S. emigrant outflows are much more likely to reflect migration push factors in origin countries rather than demand in specific U.S. labor markets.

Finally, exploiting the detailed information on industry and origin country contained in the

[14] This work contrasts with Goldsmith-Pinkham et al. (2020), who focus on exogeneity in the share component as a sufficient condition for instrument validity.

[15] A more current version of the standard instrument would use $I_{o(-g)kt} \equiv \rho_{o(-g)kt} \times I_{o(-g)t}$ instead of I_{okt}, leaving out the stock of immigrants specific to geography g. For more, see Appendix Section A.2.

[16] Orefice and Peri (2020) independently use a similar "leave-country-out" instrumentation strategy for immigration to French regions.

U.S. Census Bureau's demographic data, I am able to replace ρ_{okt} in (3.2) with

$$\rho_{o(-r(g))kt} = \frac{\sum_{r \in \{\text{U.S.}\} \setminus \{r(g)\}} [\text{Immigrant Workers}]_{orkt}}{\sum_k \sum_{r \in \{\text{U.S.}\} \setminus \{r(g)\}} [\text{Immigrant Workers}]_{orkt}}$$

where $[\text{Immigrant Workers}]_{orkt}$ represents the stock of year t immigrant workers from origin country o working in sector k in U.S. region r. $\rho_{(-r(g))okt}$ is therefore the year t share of immigrants from origin country o in all areas other than the region $r(g)$ that contains commuting zone g that work in sector k. Allocating emigrants into industry groups using $\rho_{(-r(g))okt}$ takes advantage of the fact that immigrants from particular countries tend to specialize in certain industries due to comparative advantage, but once again discards demand factors from the specific local industry being studied by leaving out region $r(g)$. $\rho_{(-r(g))okt}$ performs the role of disbursing aggregate stocks into industry groups in the way that fixed effects disburse exogenous pushes into education-experience cells in Llull (2017).[17]

The result is a new instrumental variable for year t immigrant presence in local industry gk:

$$z_{gkt}^{\text{Emigrants}} = \frac{1}{E_{gk,1980}} \sum_o \pi_{og,1980} \times \rho_{o(-r(g))kt} \times M_{ot}^{\text{non-U.S.}} \tag{3.3}$$

$z_{gkt}^{\text{Emigrants}}$ predicts the number of immigrants residing in a given commuting zone g based on network-induced locational preference, working in industry k due to country-specific comparative advantage, and pushed into the U.S. by factors that pushed their compatriots to emigrate to non-U.S. destinations as well. In Sections 4.1, 4.2, Δz_{gkt} will serve as the instrumental variable for ΔI_{gkt}, and in Section 5, z_{gkt} will serve as an instrumental variable for I_{gkt}.[18] $\Delta z_{gkt}^{\text{Emigrants}}$ is a valid instrument for ΔI_{gkt} if shifts $\Delta \left[\rho_{o(-r(g))kt} \times M_{ot}^{\text{non-U.S.}}\right]$ are conditionally uncorrelated with unobserved factors in the local industries whose commuting zones have the highest shares $\pi_{og,1980}$. Violations can occur when labor demand shocks pull immigrants into local industries in areas where their compatriots are already heavily concentrated.

A simple and relevant example that helps illustrate the utility of $\Delta z_{gkt}^{\text{Emigrants}}$ comes from the housing bubble that metastasized between 2000 and 2005, largely in the South and West of the U.S. The housing bubble created a large labor demand shock for construction workers in the South and West Census Regions of the U.S., and induced immigrant workers from Mexico to fill this de-

[17] In this paper's notation, the instruments in Llull (2017) take the form

$$\Delta z_{gkt} = \alpha_k \left[\sum_o \ln(distance)_{og} \times \text{Push Factor}_o\right] = \left[\sum_o \ln(distance)_{og} \times \alpha_k \times \text{Push Factor}_o\right]$$

where k represents an education-experience cell rather than an industry group, α_k is a fixed effect that is estimated in the first stage, and g represents a receiving country rather than a receiving sub-national commuting zone. Within this similar structure, I use the more standard $\pi_{og,1980}$ instead of $\ln(distance)_{og}$ and replace $[\alpha_k \times \text{Push Factor}]$ with $\Delta \left[\rho_{o(-r(g))kt} \times M_{ot}^{\text{non-U.S.}}\right]$. In this paper's setting, both substitutions help build the instrument's first stage power while retaining similar exclusion restriction arguments.

[18] Models in Section 5 contain firm-by-local-industry fixed effects, which take the place of the gk-level differencing seen in Equation (3.1).

mand—the kind of inflow an instrumental variable should not use for identification of β in Equation (3.1). As seen in Panel A of Figure 1, Mexican inflows into the construction sector between 2000 and 2005 were more than 10 times larger than those from the next closest country. As seen in Panel B of Figure 1, general immigrant inflows into the construction sector across commuting zones predominantly took place in housing bubble cities throughout the South and West regions of the country. On the other hand, there is no reason to believe that the U.S. housing bubble would cause large outflows of Mexican emigrants to non-U.S. OECD countries. Furthermore, relative to the national trend, the change in propensity of Mexican immigrants to locate in the construction sector, *outside* of the South and West regions was not unusually strong. Thus, the aggregate component of $\Delta z_{gkt}^{\text{Emigrants}}$ between 2000 and 2005

$$\left[\rho_{o(-r(g))k,2005} \times M_{o,2005}^{\text{non-US}} - \rho_{o(-r(g))k,2000} \times M_{o,2000}^{\text{non-US}}\right]$$

should not reflect the labor demand shocks in construction that were occurring in the South and West of the country at that time. These two factors are illustrated in Panel A of Figure 2, where Mexico has a much more modest aggregate component for the construction sector between 2000 and 2005. The ultimate result of these corrections can be seen in Panel B, where the instrument-predicted immigrant inflows are far less concentrated in bubble cities.

Results presented below, along with a series of analyses in Section A.2 test several considerations regarding the validity of $\Delta z_{gkt}^{\text{Emigrants}}$ more broadly and systematically, with a particular focus on recently-formalized concerns regarding shift-share instrumentation. All told, the emigrants-based instrument passes a battery of tests meant to vet its validity for use. $\Delta z_{gkt}^{\text{Emigrants}}$ and $z_{gkt}^{\text{Emigrants}}$ therefore become the instruments of choice for Sections 4 and 5.

3.2.2 *Fixed Effects*

With our instrument fully detailed, we can now fully describe the utility of each fixed effect in Equation (3.1). For the decade ending in year t, α_{gt} removes any effects immigrant inflows have at the commuting zone level as a whole. Under the premise that immigrants do not solely demand goods in the industry in which they work, α_{gt} insulates β from being identified by changes in consumption patterns that can result from immigration (e.g., Hong and McLaren, 2015). This premise is strengthened by the fact that we compare across 40 industry groups within a commuting zone—a level of detail allowed for by the granularity in each Census Bureau data source. Absent α_{gt}, an inflow of immigrants into the "Hospitals" industry group can generate an increase in economic activity in other nontradable industry groups because the new immigrant workers in the "Hospitals" industry group also consume goods and services locally. By including α_{gt} and thus inducing comparison across industry groups within a given commuting zone and decade, β measures the increase in economic activity in the "Hospitals" industry group above and beyond what other industry groups experienced due to this consumer demand effect.

α_{kt} plays an important role in ensuring instrument validity. $\rho_{(-r)okt}$ allocates immigrants from

origin country o into industry group k based on national level trends of industry choice for origin country o immigrants (excluding region r). In the absence of α_{kt}, national level shocks to industry k would naturally allocate all workers towards industry group k, regardless of origin. α_{kt} precludes these shocks—which would induce both an increase in economic activity in sector k across all commuting zones and in $\Delta z_{gkt}^{\text{Emigrants}}$—from contaminating β. Instead, with the inclusion of α_{kt} (or further, region-industry-year fixed effects), workers from origin country o must be locating in industry group k above and beyond the national trend, and in regions where they are not affected by labor demand shocks in commuting zone g. Thus, $\Delta z_{gkt}^{\text{Emigrants}}$ is more credibly sourced from immigrants' comparative advantages in certain industries through $\rho_{(-r)okt}$ when α_{kt} is included.

3.2.3 *Educational Content of Immigrant Inflows*[19]

An important question regarding the identification strategy relates to the skill content of the immigrant inflows represented by ΔI_{gkt}, particularly when it is instrumented for by $\Delta z_{gkt}^{\text{Emigrants}}$. When there are extant skill differences across native and foreign-born workers, the average set of native skills becomes more scarce when immigrant workers flow into the economy, generating average wage gains for native workers. This is the seminal "immigration surplus" insight in Borjas (1999) that has been built upon in much subsequent work (e.g., Dustmann et al., 2012). In this paper—including the model presented in Section 6—I consider this insight within the context of firm heterogeneity: some firms particularly rely on the skills that immigrants bring to the economy. So, when immigrants arrive into a local industry, the composition of firms shifts towards these types of firms.

Because of how they proxy for differences in labor market skill, differences in educational attainment across immigrants and natives are a crucial channel through which a connection between immigration and economic activity can arise in a manner that does not just reflect general population growth.[20] There are two important questions to ask regarding the educational composition of immigrant worker inflows ΔI_{gkt} when instrumented for by Δz_{gkt}: 1) how different is the composition from that of the receiving native population and 2) how different is the composition from that of the typical immigrant inflow to the U.S. Answering the first question tells us whether we can expect native welfare gains through standard immigration surplus channels described above. The second question is akin to asking about the local average treatment effect (LATE) associated with Δz_{gkt} under treatment effect heterogeneity.[21] By identifying the effect of immigration on firm-related outcomes using emigrants who were pushed to non-U.S. destinations rather than U.S. immigrants, are we studying the effect of a fundamentally different type of immigrant worker than

[19] This analysis uses publicly-available data in order to avoid excessive disclosure requests from the U.S. Census Bureau.

[20] Though it is far from the only: immigrants can differ on other characteristics that also imbue them with different labor market skills than natives. For example, lower-educated immigrant workers may have a comparative advantage in performing tasks that are less communication-oriented relative to lower-educated native workers (Peri and Sparber, 2009). This insight is also built into the model presented in Section 6.

[21] This is a slight abuse of terms, as the LATE is only well-defined for a binary instrumental variable. Nonetheless, this language helps us frame the question of "who is pushed by the instrument?"

was typical during the study period?

Figure 3 benchmarks the differences in educational attainment associated with immigrant inflows relative to the receiving native workforces in the local industries studied throughout this paper. The bars reflecting immigrant inflows are obtained by replacing Δy_{gkt} with $\Delta I_{gkt}^{\text{Educ. Level}}$ in Equation (3.1), where $\Delta I_{gkt}^{\text{Educ. Level}}$ represents the change in the number of immigrants in a given commuting zone-industry pair with a given educational attainment level:

$$\Delta I_{gkt}^{\text{Educ. Level}} = \alpha + \boldsymbol{\beta}\left[\Delta I_{gkt}\right] + \Gamma X_{gkt} + \alpha_{gt} + \alpha_{rkt} + \varepsilon_{gkt} \tag{3.4}$$

Exploiting the adding-up property of linear regression, estimating Equation (3.4) for mutually exclusive and exhaustive educational groupings decomposes how many workers of each educational attainment category are brought in by each immigrant, on average. The left bar of Figure 3 provides the average educational attainment of native workers across decade start-years—1980, 1990, and 2000—for comparison.

Figure 3 contains two key findings related to the question posed above. First, comparing the Emigrants IV bar to the Average Native bar reveals that whether or not immigrants pushed by $\Delta z_{gkt}^{\text{Emigrants}}$ change the educational composition of the workforce depends on how we classify workers based on education. On average, foreign-born workers who flow into the U.S. between 1980 and 2010 are more likely to have no more than a high-school degree than native workers in receiving commuting zone-industry pairings, but are just as likely to hold a college degree. Second, comparing the Emigrants IV bar to the OLS bar reveals that $\Delta z_{gkt}^{\text{Emigrants}}$ tends to push immigrants of a slightly higher educational attainment into the U.S. relative to the "typical" immigrant inflow during the study period; however, these differences are small. Section A.2.2 in the Appendix provides further details on how $\Delta z_{gkt}^{\text{Emigrants}}$ compares to the average immigrant inflow on a variety of dimensions, beyond educational attainment.

4 Immigrant Workers, Firm Entry and Exit, and Local Industries

A bevy of previous literature indicates that firm entry is integral to job creation in the overall U.S. economy (e.g., Decker et al., 2014), and that immigrant workers—both as entrepreneurs and employees—tend to be over-represented in new firms (e.g, Kerr and Kerr, 2016). This section tests a hypothesis that follows naturally from these studies: that immigrant worker inflows increase firm presence and that this increase, in turn, is critical to the absorption of immigrant workers. Section A.3 in the Appendix provides a proof of concept by pooling together two case studies—the Mariel Boatlift and the implementation of the Legal Arizona Workers Act—and documenting a positive, causal relationship between immigrant inflows and business presence. This section probes that relationship in a detailed way, studying its characteristics and its importance to immigrant absoprtion.

4.1 The Effect of Immigrant Workers on Firm Presence in Local Industries

4.1.1 Quantifying the Effect

Table 2 displays first stage, OLS, and IV results from estimating Equation (3.1) using a full set of controls and fixed effects. In it, I find a strong, positive effect of immigrant worker presence on firm presence that is larger when corrected for endogeneity. Each immigrant generates roughly 0.05 new firms, on net, when they enter a commuting zone and industry group (Column 3). This estimate survives flexible controls for any confounding factors that may affect firm presence in the commuting zone as a whole through α_{gt} (e.g., general immigrant inflows into the commuting zone or overall population growth) and any confounding factors that may affect firm presence in the industry group nationally through α_{kt} (e.g., secular growth in services sectors).

Table 3 demonstrates the stability and robustness of the estimate in Column 3 of Table 2. First, moving from Column 1 to Column 2 indicates the utility of including α_{kt} and α_{gt} relative to a traditional first differences approach (just including α_t). Nearly half of the first difference estimate disappears when we compare across industry groups within a commuting zone, relative to when we simply compare across commuting zone-industry group pairs. These are effects likely explained by consumer demand, either through immigrant inflows that are correlated within geography across industry groups or through general population growth in the commuting zone. Columns 2 through 6 then display a stable estimate, regardless of control and fixed effects sets (note that Column 4 replicates Column 3 of Table 2). Of particular note, the estimate in Column 5 survives the inclusion of an endogenous control variable for overall growth in the number of workers, indicating that the effects found in Table 2 and 3 are immigrant-specific, and not simply a general labor supply shock.[22] This column also implicitly controls for any non-nativity-specific, within-industry group demand that may generate β, and still finds essentially the same effect. Additionally, the estimates in Column 6 implement the double-instrumentation strategy proposed in Jaeger et al. (2018) to account for serial correlation that can undermine shift-share-based estimate interpretation. The relative strength of the F statistic and continued stability of the contemporaneous effect estimate indicate that Equation (3.1) passes this test. Finally, in all columns other than Column 6, I cannot reject the null hypothesis of no pre-trends based on a panel version of the test, described further in Section A.2.4.

Overall, Tables 2 and 3 find a broad-based, positive effect of immigration on firm presence within local markets defined by a commuting zone and industry group. It finds that each immigrant worker (employee or self-employed) leads to the creation of roughly 0.05 firms, on net. Because of the way Equation (3.1) is set up, and because there are over 40 industry groups, I contend that this effect primarily originates from the supply side of the product market, with changes in consumer demand largely soaked up by α_{gt}. In addition, the magnitude of the IV result in Table 2 points to both economic significance and to the importance of immigrant employees. Back-of-the-

[22] The model presented in Section 6 hypothesizes that this is due to the variety of reasons immigrant and native workers may be imperfect substitutes, including educational attainment.

envelope calculations from the 2018 release of the Business Dynamics Statistics show that there were around 0.03 new firms created, on net, per additional worker in the U.S. from 1980 through 2010. The estimated coefficient of $\beta \approx 0.05$, then, indicates that immigrant workers are substantially more active on the extensive margin.

However, while ΔI_{gkt} includes both employees and self-employed immigrants, back of the envelope calculations also tell us that the effects found here are unlikely to be fully explained by immigrant entrepreneurship. As shown in Figure A1 of Appendix Section A.2, immigrants pushed by $\Delta z_{gkt}^{\text{Emigrants}}$ are overwhelmingly not entrepreneurs themselves, with each immigrant leading to an additional 0.96 employees and only an additional 0.04 self-employed workers in a local industry. 0.04 new firms per immigrant worker due to immigrant entrepreneurship (80 percent of the total $\beta \approx 0.05$) is likely a substantial overestimate, even if it places as an upper bound on the role of immigrant entrepreneurship. A substantial number of those classifying themselves as self-employed in Census Bureau demographic data do not own employee-hiring firms. Rather, many are independent contractors, owners of non-employee-hiring firms, or—especially in the case of immigrant workers—undocumented workers who do not wish to report that they are employed by a private company. Immigrant employees appear to play a co-equal, if not central, role in generating the effects found here, and this motivates their role in the model presented in Section 6.

4.1.2 Characterizing the Effect: Entry and Exit

Figure 4 characterizes the results contained in Column 3 of Table 2 by separating the change in the stock of firms into its flow components:

$$\Delta \text{Firms}_{gkt} = \text{Firms}_{gkt}^{\text{Age}<10} - \text{Firms}_{gk,t-10}^{\text{Shut down between } t-10 \text{ and } t} + \text{Residual} \tag{4.1}$$

That is, the change in the number of firms in commuting zone g and industry group k between $t-10$ and t can be split into its relative contributions from firms that started between time $t-10$ and t and are operating in gk, firms that were operating in gk at $t-10$ that have shut down by time t, and a residual term that primarily captures net relocations and expansions into a given gk pair from other gk pairs.[23] This decomposition is only enabled through the longitudinal linkages provided in the LBD. Here and throughout the rest of the paper, firm age is measured as the age of its oldest establishment.

Figure 4 plots the results of estimating Equation (3.1) using these disaggregated outcomes, each divided by $\text{Workers}_{gk,t-10}$, such that they add up to 0.0527, the primary estimate of interest from Table 2. This figure demonstrates that 80 percent of immigrant-induced increase in firm presence comes from the creation of new firms, though there is also a non-trivial prevention of firm death. The residual term plays a negligible role, indicating that the extensive margin firm response to immigrant inflows is largely localized. Of note, the estimate marked "Survived to t+5" in gray

[23] Shut down is defined as all of a firm's *national* establishments having shut down. If all a firm's establishments in a given commuting zone and industry have shut down, but the firm is still in operation nationally, this firm would be counted negatively in the residual term.

indicates that immigrant-induced entrants are not necessarily short-lived. In fact, more than half of the firms in this category survive well past a firm's usual "critical period," until 5 years after the decade end represented by time t.

4.1.3 *Characterizing the Effect: Firm Size*

I next estimate Equation (3.1) by employee size bin (within gk), with two outcomes for each bin. The first is simply firm growth in that size bin:

$$\frac{\Delta \text{Firms}_{gkt}^{\text{Size Bin}}}{\text{Firms}_{gk,t-10}^{\text{Size Bin}}}$$

The second only reflects the portion of that growth that came from firm entry:

$$\frac{\text{Firms}_{gkt}^{\text{Size Bin, Age<10}}}{\text{Firms}_{gk,t-10}^{\text{Size Bin}}}$$

I switch to growth rates as the outcome because the overall firm size distribution is heavily skewed right. As seen in Figure A8, when purely accounting for the primary estimate of interest from Table 2, the smallest firm size bin dominates.[24] However, this is true for the overall firm size distribution in the economy. Thus, to know if immigrant-induced net firm entry is *particularly* driven by small firms, it is more useful to look at within-bin growth rates.

Figure 5 contains some of the most important results in this sub-section. It finds a robust, large effect of immigrant inflows on net firm entry throughout the firm size distribution, and one that is largest at both tails when viewed in within-bin terms. That is, when we account for the fact that most firms are small, immigrant-induced increases in firm presence are not disproportionately seen in the lower end of the firm size distribution. In addition, new firm creation almost entirely drives this effect through firms up to 99 employees. Starting with firms of at least 100 employees, a divergence emerges in which the increase total firm presence is also driven by older firms. These results are consistent with the notion that new firms tend to be smaller, but also illustrate a novel connection between immigrant workers and large firm death prevention.

4.1.4 *Characterizing the Effect: Additional Heterogeneity*

Figure 6 plots the results of additional heterogeneity analyses across industry groupings and geographic region. The top grouping provides evidence that the effects found thus far are not driven by one particular region. In particular, based on the coefficient in the West Census Region, California is not the driving force behind the results in this section. The next set of analyses designates each industry group (Table A1) as tradable or non-tradable, then estimates Equation (3.1) separately for each set of industry groups. I generate this designation by aggregating 1980 traded and non-

[24] Note that firms with "0" employees are usually births in year t.

traded employment within each industry group based on the Porter (2003) classification system for 6-digit NAICS codes. Each industry group is then designated as tradable if it had more tradable employment in 1980, and vice versa. The result of this exercise finds a larger effect in nontradable industry groups, but a large effect for tradable industry groups as well. The latter is found in Olney (2013), while the former is not. Finally, I also designate industry groups based on whether they tend to hire higher- or lower-educated workers. Similar to Doms et al. (2010), I do this by assigning industry groups with below the median share (across industry groups) of college equivalent[25] workers in 1980 the "low-education hiring" designation and industry groups with above the median share the "high-education hiring" designation. This exercise shows a slightly higher effect of immigrant workers on firm presence in low-education hiring industry groups.

4.1.5 Summary and Discussion

Immigrants appear to generate non-trivial increases in firm presence from the supply side of the product market, as workers. The various heterogeneities that underlie this effect set up the analyses that follow in Sections 4.2 and 5. Figures 4 and 5 introduce two important channels through which immigrant absorption can occur. The majority of the effect immigrant workers have on increasing firm presence comes in the form of small-to-medium-sized, new firms. While smaller firms may seem prone to less absorption capability, Decker et al. (2014) use the LBD to document that new firm creation plays a crucial role in job creation nationally, with start-up firms alone accounting for almost 20 percent of gross job creation in a given year. They also find that firms that grow by more than 25 percent year-over-year are disproportionately small and young, and yet account for almost 50 percent of job creation in a given year. Additionally, that there is a robust presence of new, medium-sized firms mitigates concerns that immigrants tend to primarily own and support "subsistence" entrepreneurship (Schoar, 2010). Meanwhile, Figures 4 and 5 also show a small effect on the prevention of firm exit, but one that is concentrated among larger firms, where the majority of workers are employed. This opens up a channel to the prevention of job loss. Understanding the distinct roles of firm entry and exit prevention in immigrant absorption, and comparing them to intensive margin firm growth responses, is the primary motivation behind Section 4.2. Meanwhile, understanding whether the prevention of firm death either prevents productive firm turnover from taking place, or reflects the preservation of more productive firms—which tend to be larger[26]—is the focus of Section 5.

That the effect is driven by firm creation and has a larger magnitude in nontradable industries also carries the possibility of new final goods varieties for local consumers, which enhances welfare in models like the one presented in Section 6. However, the existence of a large, positive, and precisely estimated effect in tradable industries also validates the interpretation that the effects detected using Equation (3.1) are driven by immigrant workers on the supply side of the product

[25] 0.5 times the number of workers with "Some College" plus all workers with at least a four-year college degree.
[26] See, e.g., Bernard and Jensen (1999); Leung et al. (2008); Baldwin et al. (2002); van Ark and Monnikhof (1996).

market.[27] In addition, the existence of a larger effect in industries that primarily utilize lower-educated labor conforms with evidence that lower-educated immigrant and native workers are less substitutable than higher-educated immigrant and native workers (see, e.g., Peri and Sparber, 2009).

4.2 The Role of Firm Entry and Exit in Immigrant Absorption

Thus far, this section chronicles a broad, heterogeneous relationship between immigration and net firm entry that stems from both gross firm entry and the prevention of firm exit. Previous literature, meanwhile, has documented the importance of business creation to job creation and overall labor demand (e.g., Decker et al., 2014; Beaudry et al., 2018). In particular, both the entry of small-to-medium sized firms and the prevention of large firm exit open up substantial channels to job creation and the prevention of job loss, respectively. The question of how immigrants are absorbed into labor markets—or, put differently, how the economy creates enough jobs to keep pace with immigrant inflows—may thus hinge on firm entry and firm exit. This sub-section conducts a decomposition exercise to test how important extensive margin firm responses—entry and exit—are to immigrant-induced job creation.

This decomposition is motivated by Dustmann and Glitz (2015), but with a particular focus on the separate margins that go into net firm entry, without restricting the analysis to the tradable sector, and in the context of U.S. local economies. Additionally, I study the effect of immigrant inflows on job creation fully within commuting zone and sector, using Equation (3.1) for estimation. Thus, unlike Hong and McLaren (2015), my results are unlikely to stem from immigrant-specific consumer demand. I utilize the following decomposition of employment, enabled by the longitudinal structure of the LBD:

$$\begin{aligned}\Delta\text{Employment}_{gkt} = &- \text{Employment}_{gk,t-10}^{\text{Shut down between } t-10 \text{ and } t} + \text{Employment}_{gkt}^{\text{Age}<10} \\ &+ \Delta\text{Employment}_{gkt}^{\text{Continuers}} + \text{Residual}\end{aligned}$$

where the first term represents job loss from firm deaths between $t-10$ and t in commuting zone g and industry group k, the second term represents gross job creation at firms that were born between $t-10$ and t, and the third term represents employment growth at firms that were alive in both $t-10$ and t and in operation in gk. The final term represents employment growth that came from net relocations or expansions into gk from other commuting zones and sectors between $t-10$ and t. As in section 4.1.2, each term in this decomposition is divided by the Census-measured workforce in gk at time $t-10$ to retain consistency with independent variable ΔI_{gkt}. Thus, the effect of ΔI_{gkt} on $\Delta\text{Employment}_{gkt}$ measures the number of LBD jobs each immigrant worker generates when they arrive and work in a commuting zone and industry group.

The results of this decomposition are seen in Table 4 and Figure 7. As a starting point, Column 1 of Table 4 and the total heights of each bar in Figure 7 provide estimates of the number of LBD

[27] Under the assumption that local demand for locally produced tradable goods is not strong.

jobs generated by each immigrant. The OLS estimate in Panel A is substantially larger than the IV estimate in Panel B (more than 40 percent). This accords with the notion that immigrants are attracted to industries and geographies with increasing labor demand and with my claim that $\Delta z_{gkt}^{\text{Emigrants}}$ corrects for some of this endogeneity. It also helps add context to results from Table 2, which found that IV estimates of immigrant worker inflows on net firm entry were higher than OLS estimates. One possible explanation that squares these results is that immigrant entrepreneurs are be attracted to areas with lower net firm entry if these areas feature lower entry costs in the form of decreased potential competition.[28] Another is that areas and industries with fewer, but larger firms are more likely to attract immigrants. This latter explanation seems especially plausible given the decomposition results discussed below.

The headline estimate from Panel B indicates that each immigrant leads to 0.6 new LBD jobs in the commuting zone and industry group she enters. There is no evidence for spillover job creation, which is entirely consistent with results in Hong and McLaren (2015), who find that spillover job creation is likely the result of increased immigrant consumer demand. When consumer demand spillovers are controlled for, as they are here, scope for some displacement is in fact to be expected, especially when looking within the fine industry groups used in the analysis and described in Table A1. A bevy of previous literature has documented native mobility across occupations in response to immigrant inflows, and Burstein et al. (2017), for example, document substantial native displacement in non-tradable industries.

Columns 2–5 in Panel B of Table 4 and each of the components of the bar on the right of Figure 7 represent the first benchmark result in this paper. They show clear evidence that localized, extensive margin firm responses play the dominant role in immigrant absorption, with the prevention of firm exit on its own accounting for nearly 50 percent. Overall, point estimates indicate that the extensive margin (including net relocation and expansion) accounts for more than 85 percent of immigrant-induced job creation, leaving only a statistically insignificant 15 percent for the growth of existing firms. Estimates in Columns 2 and 3 Table 4 accord naturally with results from Figure 5. While there are more new, small-to-medium sized firms in the market, death prevention plays an outsized role in immigrant absorption because the firms that are pushed to survive by immigrant worker inflows are large. Nonetheless, that firm entry accounts for around a quarter of immigrant-induced job creation is also consistent with its overall importance to job creation in the U.S. economy. Comparing Columns 2–5 across Panels A and B also suggests interesting conclusions regarding immigrant locational and industry choices. Immigrants appear attracted to geographies and industries that are experiencing relocations, expansions, within-firm growth, and firm entry. The stronger negative effect on firm death in Panel B relative to Panel A indicates that immigrants may also be attracted to more dynamic local economies, in which productive turnover is taking place.

In total, this sub-section makes important contributions to the literature on immigrant worker

[28] See., e.g., (Ottinger, 2020) for historical evidence that immigrants migrated to U.S. countries that were less specialized in the industries in which they worked.

absorption into U.S. local economies. Even when comparing across industries within the same commuting zone, local labor markets exhibit substantial absorption capacity for immigrant inflows. Strikingly, I cannot reject the null hypothesis that this capacity is entirely driven by firm entry and the prevention of firm exit. Figure 7 is perhaps the clearest illustration that extensive margin firm responses drive local production's response to immigration. Given the particular importance of exit prevention found here, I next turn to understanding the heterogeneous effects immigrants have on firm shut down decisions.

5 The Exit Margin

An empirical literature finds that firm turnover can play a critical role in redistributing resources from less to more productive firms, with less productive firms exiting the market (Foster et al., 2008). While Section 4.2 demonstrates that the prevention of firm death is overwhelmingly important in absorbing immigrant workers, it could also imply a mechanism through which immigration may stunt productive reallocation—by preventing the exit of low productivity firms. In this section, I test for this mechanism, stratifying a firm-level analysis of survival by correlates of initial firm total factor productivity. Contrary to these concerns, I find that immigrant inflows tend to benefit more productive firms by reducing their shut down probabilities, while culling lower productivity firms from the market. This heterogeneity implies a novel channel from extensive margin firm responses to increased local productivity in response to immigration.

5.1 Full Panel: Data and Methods

The analyses in this section utilize two panels of firms from the LBD. The first, termed the "Full Panel," covers all (over 4 million) firms that were in operation in 2000 in the commuting zones and industries covered by the analysis from Section 4. It follows these firms in 2005 and 2010 and assigns an indicator variable $\mathbb{1}[\text{Shut Down}]_{ft}$ a value of one if the firm has shut down by year t. Shut down is defined as all establishments of the owning firm having died nationally by time t. The panel is fully balanced, with one observation per firm in each g and k in which it operates for 2000, 2005, and 2010.[29] The restriction to 2000, 2005, and 2010 is necessitated by two constraints: 1) substate (e.g., commuting zone), annual estimates of the foriegn-born workforce are only available in 2000 (Decennial Census), and 2005 onwards (ACS); and 2) the instrumental variable $z_{gkt}^{\text{Emigrants}}$ relies on emigrant counts that are available in the IAB Brain Drain dataset only in 2000, 2005, and 2010.

The LBD contains two correlates of productivity, employment and mean labor earnings (payroll divided by employment), which I adjust to generate measures of initial productivity. The adjustment process takes a simple form, in which I log each variable (to ensure a relatively normal distribution of residuals) and remove firm age-by-5-digit NAICS code fixed effects. In the case

[29] Note that in the "Full Panel," this means the same firm can appear as a "firm" multiple times if it operates in multiple industries or geographies.

where productivity is being measured by employment for example, this step is motivated by the fact that productive, young firms may still be small as they settle into the market and by the fact that different detailed industries feature different labor input needs. Firms are then deemed "high productivity," if the residual from this initial regression is positive:

$$\begin{aligned} \log(\text{Prod. Measure})_{f,2000} &= \alpha + \alpha_{k'a} + u_{f,2000} \\ \mathbb{1}[\text{High Prod.}]_f &\equiv \mathbb{1}[\hat{u}_{f,2000} \geq 0] \end{aligned} \tag{5.1}$$

where a indexes firm age, k' indexes a 5-digit NAICS code, and f indexes a firm.

I then estimate the following linear probability models to test how immigrant presence heterogeneously affects firm shut down probabilities within commuting zones and industry groups:

$$\begin{aligned} \mathbb{1}[\text{Shut Down}]_{ft} = \alpha &+ \beta^{\text{total}}\left(I_{gkt}\right) \\ &+ \Gamma X_{gkt} + \alpha_f + \alpha_a + \alpha_{gt} + \alpha_{k't} + \varepsilon_{ft} \end{aligned} \tag{5.2}$$

$$\begin{aligned} \mathbb{1}[\text{Shut Down}]_{ft} = \alpha &+ \beta^{\text{main}}\left(I_{gkt}\right) + \beta^{\text{mod}}\left(I_{gkt} \times \mathbb{1}[\text{High Prod.}]_f\right) \\ &+ \Gamma X_{gkt} + \alpha_f + \alpha_a + \alpha_{gt} + \alpha_{k't} + \varepsilon_{ft} \end{aligned} \tag{5.3}$$

with $t \in \{2000, 2005, 2010\}$. I_{gkt} is the immigrant stock of workers in commuting zone g and industry group k at time t, divided by the 2000 worker count in gk. It is instrumented for by z_{gkt}, defined as in Equation (3.3), except with a denominator of the 2000 worker count in gk instead of the 1980 worker count in gk.[30,31]

Equation (5.2) can simply be thought of as breaking down one decade from Equation (3.1) to the firm level—with the crucial inclusions of firm fixed effects α_f and firm age fixed effects α_a.[32] Given our findings in Section 4.1.2, we therefore expect $\beta^{\text{total}} < 0$. Equation (5.3) serves the primary purpose for this section, extending our understanding by stratifying the analysis based on initial firm productivity. In particular, β^{main} indicates the extent to which marginal, lower productivity, firms are sustained ($\beta^{\text{main}} < 0$) or pushed out ($\beta^{\text{main}} > 0$) by immigrant worker inflows.

5.2 Full Panel: Results

Table 5 presents the results of estimating (5.2) and (5.3) on the "Full Panel." Columns 1-3 first confirm preliminaries and priors: z_{gkt} has a very similar effect on I_{gkt} here as Δz_{gkt} had on ΔI_{gkt} in Section 4 (Column 1), and immigrant inflows prevent firm death in this modified specification that hones in on the 2000s (Columns 2 and 3). Once again, extensive margin firm responses are

[30] The base year is still 1980 for shares $\pi_{og,1980}$.

[31] The primary utility of using emigrants to non-US countries over other exogenous push factors is the use of z_{gkt} in this specification, where it is available at a high (every-five-year) frequency and still strong enough to be a relevant instrument.

[32] For example, α_f subsumes commuting zone-industry group fixed effects α_{gk} and therefore the first difference seen in (3.1).

stronger after immigrant exposure is corrected for endogeneity.

Columns 5 and 7 deliver the second benchmark result in this paper: immigrant inflows into commuting zones and sectors cull lower productivity firms from the market while sustaining and reducing the chances higher productivity firms exit. This is true whether productivity is measured in terms of employment or earnings. Column 5, for example, finds that an average immigrant inflow across a decade (0.04 from Table 1) increases the 5-year exit probability for low productivity firms by a full percentage point, while reducing the 5-year exit probability for high productivity firms by more than two percentage points.

These results run directly counter the notion that immigrants prevent productive reallocation by sustaining marginal firms. Instead, not only do the most productive firms benefit, but the least productive firms exit—immigrants generate increased productive firm turnover. Section 6 posits one potential reason this could take place: some firms can better utilize immigrant labor, but at a cost that makes them positively selected on productivity. Other possibilities include Becker-style discrimination among lower productivity firms and frictions that prevent lower productivity firms from directing search to immigrant workers they may want to hire. Regardless, the empirical results contained in Table 5 provide novel evidence that immigrants increase productive reallocation across firms in local U.S. economies. They also provide yet another piece of evidence that immigrants are generating these effects from the supply-side of the product market, under the premise that increased consumer demand alone should sustain rather than cull marginal firms.

5.3 SBO Panel: Data and Methods

The remainder of this section employs a second panel that links LBD firms to employee-hiring firms (over 600,000) that were in operation and eunmerated in the 2007 Survey of Business Owners (SBO), following them until 2012—the "SBO Panel." The SBO is another restricted-access Census Bureau survey that allows for two additional advantages at the cost of a shorter and less extensive panel. First, it contains reports of firm revenues at the national level, allowing for additional and more standard measures of firm productivity. These additional productivity measures are generated in the same way as above, using Equation (5.1). Second, starting in 2007, the SBO began asking about firm owner nativity. This allows for an enriched understanding of the distributional consequences of immigrant worker inflows for firm owners.

A first set of specifications for this analysis take the form:

$$\begin{aligned}\mathbb{1}[\text{Shut Down}]_{ft} = \alpha + \beta^{\text{total}}\left(I_{gk,t-2}\right) \\ + \Gamma X_{gk,t-2} + \alpha_f + \alpha_a + \alpha_{gt} + \alpha_{k't} + \varepsilon_{ft}\end{aligned} \tag{5.4}$$

$$\begin{aligned}\mathbb{1}[\text{Shut Down}]_{ft} = \alpha + \beta^{\text{main}}\left(I_{gk,t-2}\right) + \beta^{\text{mod}}\left(I_{gk,t-2} \times \mathbb{1}[\text{High Prod.}]_f\right) \\ + \Gamma X_{gk,t-2} + \alpha_f + \alpha_a + \alpha_{gt} + \alpha_{k't} + \varepsilon_{ft}\end{aligned} \tag{5.5}$$

with $t \in \{2007, 2012\}$. The replacement of I_{gkt} with $I_{gk,t-2}$ is necessitated by the availability of

$z_{gkt}^{\text{Emigrants}}$ for $t \in \{2005, 2010\}$. Estimating Equations (5.4) and (5.5) serves two purposes: first, they add additional evidence of the productive reallocation result using more conventional productivity measures; and second, they ensure that this modified specification delivers similar results as estimating Equations (5.2) and (5.3).

This latter reason then validates the use of the following models to further understand the heterogeneity of immigrant-induced firm shut down decisions:

$$\begin{aligned}\mathbb{1}[\text{Shut Down}]_{ft} = \alpha &+ \beta^{\text{native}} \left(I_{gk,t-2}\right) \\ &+ \beta^{\text{immi}} \left(I_{gk,t-2} \times \mathbb{1}[\text{Immi Owned}]_f\right) \\ &+ \Gamma X_{gkt} + \alpha_f + \alpha_a + \alpha_{gt} + \alpha_{k't} + \varepsilon_{ft}\end{aligned} \tag{5.6}$$

$$\begin{aligned}\mathbb{1}[\text{Shut Down}]_{ft} = \alpha &+ \beta^{\text{native main}} \left(I_{gk,t-2}\right) \\ &+ \beta^{\text{native mod}} \left(I_{gk,t-2} \times \mathbb{1}[\text{High Prod.}]_f\right) \\ &+ \beta^{\text{immi main}} \left(I_{gk,t-2} \times \mathbb{1}[\text{Immi Owned}]_f\right) \\ &+ \beta^{\text{immi mod}} \left(I_{gk,t-2} \times \mathbb{1}[\text{Immi Owned}]_f \times \mathbb{1}[\text{High Prod.}]_f\right) \\ &+ \Gamma X_{gkt} + \alpha_f + \alpha_a + \alpha_{gt} + \alpha_{k't} + \varepsilon_{ft}\end{aligned} \tag{5.7}$$

Equation (5.6) illustrates the differential shut down responses of immigrant- and native-owned firms, on average, an analysis uniquely available by combining the SBO and LBD. Equation (5.7) then combines the analyses in Equations (5.5) and (5.6) by stratifying firm shut down responses on both ownership nativity and productivity.

These specifications test several hypotheses regarding firm ownership and productivity. β^{immi}, for example, is ambiguous in sign: while there may be linkages between immigrant owners and employees that would suggest $\beta^{\text{immi}} > 0$, immigrant firm owners may face more intense competition from other immigrant entrants if immigrant-owned firms are distinct from native-owned firms in terms of employee pool or output within 5-digit NAICS codes. Similar considerations apply to the immigrant-specific coefficients in Equation (5.7).

5.4 SBO Panel: Results

Column 1 of Table 6 shows a still-negative, but imprecise relationship between immigrant presence and firm shut down probability in the SBO Panel. Columns 2–5, however, embody no such ambiguity, and additionally find that revenue-based measures of productivity deliver the same pattern found in Table 5: increased immigrant presence sustains higher productivity firms and culls lower productivity firms.

Table 7 builds on these results. First, Column 1 indicates that, on average, the entire negative relationship between immigrant worker presence and shut down probability is due to immigrant-owned firms. Given that my specifications flexibly control for commuting zone-wide factors like a larger immigrant customer base, this is highly indicative of linkages between immigrant firm

owners and immigrant employees that are advantageous to immigrant-owned firms. Columns 2–5 add a significant degree of nuance to this result. Among lower productivity firms, those that are owned by immigrants are substantially less likely to shut down in response to increased exposure to immigrant workers than those owned by natives. However, this is a *relative* gain; low-productivity immigrant-owned firms either do not change their shut down behavior or are still more likely to shut down in response to increased exposure to immigrant workers as a whole (adding up coefficients in the first two rows of Panel B). Furthermore, the advantage among high-productivity firms does not appear to be heterogeneous across owner nativity, with the immigrant advantage for low-productivity firms in the second row of Panel B negated by the fourth row. Thus, among firm owners, a more complete picture emerges: high productivity firm owners are much less likely to exit, regardless of nativity, while native owners of lower-productivity firms are far more likely to exit in response to increased immigrant worker presence. Figure 8 summarizes the full set of result from Sections 5.2 and 5.4.

5.5 Summary and Discussion

The results found in this section regarding the heterogeneous way in which firms' shut down decisions respond to increased immigrant exposure have substantial implications for the overall effect of immigrant workers on local economies. In conjunction with the large increases in firm entry found in Section 4, they provide novel evidence that immigrants increase local business dynamism—creative destruction—on the extensive margin. In the context of models that incorporate firm heterogeneity and a non-trivial firm mass, this dynamism has important welfare implications. Next, in Section 6, I use one such model to describe how these results can arise in general equilibrium, then show it generates welfare increases from immigration that a canonical model of local production would not.

This increased dynamism is not without distributional consequences, however. Just as the literature on how immigration affects employees has focused on natives at risk of being substituted for in production, it appears that there is a subset of natives who own low productivity firms that are most at risk of having to shut down their business in response to increased immigrant presence. This likely arises because of direct competition with immigrant entrepreneurs and because of advantages immigrant entrepreneurs have in hiring and utilizing immigrant workers that translate to a competitive advantage.

It is also important to note caveats that stem from data limitations that force me to use proxies for firm total factor productivity rather than more direct measures. The measure I employ that has the most in common with the literature is revenues per worker. At best, this is a measure of labor productivity, but at worst simply a measure of the dispersion in use of non-labor inputs by different firms. The key assumption for the validity of this measure, based on my methodology, is that firms within the same 5-digit NAICS code have comparable non-labor input requirements. Even in the case where this is true, some imperfection in the labor market must exist for there to be a direct link between labor and total factor productivity. In models with competitive labor markets—including

the one presented below—revenues per worker are independent of total factor productivity. These models, instead, have a direct link between firm size (both employment and revenues) and firm total factor productivity, which is why I prefer size-based measures here. Nonetheless, in practice, firms can differ in size because of total factor productivity or because of idiosyncratic differences in the demand for goods across firms (e.g., due to a foothold in the market). The key assumption for my preferred productivity measures, then, is that 5-digit NAICS code by firm age fixed effects remove enough of the variation in idiosyncratic demand differences across firms such that the remaining variation primarily measures differences in firm total factor productivity.

6 Synthesis Through Theory

The previous two sections have delivered key empirical insights into how immigrant workers affect local economies in partial equilibrium (i.e., comparing across sectors within the same commuting zone). This section relies on theory to show how accounting for the kind of firm heterogeneity implied by the partial equilibrium results ultimately impacts general equilibrium analyses of immigration.

6.1 Motivation

By definition, models featuring perfect competition are not compatible with firm heterogeneity in the final goods markets, and models featuring both perfect competition and perfect substitutability in the market for foreign-born and domestic labor are not compatible with immigrant-specific effects on firm outcomes. Melding a Melitz (2003) framework with imperfect substitutability in the labor market across immigrant and native workers allows immigrant employees to generate distinct effects on firm outcomes relative to native employees and potentially change the productivity distribution of firms.

However, this combination alone does not capture specific linkages between higher-productivity firms and immigrant employees. Such linkages are both directly implied by the results in Section 5 and indirectly by previous work. Mitaritonna et al. (2017), for example, find that manufacturing firms in France employing immigrant workers are more than 11 percent more productive than their counterparts that do not. Kerr and Kerr (2018) find that immigrant-owned firms in the U.S. feature higher sales per employee than native-owned firms in the same state and two-digit sector. This result only gets stronger with the inclusion of finer sector definitions, gender, ethnicity, age, and education of firm owners. Under the premise that immigrant-owned firms are more likely to hire immigrant employees, their results also imply that firms with more immigrant employees are more productive.

Linkages between immigrant employees and higher-productivity firms can arise if firms have to pay higher fixed operational costs in order to access immigrant employee networks and retain immigrant workers for production. These costs can include (but are hardly limited to) hiring translators and liaisons to be able to enter into immigrant job search networks and direct search for im-

migrants[33], hiring lawyers to work on visa issues, and paying enforcement costs (in expectation) when hiring undocumented immigrants. In the presence of such costs, firms with direct ties to immigrants will be positively selected on productivity because they must be able to afford them.

In order to capture productivity-related reallocative responses to immigration, I thus add an additional heterogeneity to my theoretical framework. In the spirit of Bustos (2011), I introduce two technology types—one of which is more suited to utilize immigrant labor. As motivated in the discussion above, firms must pay an additional fixed operating cost to access this technology, which means they are positively selected on productivity relative to their counterparts using the less-immigrant-heavy technology. Immigrant-heavy firms save more on labor costs when immigrants enter the labor market, pass through their savings to consumers, and thus gain market share by competing it away from firms who do not have special ties to immigrant workers. Their counterparts are forced to exit, a culling of the lowest-productivity firms in the market as a whole. In sum, this model shows how firm entry and exit can drive immigrant-induced endogenous technological change by changing the composition of firms in the economy.

6.2 Setup

Individuals are consumer-employees of type $i \in \{I_e, N_e\}$, with I representing foreign-born individuals and N representing native-born individuals and $e \in \{L, S\}$, where L stands for high school degree or *L*ess and S stands for at least *S*ome college. The mass of each labor type in the economy is fixed and employees supply their labor inelastically—the primary comparative static will increase immigrant mass by increasing both I_S and I_L (as an average immigrant inflow into the U.S. does). Entrepreneurs are indexed by j with $j \in \{0, 1\}$. Type 1 entrepreneurs choose to produce with a technology that is more immigrant-dependent.

6.2.1 Consumer Preferences

Consumer preferences are uniform across consumers. Preferences across firms are of the form presented in Dixit and Stiglitz (1977):

$$\mathcal{U} = \left[F^{\frac{\eta-1}{\mu}} \sum_j \int_{F_j} Q(f)^{\frac{\mu-1}{\mu}} \right]^{\frac{\mu}{\mu-1}}$$

where F_j is the mass of firms owned by entrepreneurs of type j, $F = \sum_j F_j$, $Q(f)$ is the amount demanded by consumers at firm f, which is a single firm in the local economy. $\mu > 1$ is the elasticity of substitution of consumption across firms. When $\eta = 1$, consumers have a taste for variety, as the original Dixit and Stiglitz (1977) model of monopolistic competition dictates. This taste for variety generates external scale effects through which an increasing market size increases welfare. When $\eta = 0$, we shut down this channel and focus on the firm productivity distribution (see, e.g., Egger

[33] See e.g., this Center for American Progress report about Tyson Fresh Meats and its willingness to hire translators, liaisons, and chaplains in order to utilize immigrant labor for an example.

and Kreickemeier, 2009).

This results in the following demand curves for each firm, which are downward sloping due to product differentiation and substitutability across goods:

$$Q_j(f) = YF^{\eta-1}P^{\mu-1}p_j(f)^{-\mu} \tag{6.1}$$

where $p_j(f)$ is the price charged by firm f of type j and Y is total consumer spending, and the price index P is given by $P^{1-\mu} \equiv F^{\eta-1}\sum_j \int_{F_j} p_j(f)^{1-\mu}$.

6.2.2 *Firms*

Firms have some market power but are non-strategic and take their downward-sloping demand curves as given—a typical monopolistic competition setup. Firm production functions are given by

$$\begin{aligned}
Q_j(z) &= zq_j(z) \\
q_j(z) &= \left[a\left(L_j(z)\right)^{\frac{\sigma_E-1}{\sigma_E}} + \left(S_j(z)\right)^{\frac{\sigma_E-1}{\sigma_E}}\right]^{\frac{\sigma_E}{\sigma_E-1}} \\
L_j(z) &= \left[b_j\left(I_{Lj}(z)\right)^{\frac{\sigma_I-1}{\sigma_I}} + \left(N_{Lj}(z)\right)^{\frac{\sigma_I-1}{\sigma_I}}\right]^{\frac{\sigma_I}{\sigma_I-1}} \\
S_j(z) &= I_{Sj}(z) + N_{Sj}(z)
\end{aligned}$$

where z is a draw of total factor productivity, $q_j(z)$ is a CES aggregator of less-educated labor (L_j) and more-educated labor (S_j), and the lower education labor group is itself a CES aggregator of immigrant and native labor. I consider high education workers to be indistinguishable across nativity.[34] The elasticities σ_E and σ_I govern how substitutable workers of different education and different nativities are, respectively. z is drawn from the same Pareto distribution regardless of entrepreneur type, with shape parameter ϕ and minimum value m. The parameter a governs relative productivity across less- and more-educated workers.

The key difference across firms of type j is the parameter b_j within the low-education aggregator. I assume type $j = 1$ firms depend more on, and better use immigrant labor:

$$\Delta_b \equiv b_1 - b_0 > 0$$

This assumption stands in for a variety of reasons why firms that are more productive are more adept at using immigrants in production. They may be better at allocating immigrants and natives to different tasks, have better access to search networks where there are immigrant job-seekers, or may be less discriminatory toward (suffer less distaste from hiring) immigrant workers.

[34] There is more robust evidence for imperfect substitutability among low-education workers. See, e.g., Peri and Sparber (2009).

The cost function is given by

$$\left(\frac{c_j}{z}\right) Q_j(z) + c_j \kappa_j^f$$

where

$$c_j \equiv \left[a^{\sigma_E} \left(c_{Lj}\right)^{1-\sigma_E} + \left(w_S\right)^{1-\sigma_e}\right]^{\frac{1}{1-\sigma_E}}$$

and

$$c_{Lj} \equiv \left[b_j^{\sigma_I} \left(w_{IL}\right)^{1-\sigma_I} + \left(w_{NL}\right)^{1-\sigma_I}\right]^{\frac{1}{1-\sigma_I}}$$

and w_{ie} represents the wage for a worker nativity i and education e and $w_S \equiv w_{NS} = w_{IS}$ because of perfect substitutability among higher-educated workers. κ_j^f is a fixed operating cost that is allowed to vary by entrepreneur type for reasons mentioned above—immigrant-linked firms often appear to pay additional fixed operational costs in order to utilize immigrant labor. Thus, in order to access the immigrant-specific production boost represented by $b_1 > b_0$, they must pay a proportional cost every period, τ, such that $\kappa_1^f = \tau \kappa_0^f$.

The cost function leads to a familiar pricing rule in models of monopolistic competition and Dixit and Stiglitz (1977) preferences:

$$p_j(z) = \left(\frac{\mu}{\mu - 1}\right)\left(\frac{c_j}{z}\right) \tag{6.2}$$

That is, the firm still charges a constant markup over its marginal cost, but the firm's marginal cost reflects the two different types of labor it aggregates. Firms compete through prices, and so firms that are able to pass on declines in c_j to consumers through p are able to gain in market share.

6.3 Equilibrium Definition

Entrepreneurs only stay in the market if they are profitable. This defines a cutoff productivity for type 0 firms:

$$\pi_0(z_0^*) \equiv 0 \tag{6.3}$$

A second cutoff exists, at which marginal producers are indifferent between the immigrant-heavy (type 1) and immigrant-light (type 0) production mode:

$$\pi_0(z_1^*) \equiv \pi_1(z_1^*) \tag{6.4}$$

Entrepreneurs with productivities below z_0^* exit the market, entrepreneurs with productivities in $[z_0^*, z_1^*]$ produce with technology 0, and entrepreneurs with productivities above z_1^* produce with technology 1. Entrepreneurs do not know their z prior to entry, and must pay an entry cost. The next equilibrium condition is free entry:

$$\mathbb{E}[\pi(z)] = \mathbb{E}[\pi(z)|z > z_0^*]\mathbb{P}[z > z_0^*] = c_0 \kappa^e \tag{6.5}$$

where κ^e is a sunk (entry) cost entrepreneurs pay to take productivity draws, denominated in units of output. When profits are high enough, entrepreneurs enter until they no longer expect to recover their entry costs.[35] The price level, P is given by

$$P \equiv n_e \left[\int_{z_0^*}^{z_1^*} p_0(z)^{1-\mu} g(z) dz + \int_{z_1^*}^{\infty} p_1(z)^{1-\mu} g(z) dz \right] \tag{6.6}$$

where n_e is the endogenous mass of entrepreneurs who take productivity draws. Consumer spending Y is set equal to labor payments, and the final equilibrium conditions occur in the labor market, setting labor supply and labor demand equal for low-education immigrant and native workers. High-education worker wages are set to be the numeraire, $w_S \equiv 1$.

6.4 Equilibrium

The key items of interest revolve around z_0^*. First, I define

$$R_z \equiv \frac{z_1^*}{z_0^*} = \left[(c_0)^{\mu} \left(\frac{c_1 \tau - c_0}{(c_1)^{1-\mu} - (c_0)^{1-\mu}} \right) \right]^{\frac{1}{\mu - 1}} \tag{6.7}$$

and

$$\theta \equiv 1 + R_z^{-\phi} \left(\frac{c_1 \tau - c_0}{c_0} \right) \tag{6.8}$$

Solving Equations (6.3) through (6.6) then yield

$$z_0^* = m \left[\left(\frac{\kappa_0^f}{\kappa^e} \right) \left(\frac{\mu - 1}{\phi - (\mu - 1)} \right) \theta \right]^{\frac{1}{\phi}} \tag{6.9}$$

$$F = Y \left(\frac{1}{c_0 \kappa_0^f} \right) \left(\frac{\phi - (\mu - 1)}{\phi \mu} \right) \tag{6.10}$$

The key variable in this solution is θ, which sets Equation 6.9 apart from standard productivity cutoff expressions derived in similar models (e.g., Melitz, 2003). It introduces the notion that entry and exit decisions for marginal type 0 firms depend on type 1 firms, through their ability to steal away market share when their costs go down. If c_1 goes down by more than c_0 in response to a shock, θ rises, which causes z_0^* to rise as well. The rise in z_0^* forces marginal type 0 firms to exit the market.

This mechanism drives the results below because of how it relates to the labor market. Section A.6.2 derives equilibrium in the labor market, with the upshot that demand curves slope downward. Thus, when a low-education tilted inflow of immigrants occurs, the wages of less-educated

[35] Note that the assumption that entry costs scale with c_0 (instead of c_1 or a combination) is mostly made for analytical convenience. However, a simple, plausible justification is that producers do not invest in the costs to access immigrant labor until after entry activities have been completed and they find out they have a draw of z above z_1^*. Thus, the entry activities are paid for using type 0 technology.

immigrants deteriorate the most of any group. In turn, c_1 falls by more than c_0 because $b_1 > b_0$.

6.4.1 *Value Added of the Model: P*

Price index P is inversely proportional to welfare. With z_0^* in hand, we can show[36]

$$P^{1-\mu} = [\text{Const.}](c_0)^{1-\mu} F^{\eta} (z_0^*)^{\mu-1} \theta$$

where F stands for firm mass. We then have

$$-\frac{d\log(P)}{dI} = \underbrace{-\frac{d\log(c_0)}{dI}}_{\text{Analogous to rep. firm model}} + \underbrace{\left(\frac{\eta}{\mu-1}\right)\frac{d\log(F)}{dI}}_{\text{Increased variety through more firms}} + \underbrace{\frac{d\log(z_0^*)}{dI}}_{\text{Culling of marginal firms}} + \underbrace{\left(\frac{1}{\mu-1}\right)\frac{d\log(\theta)}{dI}}_{\text{Technology switching}} \tag{6.11}$$

This expression clarifies the value added of this modeling framework. First, in a canonical, representative firm model of production in which all firms have access to type 0 technology, the welfare impact of immigrants on native workers through prices would be defined only by the first term of Equation (6.11). This expression contains three additional avenues that this canonical framework misses.

The next two terms are driven by extensive margin changes: firm mass and the productivity level at the shut down margin. Sections 4 and 5 each delivered evidence that these reduced form parameters are positive in sign in partial equilibrium. Setting $\Delta_b = 0$, τ =1, and $c_0 = c_1$ implies a model that simply meld monopolistic competition in the output market with imperfect substitutability in the labor market. In such a model, Equations (6.7) through (6.9) show that $\theta = 1$ and that z_0^* is therefore constant. Thus, such a model would open up an avenue from firm mass to welfare through product variety—as long as consumers demand variety ($\eta = 1$)—but would not affect the firm productivity distribution. A model with $\Delta_b > 0$ and $\tau > 1$ opens the door to additional increases in welfare through a rising θ—which increases welfare both independently and through z_0^*. Simulation results below separate these channels.

6.5 Simulations

6.5.1 *Calibration*

Table 8 shows key model calibrations, set to match the U.S. economy in 2000, which had an immigrant share of 0.12 (55 percent of which has at most a high school degree) and 0.07 establishments per employee. Two calibrations are particularly difficult without employer-employee linked data. The first is the difference between b_1 and b_0, Δ_b. I will show results that vary this difference in order to demonstrate how big it has to be for θ to rise and for there to be productive reallocation across firms. For a given Δ_b, b_0 is pinned down by the immigrant-native wage gap among low-education workers.

[36] $[\text{Const.}] = \left(\frac{\mu}{\mu-1}\right)^{1-\mu}\left(\frac{\phi}{\phi-(\mu-1)}\right)$

The second difficult parameter is τ, which controls the cost firms pay to obtain Δ_b, and determines how selected on productivity firms that pay it end up being. I also vary τ in simulations rather than set an arbitrary calibration, but this process revealed that $\tau < 1.5$ leads to unstable simulations and $\tau \geq 1.6$ leads to simulations that are essentially indistinguishable, when all other parameters are held fixed. I thus set τ to 2 for the figures presented below (see Table 9).

Under these calibrations, I run an experiment that increases the immigrant stock in the workforce in a specific way that matches the empirical content of the immigrant inflows in this paper. Each additional immigrant represents 0.58 additional immigrants with no more than a high school degree and 0.42 immigrants with at least some college (see Table 3). As with a general immigrant inflow to the U.S. over the last 30 years, this experiment tilts the labor force towards lower educational attainment workers.

6.5.2 Results

Figure 9 shows the results from an example simulation with $\Delta_b = 0.3$ and $\tau = 2$. The top left figure shows that labor costs fall more for type 1 firms. This mechanism filters through to the rest of the results: because type 1 firms see lower marginal costs, the cutoff for switching to type 1 technology moves down. The same is not true for type 0 firms, even through immigrant entry does lower their production costs. This is because type 1 firms are able to price compete away market share, leading to a higher productivity bar for type 0 firms to be able to stay in the market. The result is more entry overall (of both types, but particularly of type 1 firms), exit by marginal type 0 firms, and an increase in native welfare. An immigration shock equivalent to a one percent increase in the population generates a 0.49 percent increase in native welfare. We can then use (6.11) to decompose this effect results into its component parts. Specifically,

$$\begin{aligned}
\mathcal{W}_I &\equiv \frac{d\log(\text{Real Native Income})}{dI} \\
&= \frac{d\log(w_{NU}N_U + w_S N_S)}{dI} - \frac{d\log(P)}{dI} \\
&= \underbrace{\frac{d\log(w_{NU}N_U + w_S N_S)}{dI} - \frac{d\log(c_0)}{dI}}_{\text{Standard}} + \underbrace{\left(\frac{\eta}{\mu-1}\right)\frac{d\log(F)}{dI}}_{\text{Variety}} + \underbrace{\frac{d\log(z_0^*)}{dI}}_{\text{Culling}} + \underbrace{\left(\frac{1}{\mu-1}\right)\frac{d\log(\theta)}{dI}}_{\text{Switching}}
\end{aligned}$$

where N_L and N_S are the fixed stock of native workers with at most a high school degree and more than a high school degree, respectively. This expression simply adds changes to native nominal income, $(w_{NL}N_L + w_S N_S)$, to Equation (6.11).

The results of model simulations over a range of Δ_b are captured in Figure 10.[37] Three important findings emerge: first, the "standard" portions of the immigrants surplus that accrue to natives through wage and price changes, $\frac{d\log(w_{NL}N_L + w_S N_S)}{dI} - \frac{d\log(c_0)}{dI}$ (in blue), are a relatively small component of the immigrant surplus when we account for firm heterogeneity—less than 20 percent in the simulations conducted here. Gains from variety through increased firm presence, $\left(\frac{1}{\mu-1}\right)\frac{d\log(F)}{dI}$ (in gray), are the largest component of the immigrant surplus—insofar as consumers

[37] Note that when $\Delta_b = 0$, τ is set to 1. Otherwise, $\tau = 2$ as usual.

value variety. See Table 10 for more details on the decomposition.

However, productive reallocation across firms, $\frac{d\log(z_0^*)}{dI} + \left(\frac{1}{\mu-1}\right)\frac{d\log(\theta)}{dI}$ (in red), particularly through the culling of marginal firms, $\frac{d\log(z_0^*)}{dI}$ (in darker red), plays a significant role as well—at least 30 percent of the immigrant surplus comes from productive reallocation. Returning to a primary motivation in this paper, these general equilibrium reallocation effects stem from the supply side of the product market—they occur due to immigrant characteristics as employees (making labor costs cheaper) and because they induce and increase entrepreneur mass n_e, which ultimately raises z_0^* through increased competition. Even if we are to believe that gains through variety are over-stated in models of monopolistic competition, taking firm heterogeneity into account is critical to understanding how immigration affects the economy. Specifically, the bifurcation in productivity that is generated by allowing firms to pay a cost to better-utilize immigrant workers more than doubles the native welfare gain that is associated with immigration.

6.6 Discussion

These exercises, taken together with the empirical results presented above, demonstrate why accounting for heterogeneous firm responses can lead to estimates of immigrant-generated welfare that are substantially larger than those that come from canonical models of labor demand. By allowing for dispersion of productivity across firms, models with the Melitz (2003) structure open a channel to welfare through the productivity distribution. In particular, a rising productivity cutoff increases welfare by lowering prices—a *first-order* welfare gain analogous to shifting out the production possibilities frontier. Yet another first-order welfare gain—not modeled here—could arise if competition among firms raised the elasticity of substitution across products (see, e.g., Blanchard and Giavazzi, 2003). Welfare gains that arise from changes to wages and firm input costs, by contrast, are small because the labor market is characterized by perfect competition. This is also the case with accounting exercises conducted when both the labor market and the product market are characterized by perfect competition (see, e.g., Borjas, 1999 and Ottaviano and Peri, 2008).

7 Conclusion

This paper documents several empirical relationships that reveal the critical role firm entry and exit play in both absorbing immigrants into and mediating the effects immigrants have on local economies. A causal, positive relationship between immigrants and business presence is driven by small-to-medium sized firm creation and prevents exit by older, large firms within local industries over three decades in which immigration was a defining feature of demographic change in the U.S. These extensive margin firm responses were responsible for the majority of job creation that absorbed immigrants into local labor markets. Contrary to what we would expect if these effects were driven solely by consumer demand or uniformly lower labor costs across firms, immigrant inflows appear to cull lower-productivity firms from a local economy. Ties between immigrant workers and higher-productivity firms imply a substantially larger "immigration surplus" than we would

estimate with standard, representative firm models of the product market. In fact, responses by firm entry and exit—and subsequent changes to firm composition—represent a plausible channel through which the immigrant surplus can be first-order.

Future work will seek to delve into and contextualize the link between immigrant workers, firm entry and exit, and higher-productivity firms. Employer-employee linked data, for example, can help test the model's assertion that more productive firms within U.S. industries tend to both hire more immigrant workers and benefit more from immigrant inflows. Additionally, cross-geographic comparisons that stratify immigrant absorption outcomes—including wage changes, native displacement, and productivity—by variables that reflect the ease of starting and shutting down a business can help validate this paper's suggestion that flexibility on the extensive margin is a key determinant of the relative success in U.S. immigrant labor market assimilation.

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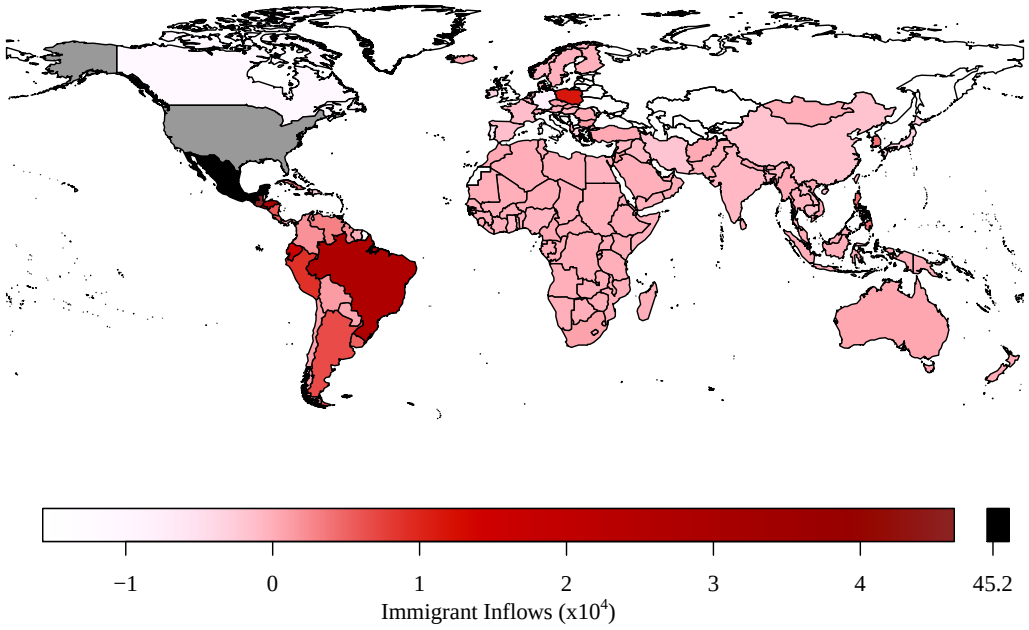
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Figures and Tables

Figure 1: Endogenous Immigrant Inflows into the Construction Industry, 2000–2005

Panel A: Net Immigration by Country, k=Construction

$[I_{ok,2005} - I_{ok,2000}]$



Panel B: Immigrant Inflows into k=Construction

$[I_{gk,2005} - I_{gk,2000}]$

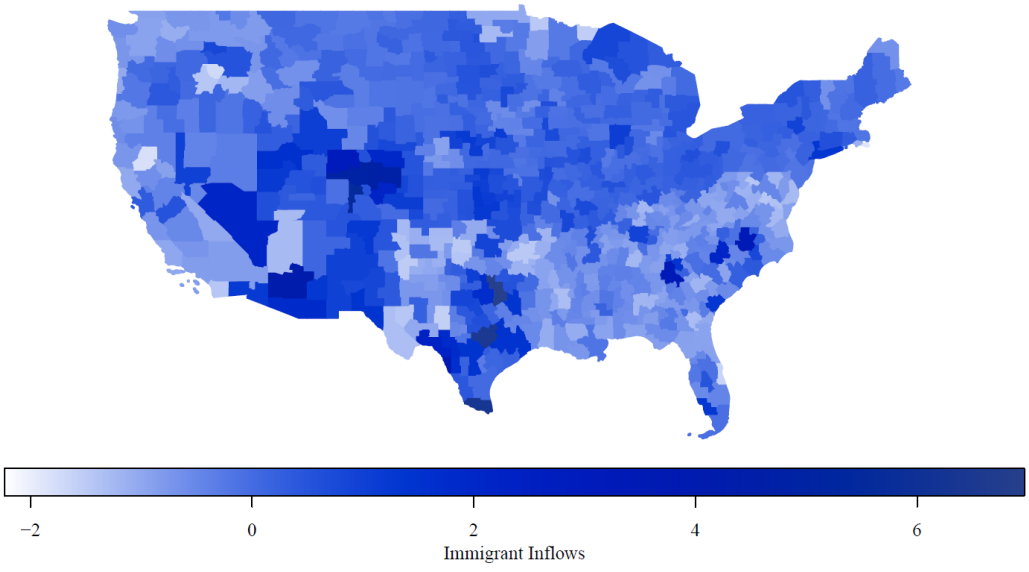
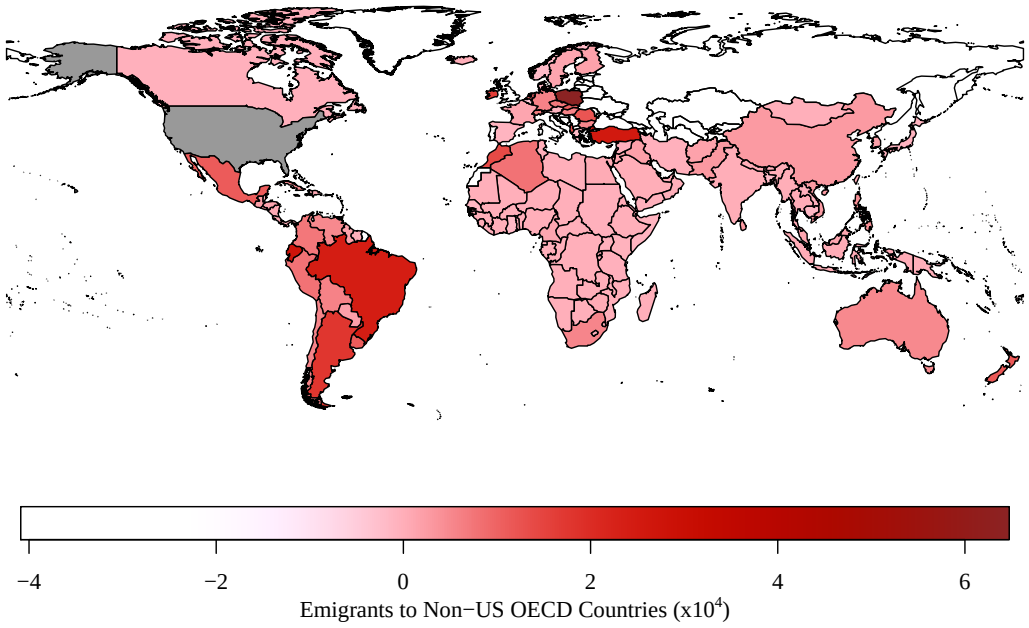


Figure 2: Exogenous Immigrant Inflows into the Construction Industry, 2000–2005

Panel A: Emigration Shock, k=Construction

$$\left[(\rho_{o(-r(g))k,2005} \times M_{o,2005}^{\text{non-US}}) - (\rho_{o(-r(g))k,2000} \times M_{o,2005}^{\text{non-US}})\right]$$



Panel B: Instrument-Predicted Inflows into k=Construction

$$\left[z_{gk,2005} - z_{gk,2000}\right]$$

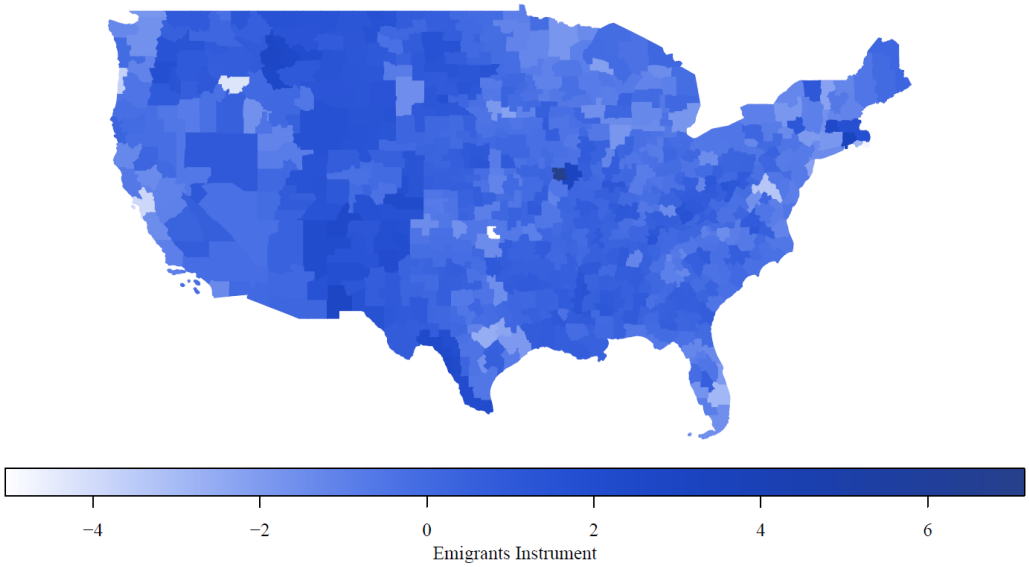
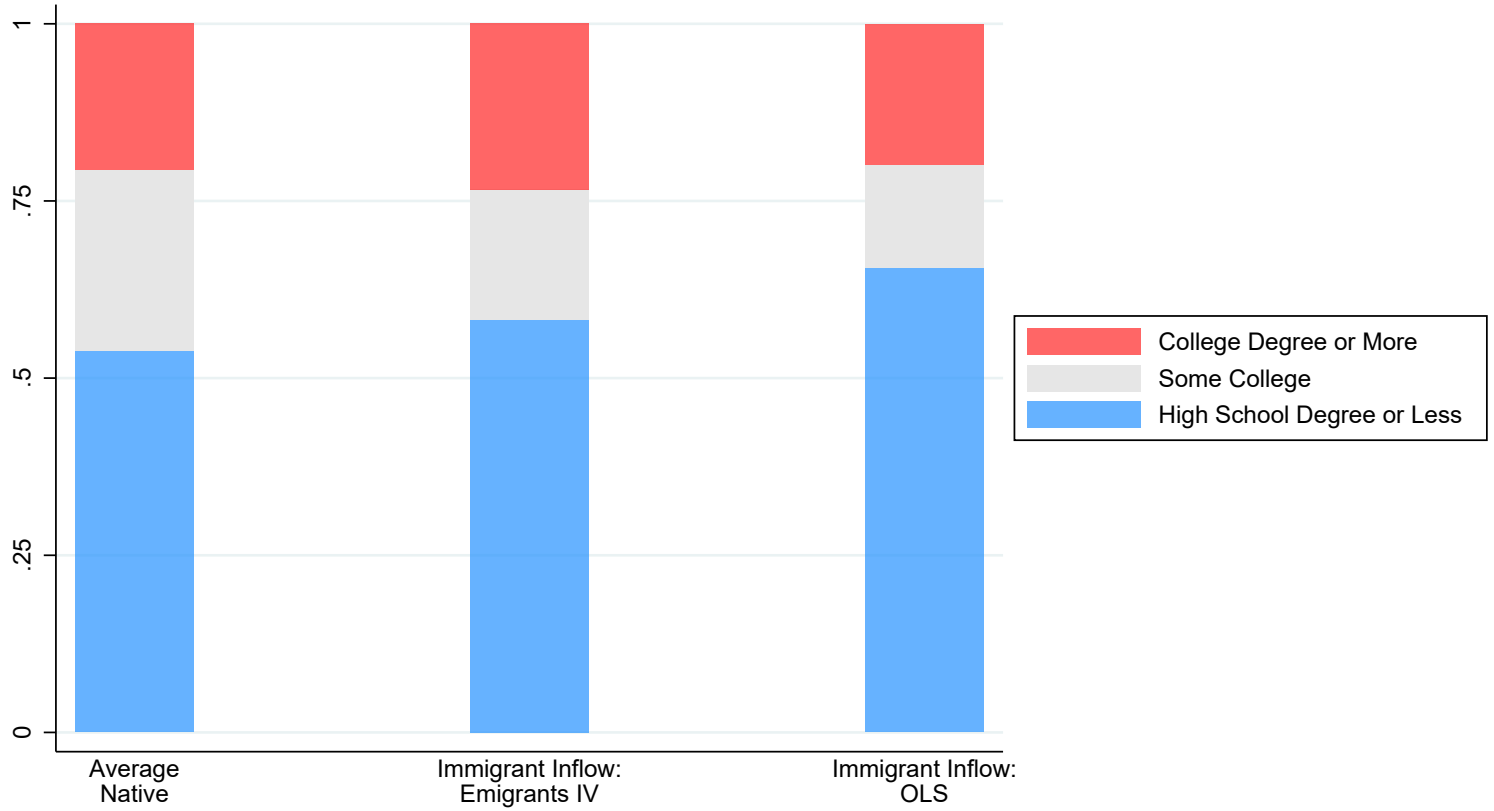
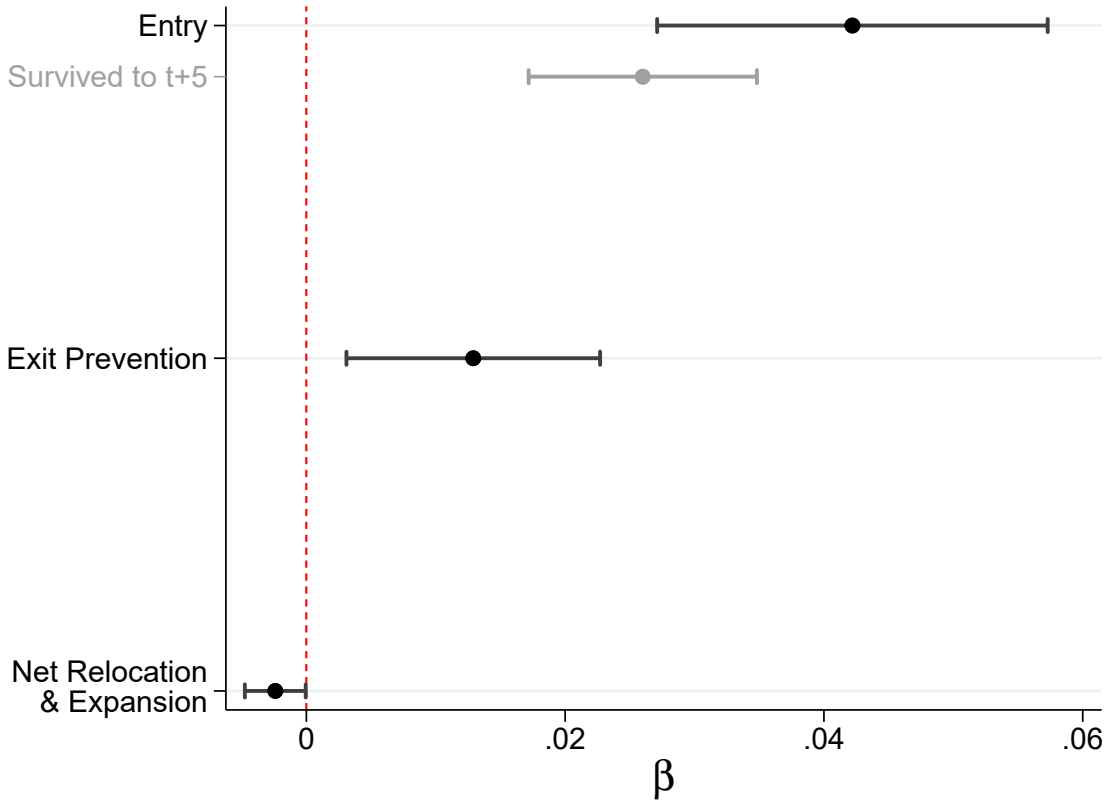


Figure 3: Educational Attainment of Immigrant Inflows and Receiving, Native Population



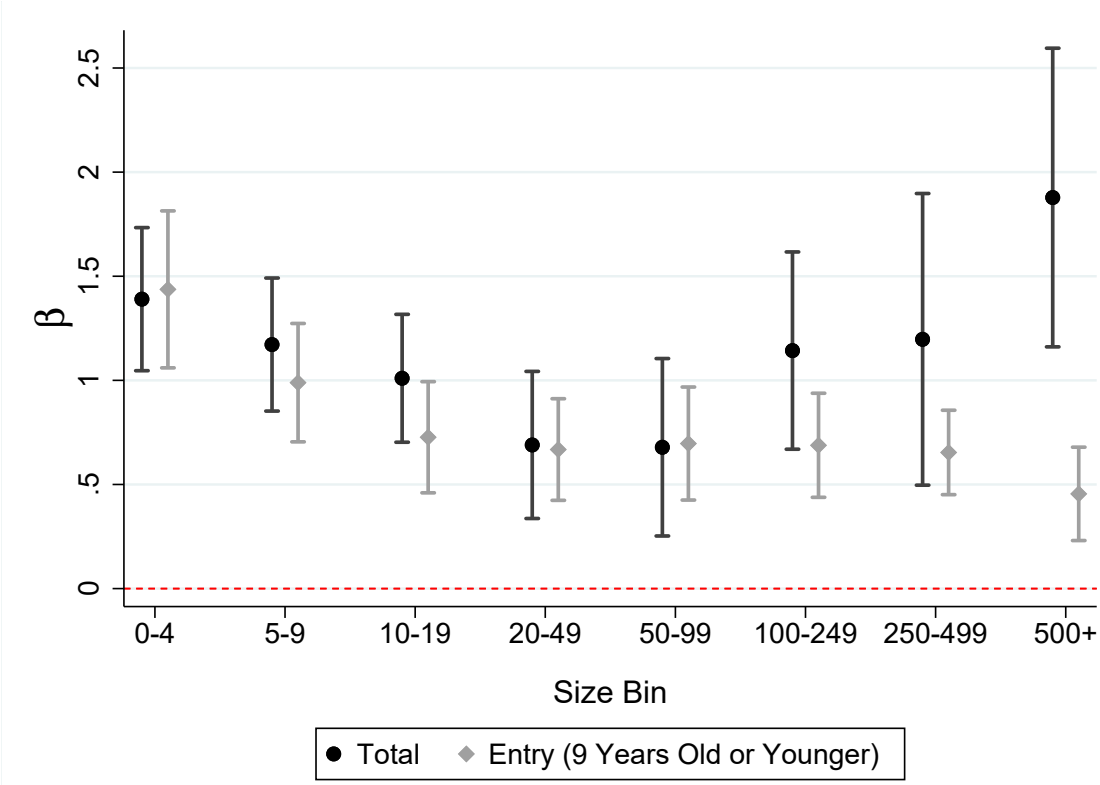
Notes: Data obtained from IPUMS-USA. Average native educational attainment (left-most bar) taken in 1980, 1990, and 2000. Composition of immigrant inflows (middle and right-most bar) obtained from estimating Equation (3.4) over the three decades covered by the time period 1980–2010.

Figure 4: The Effect of Immigration on Firm Presence—Flow Decomposition (IV Results)



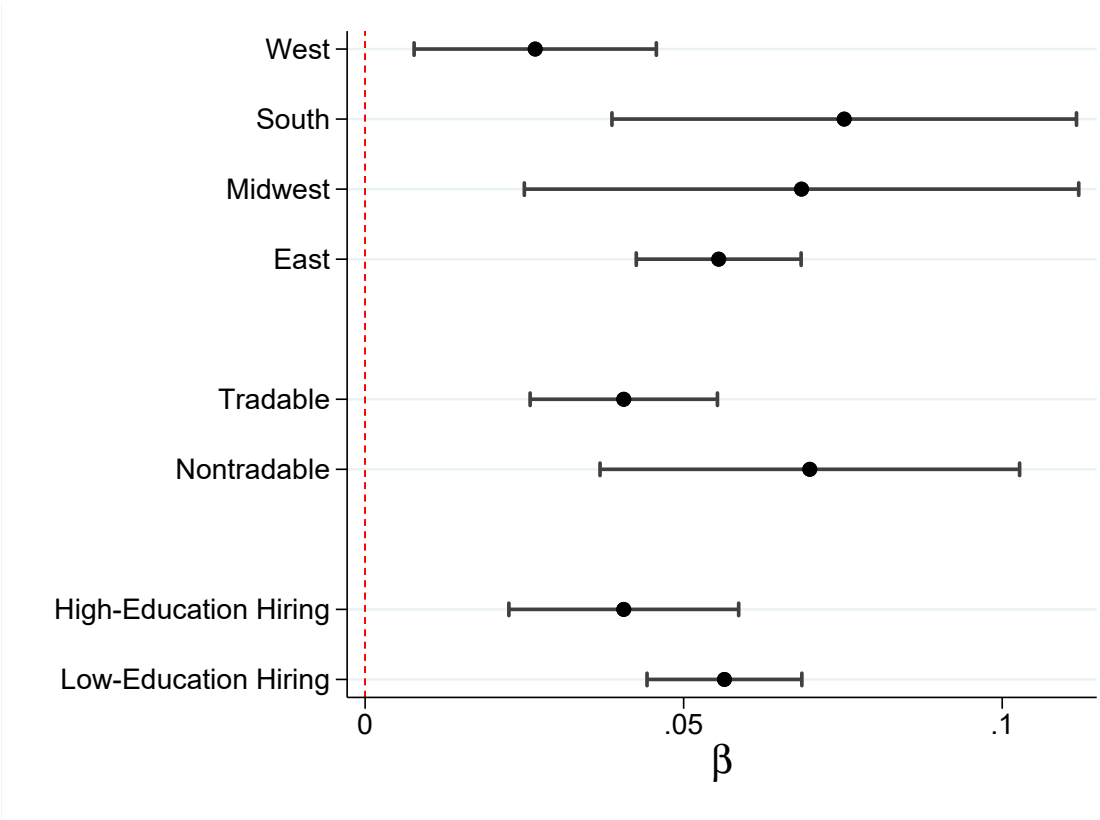
Notes: See Equation (3.1) for specification. See Section 4.1.2 for details on outcome variables. Data accessed and analyzed in Michigan Census Research Data Center.

Figure 5: The Effect of Immigration on Firm Presence—Within Size Bin (IV Results)



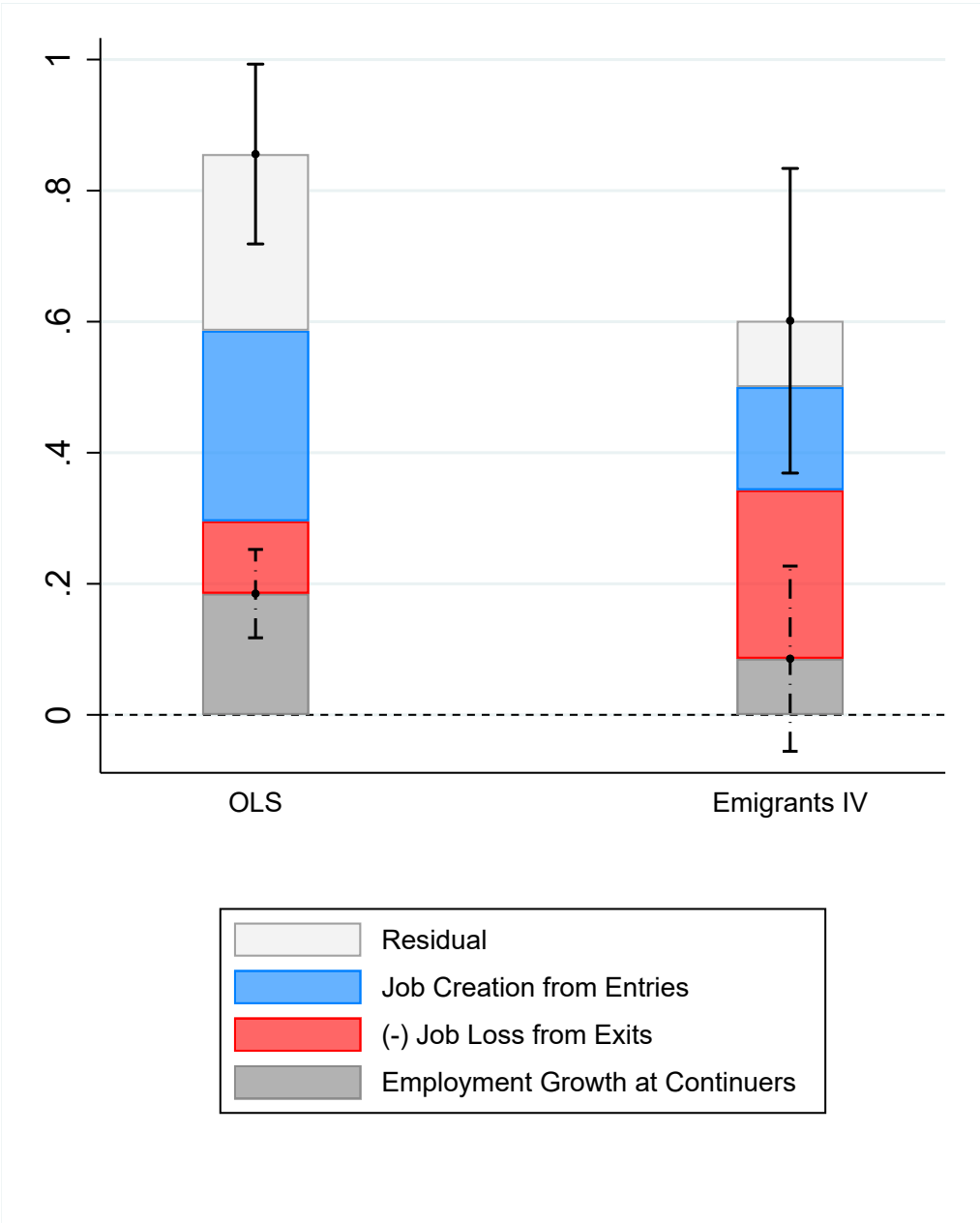
Notes: See Equation (3.1) for specification. See Section 4.1.3 for details on outcome variables. Data accessed and analyzed in Michigan Census Research Data Center.

Figure 6: The Effect of Immigration on Firm Presence—Heterogeneity (IV Results)



Notes: See Equation (3.1) for specification. Data accessed and analyzed in Michigan Census Research Data Center.

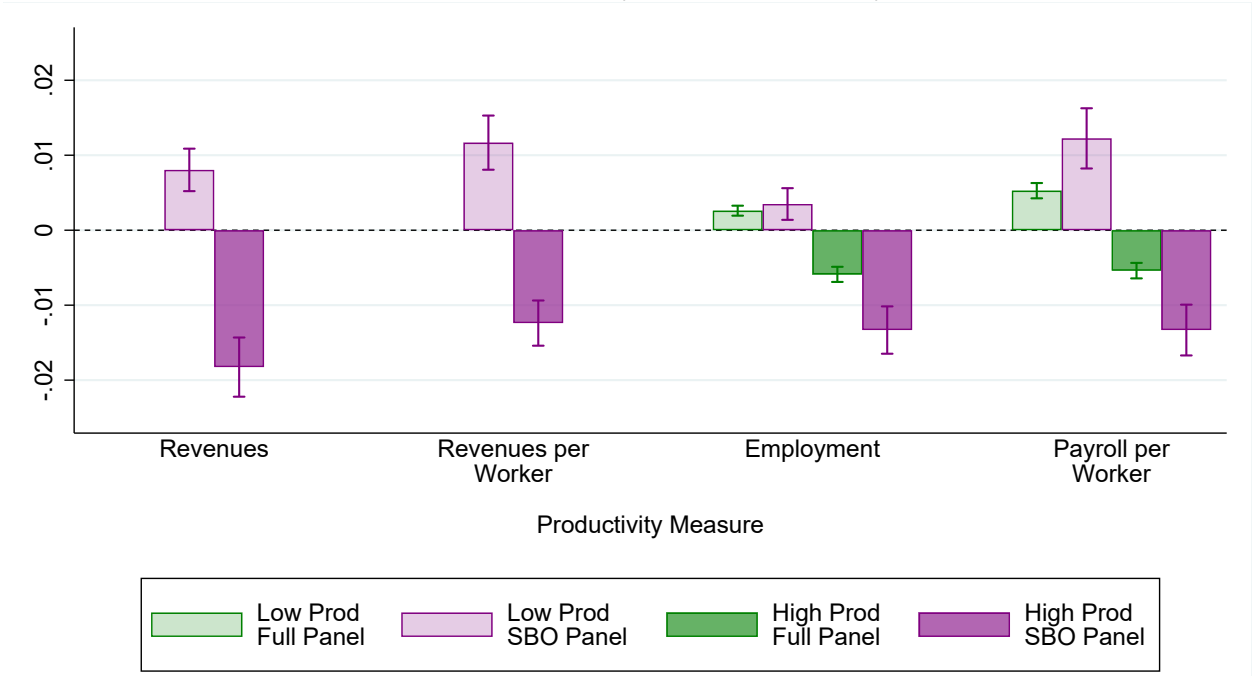
Figure 7: Decomposition of Net Job Creation per Immigrant Worker



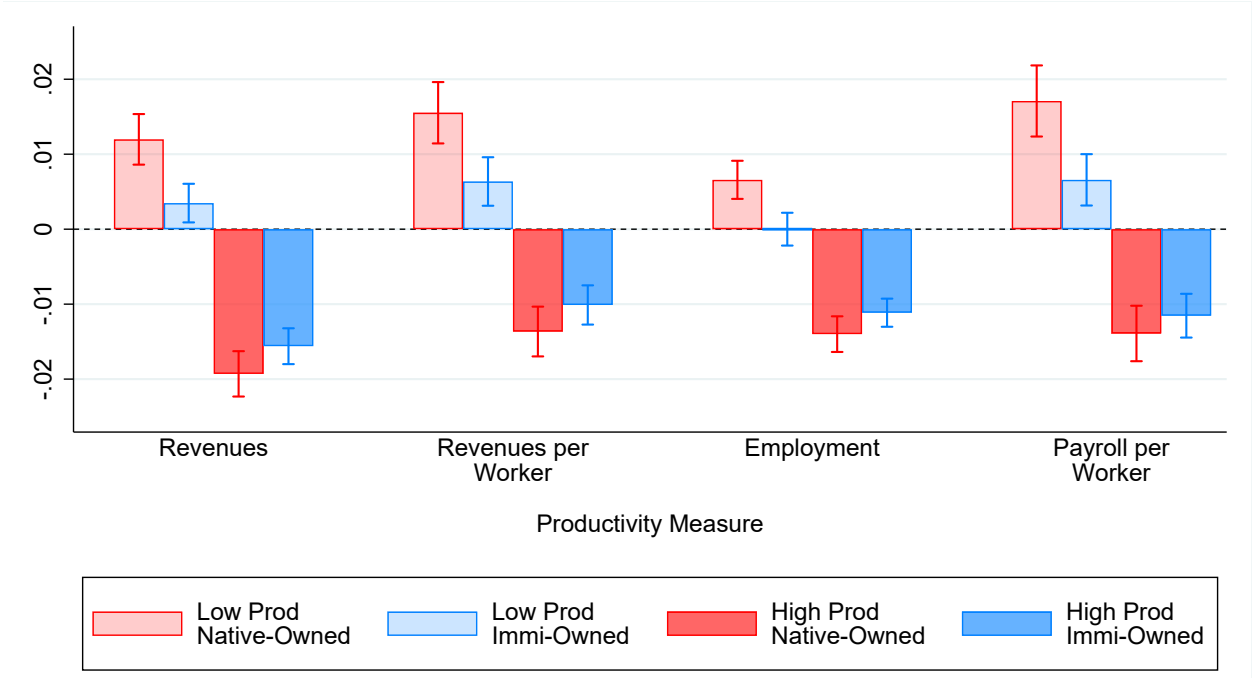
Notes: See Equation (3.1) for specification. Dot-dashed confidence interval is for Employment Growth at Continuers. Solid confidence interval is for the overall jobs created per immigrant worker (all components added up). Data accessed and analyzed in Michigan Census Research Data Center.

Figure 8: Effect of a 1% Immigration Shock on Firm Shut-Down Probability (IV Results)

Panel A: Stratified by Initial Productivity

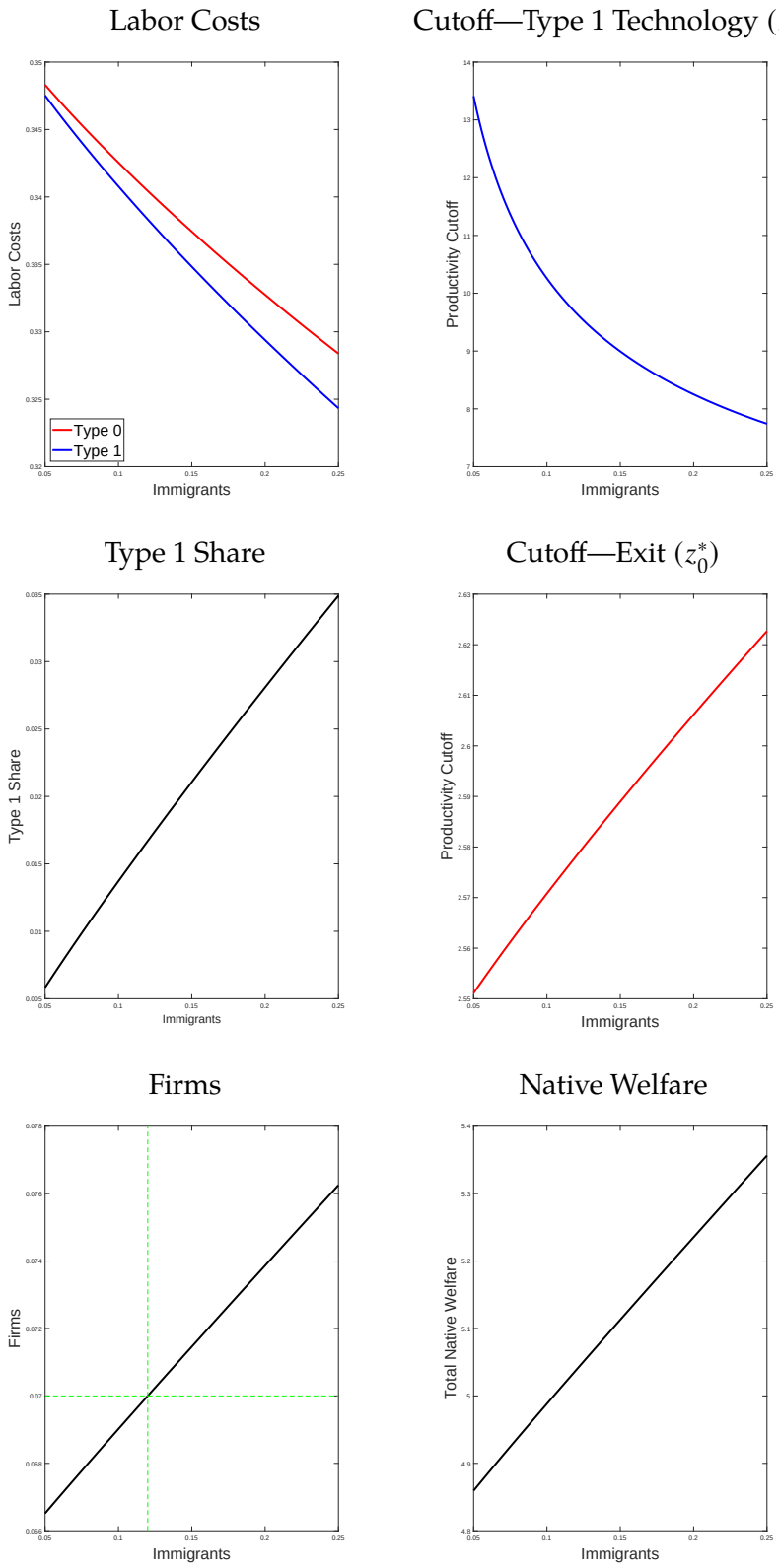


Panel B: Stratified by Initial Productivity and Ownership Nativity (SBO Panel only)



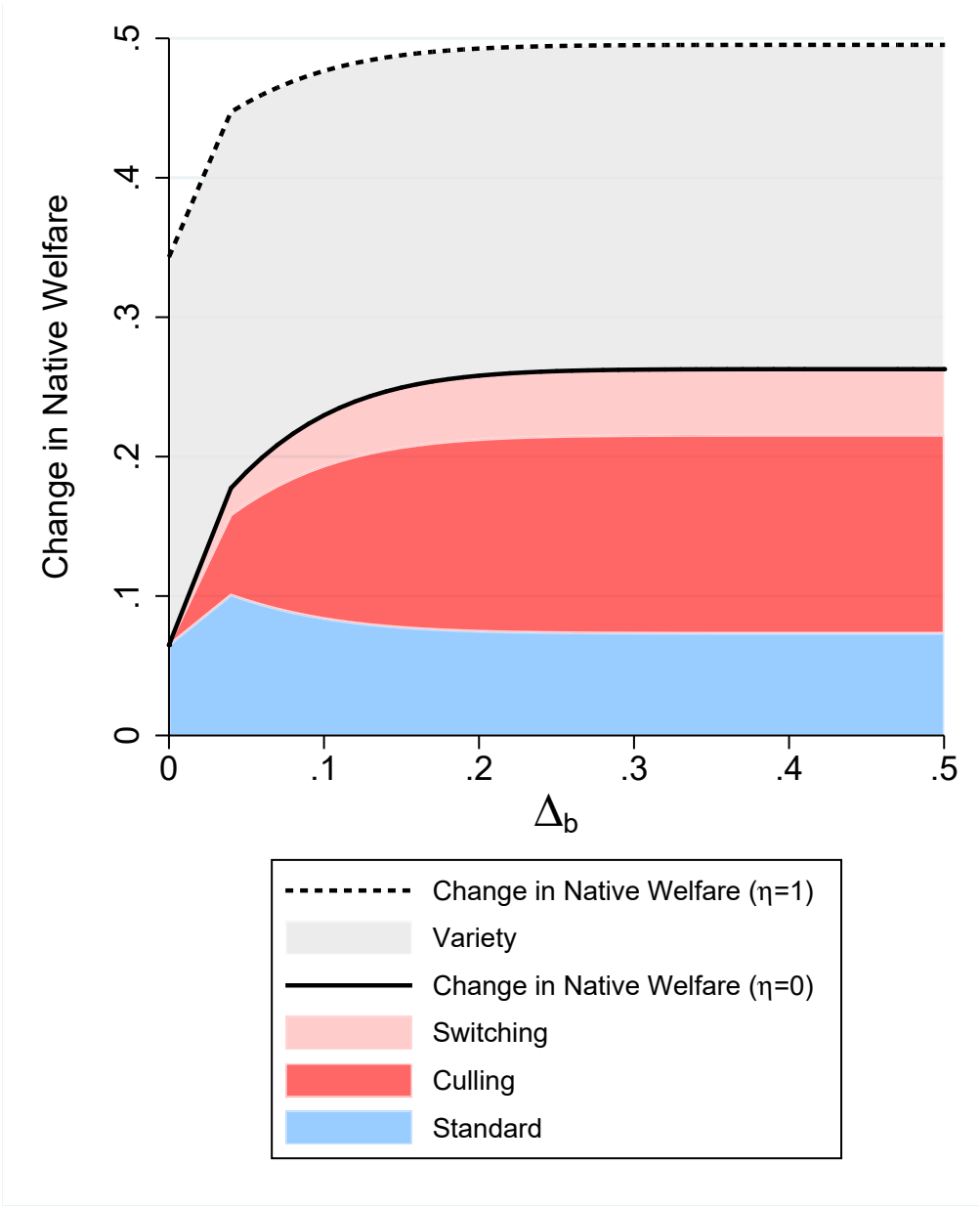
Notes: "Full Panel" covers all firms in operation as of 2000 in the years 2000, 2005, and 2010. "SBO Panel" covers a representative sample of firms in operation as of 2007 in the years 2007 and 2012. See Equations (5.2), (5.3), (5.5), and (5.7) for specifications. See Tables 5, 6, and 7 for underlying coefficients. Data accessed and analyzed in Michigan Census Research Data Center.

Figure 9: Example Simulation with $\Delta_b = 0.2$ and $\tau = 2$



Notes: Green dashed lines indicated data moments that were targeted in calibration.

Figure 10: Simulations—Percent Change in Native Welfare from a 1% Immigration Shock



Notes: When $\Delta_b = 0$, $\tau = 1$; otherwise, $\tau = 2$.

Table 1: Summary Statistics (Publicly-Available Data)

	1980 Workforce	1980–2010 ΔI_{gkt}: Immigrant Inflows per Initial Worker		1980–2010 Δ Workforce per Initial Worker		2000–2010 Δ Establishments per Initial Worker	
Industry Group	Mean	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Admin. & Support Services	28,412	0.143	0.162	0.612	0.604	0.010	0.012
Bus & Taxi	11,506	0.095	0.146	0.162	0.906	0.004	0.027
Construction	51,145	0.070	0.109	0.232	0.347	-0.007	0.012
Eating & Drinking Places	48,400	0.075	0.094	0.394	0.333	0.015	0.010
Educational Services	28,537	0.027	0.062	0.254	0.344	0.006	0.005
Entertainment Services	24,966	0.044	0.072	0.412	0.605	0.002	0.010
Health Services excl. Hospitals	23,807	0.065	0.093	0.629	0.352	0.025	0.017
Hospitals	48,735	0.036	0.055	0.297	0.297	<0.001	<0.001
Insurance	33,594	0.012	0.034	0.154	0.300	0.001	0.009
Lodging	11,515	0.077	0.114	0.230	0.435	0.003	0.012
Management of companies	25,535	0.055	0.089	0.489	0.934	0.002	0.022
Manufacturing, Clothing	40,229	-0.020	0.137	-0.268	0.457	-0.011	0.012
Manufacturing, Electrical & Household	78,275	0.025	0.075	0.001	0.404	-0.003	0.003
Manufacturing, Food	16,349	0.045	0.099	-0.015	0.314	<0.001	0.005
Manufacturing, Metals & Machinery	74,356	-0.002	0.046	-0.117	0.280	-0.004	0.005
Manufacturing, Plastics +	36,251	0.023	0.074	0.018	0.386	<0.001	0.003
Manufacturing, Transportation	101,875	0.016	0.060	0.053	0.653	-0.003	0.004
Manufacturing, Wood & Furniture +	20,281	0.015	0.059	-0.052	0.353	-0.004	0.004
Non-Telephone Communication	4,352	0.038	0.087	0.396	0.682	-0.009	0.016
Nursing & Residential Care Facilities	9,714	0.056	0.097	0.460	0.431	0.008	0.008
Personal Services	15,327	0.057	0.104	0.114	0.330	0.003	0.015
Professional Services	81,687	0.038	0.052	0.380	0.328	0.018	0.015
Real Estate	25,828	0.039	0.067	0.294	0.455	0.028	0.022
Repair Services	16,736	0.043	0.079	0.142	0.287	-0.011	0.010
Retail Trade, Household Durables	15,068	0.026	0.062	0.234	0.376	-0.008	0.010
Retail Trade, Apparel	15,837	0.018	0.080	0.095	0.369	-0.008	0.031
Retail Trade, Dept. & Variety Stores	27,785	0.020	0.056	0.080	0.263	0.003	0.003
Retail Trade, Food & Gas	32,599	0.031	0.059	0.102	0.214	-0.005	0.009
Retail Trade, Fuel, Catalog, Vending	6,847	0.025	0.071	0.095	0.576	0.018	0.025
Retail Trade, Misc.	19,697	0.032	0.059	0.284	0.274	-0.007	0.010
Retail Trade, Vehicles	11,246	0.021	0.052	0.124	0.223	-0.005	0.009
Savings Institutions	41,095	0.030	0.052	0.216	0.302	0.008	0.010
Social Services	3,743	0.106	0.173	0.699	0.673	0.018	0.013
Telecomm & Data Processing	28,661	0.059	0.085	0.267	0.411	<0.001	0.008
Transportation	20,591	-0.002	0.049	-0.069	0.386	-0.001	0.005
Trucking	13,974	0.040	0.075	0.236	0.331	<0.001	0.015
Unions & Religious Organizations	12,085	0.016	0.061	0.220	0.327	0.008	0.014
Utilities	7,219	0.025	0.051	0.172	0.348	0.005	0.005
Warehousing & Storage	2,840	0.086	0.203	0.444	3.252	0.031	0.046
Wholesale Trade, Durable	32,044	0.019	0.053	0.088	0.364	0.056	0.017
Wholesale Trade, Nondurable	25,090	0.029	0.076	-0.008	0.241	0.037	0.019
Total	43,955	0.035	0.084	0.162	0.454	0.011	0.025

Notes: Data obtained from IPUMS-USA and County Business Patterns. Weighted by 1980 workers in local industry.

Table 2: The Effect of Immigration on Firm Presence

	Outcome: ΔI_{gkt}	Outcome: ΔFirms_{gkt}	
	(1)	(2)	(3)
$\Delta z_{gkt}^{\text{Emigrants}}$: Emigrants Instrument	0.2410***		
	(0.0204)		
ΔI_{gkt}: Immigrant Inflows per Initial Worker		0.0322***	0.0527***
		(0.0030)	(0.0055)
Specification Type	1st Stage	OLS	Emigrants IV
Within R^2	0.1211	0.0260	0.0348
α_{gt}, α_{kt}	✓	✓	✓
Region × Industry Group × Year FE	✓	✓	✓
1980 Controls × Year FE	✓	✓	✓
Observations	59,000	59,000	59,000

Notes: See Equation (3.1) for specification. Outcome variable ΔFirms_{gkt} is divided by initial workforce in gk to retain consistent scaling with ΔI_{gkt}. All specifications include control variables for 1980 log employment, 1980 establishments per worker, 1980 self-employment share, 1980 college share, and 1980 under-40 share in the local industry interacted with year fixed effects. Observations weighted by 1980 local industry workforce size. Standard errors clustered at the local industry level. Data accessed and analyzed in Michigan Census Research Data Center. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 3: The Effect of Immigration on Firm Presence—Stability and Robustness of IV Estimates

	ΔFirms_{gkt}: Net Firm Entry per Initial Worker					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔI_{gkt}: Immigrant Inflows per Initial Worker	0.0835***	0.0448***	0.0481***	0.0527***	0.0464***	0.0569***
	(0.0070)	(0.0057)	(0.0059)	(0.0055)	(0.0059)	(0.0122)
$\Delta I_{gk,t-10}$: Lagged Immigrant Inflows per Initial Worker						-0.0157
						(0.0146)
Instrument(s)	$\Delta z_{gkt}^{\text{Emigrants}}$	$\Delta z_{gkt}^{\text{Emigrants}}$	$\Delta z_{gkt}^{\text{Emigrants}}$	$\Delta z_{gkt}^{\text{Emigrants}}$	$\Delta z_{gkt}^{\text{Emigrants}}$	$\begin{pmatrix}\Delta z_{gkt}^{\text{Emigrants}} \\ \Delta z_{gk,t-10}^{\text{Emigrants}}\end{pmatrix}$
Panel Pre-Trends Test p-value	0.3244	0.7193	0.7620	0.2697	0.3750	0.0820
Kleibergen-Paap Wald 1st Stage F Statistic	261.8	81.80	88.74	140.1	129.7	29.30
Within R^2	0.0482	0.0305	0.0506	0.0348	0.0674	0.0315
α_{gt}, α_{kt}		✓	✓	✓	✓	✓
1980 Controls × Year FE			✓	✓	✓	✓
Region × Industry Group × Year FE				✓	✓	✓
Control for $\frac{\Delta\text{Workers}_t}{\text{Workers}_{t-10}}$					✓	
Observations	59,000	59,000	59,000	59,000	59,000	40,000

Notes: See Equation (3.1) for specification. All specifications include control variables for 1980 log employment, 1980 establishments per worker, 1980 self-employment share, 1980 college share, and 1980 under-40 share in the local industry interacted with year fixed effects. Observations weighted by 1980 workforce size. Standard errors clustered at the local industry level. Data accessed and analyzed in Michigan Census Research Data Center. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 4: Decomposition of Immigrant-Induced Job Creation

			Jobs Created at Firm Type (per Initial Worker):							
	Total		Deaths		Entrants		Continuers		Net Relocations & Expansions	
	(1)	=	− (2)		+ (3)		+ (4)		+ (5)	
Panel A: OLS										
ΔI_{gkt}: Immigrant Inflows per Initial Worker	0.8558***		-0.1106***		0.2906***		0.1850***		0.2695***	
	(0.0700)		(0.0352)		(0.0347)		(0.0344)		(0.0413)	
Percent of Total	100		12.92		34.00		21.62		31.49	
Panel B: Emigrants IV										
ΔI_{gkt}: Immigrant Inflows per Initial Worker	0.6014***		-0.2573***		0.1572***		0.0857		0.1012	
	(0.1186)		(0.0828)		(0.0575)		(0.0721)		(0.0800)	
Percent of Total	100		42.78		26.14		14.25		16.83	

Notes: See Equation (3.1) for specification. See Section 4.2 for details on outcome variables. All specifications include control variables for 1980 log employment, 1980 establishments per worker, 1980 self-employment share, 1980 college share, and 1980 under-40 share in the commuting zone-sector interacted with year fixed effects. Observations weighted by 1980 workforce size. Standard errors clustered at the commuting zone-industry group level. Data accessed and analyzed in Michigan Census Research Data Center. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 5: Immigrant Presence and Firm Exit, Stratified by Productivity (Full Panel)

	Outcome: I_{gkt}	Outcome: $\mathbb{1}[\text{Shut Down}]_{ft}$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
z_{gkt}: Emigrants Instrument	0.2732***						
	(0.0265)						
I_{gkt}: Immigrants per Initial Worker (β^{main})		-0.0336***	-0.0709***	0.1911***	0.2604***	0.3327***	0.5273***
		(0.0041)	(0.0269)	(0.0131)	(0.0339)	(0.0213)	(0.0521)
$I_{gkt} \times \mathbb{1}[\text{High Prod.}]$ (β^{mod})				-0.5001***	-0.8494***	-0.7073***	-1.067***
				(0.0315)	(0.0642)	(0.0431)	(0.0797)
Effect for High Prod. Firms ($\beta^{\text{main}} + \beta^{\text{mod}}$)					-0.5890***		-0.5393***
					(0.0515)		(0.0526)
Specification Type	1st Stage	OLS	Emigrants IV	OLS	Emigrants IV	OLS	Emigrants IV
Productivity Measure (logged)	—	—	—	Employment	Employment	Payroll per Employee	Payroll per Employee
α_{gt}, α_{kt}	✓	✓	✓	✓	✓	✓	✓
Region × Industry Group × Year FE	✓	✓	✓	✓	✓	✓	✓
2000 Controls × Year FE	✓	✓	✓	✓	✓	✓	✓
Within R^2	0.0616	0.0001	<0.0001	0.003	0.0014	0.0059	0.0044
Observations	15,000,000	15,000,000	15,000,000	15,000,000	15,000,000	15,000,000	15,000,000

Notes: See Equations (5.2) and (5.3) for specification and (5.1) for productivity definitions. All specifications include control variables for 2000 log employment, 2000 establishments per worker, 2000 self-employment share, 2000 college share, and 2000 under-40 share in the commuting zone-sector interacted with year fixed effects. Standard errors clustered at the commuting zone-industry group level. Data accessed and analyzed in Michigan Census Research Data Center. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 6: Immigrant Presence and Firm Exit, Stratified by Productivity (SBO Panel)

	Outcome: $\mathbb{1}[\text{Shut Down}]_{ft}$				
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS					
$I_{gk,t-2}$: Immigrants per Initial Worker	-0.0269*	0.1433***	0.1854***	0.0620**	0.1806***
	(0.0161)	(0.0314)	(0.0373)	(0.0247)	(0.0384)
$I_{gk,t-2} \times \mathbb{1}[\text{High Prod.}]$		-0.5617***	-0.4687***	-0.3214***	-0.5049***
		(0.0861)	(0.0730)	(0.0641)	(0.0826)
Panel B: Emigrants IV					
$I_{gk,t-2}$: Immigrants per Initial Worker	-0.1080	0.8044***	1.168***	0.3494***	1.225***
	(0.0763)	(0.1446)	(0.1843)	(0.1077)	(0.2048)
$I_{gk,t-2} \times \mathbb{1}[\text{High Prod.}]$		-2.630***	-2.407***	-1.681***	-2.557***
		(0.2876)	(0.2882)	(0.2023)	(0.3289)
Productivity Measure (logged)	—	Employment	Payroll per Employee	Revenues	Revenues per Employee
α_{gt}, α_{kt}	✓	✓	✓	✓	✓
Region × Industry Group × Year FE	✓	✓	✓	✓	✓
2000 Controls × Year FE	✓	✓	✓	✓	✓
Observations	611,000	611,000	611,000	611,000	611,000

Notes: See Equations (5.4) and (5.5) for specification and (5.1) for productivity definitions. All specifications include control variables for 2000 log employment, 2000 establishments per worker, 2000 self-employment share, 2000 college share, and 2000 under-40 share in the commuting zone-sector interacted with year fixed effects. Observations weighted by SBO survey weights. Standard errors clustered at the commuting zone-industry group level. This table will be supplemented with Within R^2 measures and a First Stage estimate in future drafts. Data accessed and analyzed in Michigan Census Research Data Center. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 7: Immigrant Presence and Firm Exit—The Role of Immigrant Entrepreneurship

	Outcome: $\mathbb{1}[\text{Shut Down}]_{ft}$				
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS					
$I_{gk,t-2}$: Immigrants per Initial Worker	0.0097	0.1816***	0.2130***	0.1108***	0.2136***
	(0.0175)	(0.0326)	(0.0351)	(0.0271)	(0.0406)
$I_{gk,t-2} \times \mathbb{1}[\text{Immi Owned}]$	-0.1422***	-0.1456***	-0.1254*	-0.1753***	-0.1277**
	(0.0358)	(0.0479)	(0.0642)	(0.0443)	(0.0509)
$I_{gk,t-2} \times \mathbb{1}[\text{High Prod.}]$		-0.5530***	-0.4821***	-0.3424***	-0.4900***
		(0.0831)	(0.0675)	(0.0651)	(0.0857)
$I_{gk,t-2} \times \mathbb{1}[\text{Immi Owned}] \times \mathbb{1}[\text{High Prod.}]$		-0.0470	0.0737	0.0377	-0.0611
		(0.1085)	(0.1029)	(0.0906)	(0.0802)
Panel B: Emigrants IV					
$I_{gk,t-2}$: Immigrants per Initial Worker	0.0223	1.198***	1.553***	0.6582***	1.710***
	(0.0846)	(0.1721)	(0.2088)	(0.1296)	(0.2419)
$I_{gk,t-2} \times \mathbb{1}[\text{Immi Owned}]$	-0.2790***	-0.8495***	-0.9173***	-0.6581***	-1.052***
	(0.0908)	(0.1356)	(0.1469)	(0.1255)	(0.1776)
$I_{gk,t-2} \times \mathbb{1}[\text{High Prod.}]$		-3.128***	-2.919***	-2.059***	-3.101***
		(0.3426)	(0.3280)	(0.2585)	(0.3781)
$I_{gk,t-2} \times \mathbb{1}[\text{Immi Owned}] \times \mathbb{1}[\text{High Prod.}]$		1.219***	1.272***	0.9445***	1.289***
		(0.2347)	(0.2296)	(0.2330)	(0.2590)
Productivity Measure (logged)	—	Employment	Payroll per Employee	Revenues	Revenues per Employee
α_{gt}, α_{kt}	✓	✓	✓	✓	✓
Region × Industry Group × Year FE	✓	✓	✓	✓	✓
2000 Controls × Year FE	✓	✓	✓	✓	✓
Observations	611,000	611,000	611,000	611,000	611,000

Notes: See Equations (5.6) and (5.7) for specification and (5.1) for productivity definitions. All specifications include control variables for 2000 log employment, 2000 establishments per worker, 2000 self-employment share, 2000 college share, and 2000 under-40 share in the commuting zone-sector interacted with year fixed effects. Observations weighted by SBO survey weights. Standard errors clustered at the commuting zone-industry group level. This table will be supplemented with Within R^2 measures and a First Stage estimate in future drafts. Data accessed and analyzed in Michigan Census Research Data Center. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 8: Key Calibrations

Parameter	Value	Target Moments	Source
Panel A: Individually Calibrated			
σ_E	1.5	—	Ottaviano and Peri (2012)
σ_I	10	—	Ottaviano and Peri (2012)
μ	4	Average U.S. Markup = 32%	Christopoulou and Vermeulen (2012)
ϕ	3.1	$\phi > \mu - 1$	—
κ^e	3	—	—
m	1	—	—
Panel B: Jointly Calibrated			
a	0.64	$\frac{w_{NU}}{w_S} = 0.52$	2000 Census
b_0	[0.15, 0.55]	$\frac{w_{IU}}{w_S} = 0.4$	2000 Census
κ_0^f	0.25	$F = 0.05$	2000 Business Dynamics Statistics

Table 9: Percent Change in Native Welfare for a One Percent Increase in Workforce Due to Immigration

		Δ_b				
		0.1	0.2	0.3	0.4	0.5
	1.6	0.479	0.495	0.497	0.498	0.498
	1.7	0.479	0.495	0.497	0.498	0.498
τ	1.8	0.479	0.495	0.497	0.498	0.498
	1.9	0.479	0.495	0.498	0.498	0.498
	2	0.479	0.495	0.498	0.498	0.498

Table 10: Components of Immigrant Surplus

	Δ_b				
	0.1	0.2	0.3	0.4	0.5
Standard: $\frac{d\log(w_{NU}N_U+w_SN_S)}{dI} - \frac{d\log(c_0)}{dI}$	0.176	0.152	0.149	0.148	0.148
Firm Mass ($\eta = 1$): $\left(\frac{\eta}{\mu-1}\right)\frac{d\log(F)}{dI}$	0.518	0.476	0.470	0.470	0.470
Culling: $\frac{d\log(z_0^*)}{dI}$	0.230	0.279	0.286	0.286	0.286
Switching: $\left(\frac{1}{\mu-1}\right)\frac{d\log(\theta)}{dI}$	0.077	0.093	0.095	0.095	0.095
Total:	1	1	1	1	1

A Appendix

A.1 Industry Classifications

Table A1: Industry Groups

Grouping	1990 Census Codes	2007 NAICS Codes
Construction	60	23
Management of companies	710	55
Utilities	422, 450, 451, 470–472	22, 486, 562
Manufacturing – Food	100, 101, 102, 110 , 111, 112, 120, 121, 122, 130, 610	311–312
Manufacturing – Clothing	132, 140, 142, 150, 151, 152, 220, 221, 222	313–316
Manufacturing – Wood & Furniture +	160–162, 231, 232, 241, 242, 250–252, 261, 262	321, 322, 327, 337
Manufacturing – Plastics +	180–182, 190–192, 200, 201, 210–212	324–326
Manufacturing – Metals & Machinery	270–272, 280–282, 290–292, 300, 301, 310–312, 320, 321, 331, 332, 380	331–333
Manufacturing – Electrical & Household	322, 340–342, 350, 371, 372, 381, 390, 391	334, 335, 339
Manufacturing – Transportation	351, 352, 360–362, 370	336
Wholesale Trade – Durable	500, 501, 502, 510–512, 521, 530–532	423
Wholesale Trade – Nondurable	540–542, 550–552, 560–562	424
Retail Trade – Vehicles	612, 620, 622	441
Retail Trade – Household Durables	580–582, 631–633	442–444
Retail Trade – Food & Gas	601, 602, 611, 621, 650	445, 447
Retail Trade – Misc.	590, 640, 642, 651, 652, 661, 662, 681, 682	446, 451, 453
Retail Trade – Apparel	623, 630, 660	448
Retail Trade – Dept. & Variety Stores	591, 592, 600	452
Retail Trade – Fuel, Catalog, Vending	663, 670–672	454
Transportation	400, 420, 421	481–483
Trucking	410	484, 492
Bus & Taxi	401, 402	485
Warehousing & Storage	411	493
Non-Telephone Communication	440, 852	515, 519
Telecomm & Data Processing	441, 442, 732	517, 518
Savings Institutions	700–702	521, 522
Insurance	711	524
Real Estate	712	531
Professional Services	12, 721, 741, 841, 882, 890–893	541, 711
Admin. & Support Services	20, 432, 722, 731, 740	561
Educational Services	842, 850, 851, 860	611
Health Services excl. Hospitals	812, 820–822, 830, 840	621
Hospitals	831	622
Nursing & Residential Care Facilities	832, 870	623
Social Services	861–863	624
Entertainment Services	742, 800–802, 810, 872	512, 532, 712, 713
Lodging	762, 770	721
Eating & Drinking Places	641	722
Repair Services	750–752, 760, 782, 790	811
Personal Services	771, 772, 780, 781, 791	812
Unions & Religious Organizations	873, 880, 881	813

A.2 Instrument Vetting

This section presents a variety of analyses and visualizations that bolster the case for $z_{gkt}^{\text{Emigrants}}$ as a relevant and valid instrument in Sections 4 and 5. As of this draft, these analyses are done using publicly-available data in order to limit the size of disclosure requests from the U.S. Census Bureau. That means independent variables like I_{gkt} are measured from IPUMS-USA (Ruggles et al., 2019). Estimated specifications are from Equation (3.1), but with y_{gkt} generally corresponding to outcomes that can be measured from IPUMS-USA—primarily the change in employment in a given commuting zone-industry pairing (local industry) gk. Note that the change in employment growth does not include self-employed individuals for comparability with the LBD-measured employment used in the main text (Figure 7 and Table 4. Using this outcome allows me to utilize the consistent industrial classification system provided by the IPUMS-USA variable `ind1990` and use the 1970s as a pre-period for placebo tests. Pre-trends and other issues with estimation using employment changes as an outcome should portend similar issues using outcomes related to changes in establishment presence, changes in firm presence, and changes in employment measured from the LBD. Also note that the observation counts in the analyses presented in this section vary from those presented in the main text because the sample restrictions throw out many more local industries in the publicly-available data than they do in the restricted-access data—yet another demonstration of the latter's value. Throughout this section, I will also present comparisons between $z_{gkt}^{\text{Emigrants}}$ and $z_{gkt}^{\text{Standard}}$ to highlight changes induced by the adjustment I make to the standard immigration shift-share instrument.

A.2.1 Comparability of Results: Immigration and Establishment Presence Using Publicly-Available Data

This section compares results from regressions using publicly-available data to results in Column 1 Table 4 and across use of different instruments. It does so using two measures of the change in the number of employees per initial worker for a given decade as Δy_{gkt} in Equation (3.1). The first, used for the majority of this appendix section, comes from IPUMS-USA, and simply measures the change in the number of individuals classified as private employees based on their survey responses to the 1980, 1990, 2000 Decennial Long-Form Censuses and the 2007-2011 American Community Survey. The second is enabled by recent work in Eckert et al. (2020), whose imputation procedure enable employment counts from the County Business Patterns (CBP) at the county level across consistent NAICS codes from 1980 to the present. The CBP and LBD have the same source data, so this second outcome should more closely correspond to the outcome used in Column 1 of Table 4.

Table A2 demonstrates that across these two outcomes, $\Delta z_{gkt}^{\text{Emigrants}}$ delivers similar results using publicly-available data as it does using restricted-access data. Of particular note is the similarity between Columns 2 and 7, which points both to the utility of the Eckert et al. (2020) imputation procedure and the utility of publicly-available data to study this outcome. Thus, while future drafts will finalize the checks contained in Section A.2 using restricted-access data, Table A2 is a "proof of concept" for the rest of this section, indicating that checks using publicly-available data presented in this draft are likely still informative.

Table A2: Results Across Instruments (Publicly-Available Data)

	Outcome: Change in Employees per Initial Worker							
	Source: Table 4		Source: IPUMS-USA			Source: CBP (Eckert et al., 2020)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔI_{gkt}: Immigrant Inflows per Initial Worker	0.856***	0.601***	1.587***	0.728***	1.052***	0.733***	0.602***	0.581**
	(0.070)	(0.1186)	(0.114)	(0.195)	(0.207)	(0.0854)	(0.224)	(0.262)
Instrument	None—OLS	Emigrants	None—OLS	Emigrants	Standard	None—OLS	Emigrants	Standard
1st Stage F Statistic	—	140.1	—	48.52	47.07	—	48.52	47.07
Within R^2	Not disclosed	Not disclosed	0.143	0.101	0.127	0.022	0.021	0.021
α_{gt}, α_{kt}	✓	✓	✓	✓	✓	✓	✓	✓
Region × Industry Group × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
1980 Controls × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	59,000	59,000	29,091	29,091	29,091	29,091	29,091	29,091

Notes: See Equation (3.1) for specification. Data obtained from IPUMS-USA and County Business Patterns via Fabian Eckert. All specifications include control variables for 1980 log employment, 1980 establishments per worker, 1980 self employment share, 1980 college share, and 1980 under-40 share in the local industry interacted with year fixed effects. Observations weighted by 1980 local industry workforce size. Standard errors clustered at the commuting zone-sector level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

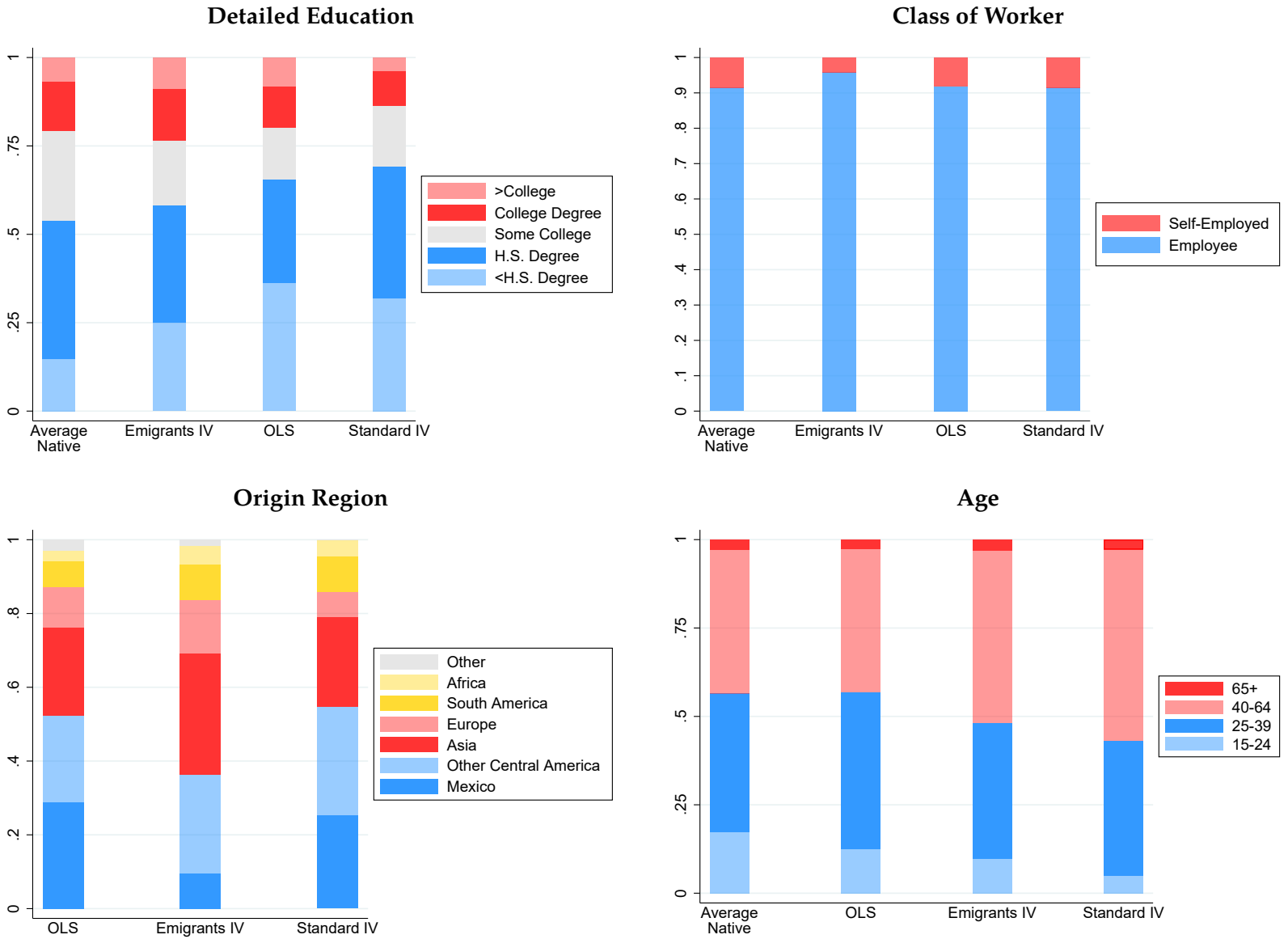
A.2.2 Additional Characteristics of Inflows

The following figure decomposes immigrant inflows in ΔI_{gkt} by various characteristics based on the following specification:

$$\Delta I_{gkt}^{\text{Characteristic}} = \alpha + \boldsymbol{\beta}\left[\Delta I_{gkt}\right] + \Gamma X_{gkt} + \alpha_{gt} + \alpha_{rkt} + \varepsilon_{gkt} \tag{A.1}$$

Equation A.1 exploits the adding-up property of linear regression for mutually exclusive and exhaustive groupings, decomposing how many workers of each characteristic are brought in by each immigrant, on average. Figure 3 of the main text already uses Equation (A.1) to decompose the composition immigrant inflows into educational categories. Here, I utilize Equation (A.1) for a variety of additional illustrative decompositions. As in the main text, the purpose of this figure is to ascertain whether the individuals pushed into immigrating to U.S. local industries by $\Delta z_{gkt}^{\text{Emigrants}}$ are similar to 1) the receiving native workforce and 2) the typical immigrant inflow to a U.S. local industry, which can be seen in the OLS bar of each panel.

Figure A1: Additional Characteristics of Immigrant Inflows



A.2.3 *Country-Level Pushes*

In order for $z_{gkt}^{\text{Emigrants}}$ to provide a good source of exogenous variation for I_{gkt}, we not only need it to be randomly assigned, but also to be relevant. In this section, I show simple evidence that $M_{ot}^{\text{non-US}}$ is a relevant predictor of I_{ot}—total immigrant stock in the U.S. from country o. Crucially, this is true both in levels and changes (including a country fixed effect)—outflows to non-U.S. OECD countries predict inflows to the U.S. Thus, $z_{gkt}^{\text{Emigrants}}$ is not simply replacing the "shift" component of the "shift-share" instrument with noise. Instead, it is replacing it with a relevant factor that is plausibly exogenous relative to commuting zone-industry level outcomes in the U.S. The regressions take the form of

$$f(I_{ot}) = \alpha + \beta^{\text{Push}} f(M_{ot}^{\text{non-US}}) + g(\alpha_o, \alpha_t) + \varepsilon_{ot}$$

where $f(x)$ either logs x, keeps x level, or divides x by origin o's 1980 population. $g(\cdot)$ represents a linear combination. Table A3 presents the results. Note that because these results use publicly-available they do not reflect the full set of over 150 countries used to generate $z_{gkt}^{\text{Emigrants}}$ in the main results using restricted-access data. Future drafts will update these results accordingly.

Table A3: Push Factors

	Outcome: $\frac{I_{ot}}{\text{Population}_{o,1980}}$		Outcome: $\log(I_{ot})$		Outcome: I_{ot}	
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{M_{ot}^{\text{non-US}}}{\text{Population}_{o,1980}}$	0.6861***	0.7719***				
	(0.1196)	(0.1128)				
$\log(M_{ot}^{\text{non-US}})$			0.4430***	0.5516***		
			(0.0666)	(0.0616)		
$M_{ot}^{\text{non-US}}$					0.1883**	0.3724**
					(0.0748)	(0.1889)
Within R^2	0.413	0.400	0.247	0.377	0.017	0.012
Year FE	✓	✓	✓	✓	✓	✓
Country FE		✓		✓		✓
Observations	420	420	420	420	420	420
Countries	105	105	105	105	105	105

Notes: Dependent variables obtained from IPUMS-USA. Indpendent variables obtained from the IAB, and the United Nations' World Population Prospects 2017 for population denominator. Standard errors clustered at the country level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

A.2.4 *Pre-Trends and Balance Tests*

A distinct advantage of publicly-available employment measured by IPUMS-USA relative to the CBP is that IPUMS-USA contains employment with a consistent industry classification going back to 1970. This enables a pure pre-trends test that is not often available in panel, shift-share settings. This pre-trends test uses the change in employees per initial worker in the 1970s as the outcome in Equation (3.1). For comparison, I plot the results of this pre-trends test against the in-study-period

effect (Columns 4 and 5 in Table A2). That is,

$$\Delta y_{gkt} = \alpha + \beta_{\text{study period}} \left(\Delta I_{gkt}\right) + \Gamma X_{gkt} + \alpha_{gt} + \alpha_{r(g)kt} + \varepsilon_{gkt}$$
$$\Delta y_{gk,1980} = \alpha + \beta_{\text{pre-period}} \left(\Delta I_{gkt}\right) + \Gamma X_{gkt} + \alpha_{gt} + \alpha_{r(g)kt} + \varepsilon_{gkt}$$

The results can be seen below, in Figure A2. Interestingly, the OLS coefficient in the pre-period shows no sign of a pre-trend. This, of course, does not preclude the need for an instrument, as discussed in detail in the main test: the exclusion restriction must hold *during the study period*. Nonetheless, this may increase interest in the OLS results presented throughout the paper. The rich fixed effects structure contained in Equation (3.1) may account for some of the biases we are used to seeing when we study the effect of immigration on economic outcomes. There is a significant, negative effect of immigration during the study period on pre-period changes in employment when we use the standard instrument $\Delta z_{gkt}^{\text{Standard}}$ that is not statistically detectable when we use $\Delta z_{gkt}^{\text{Emigrants}}$. Using $\Delta z_{gkt}^{\text{Standard}}$ may, for example, confound a direct effect of immigration on employment growth with reversion to the mean.

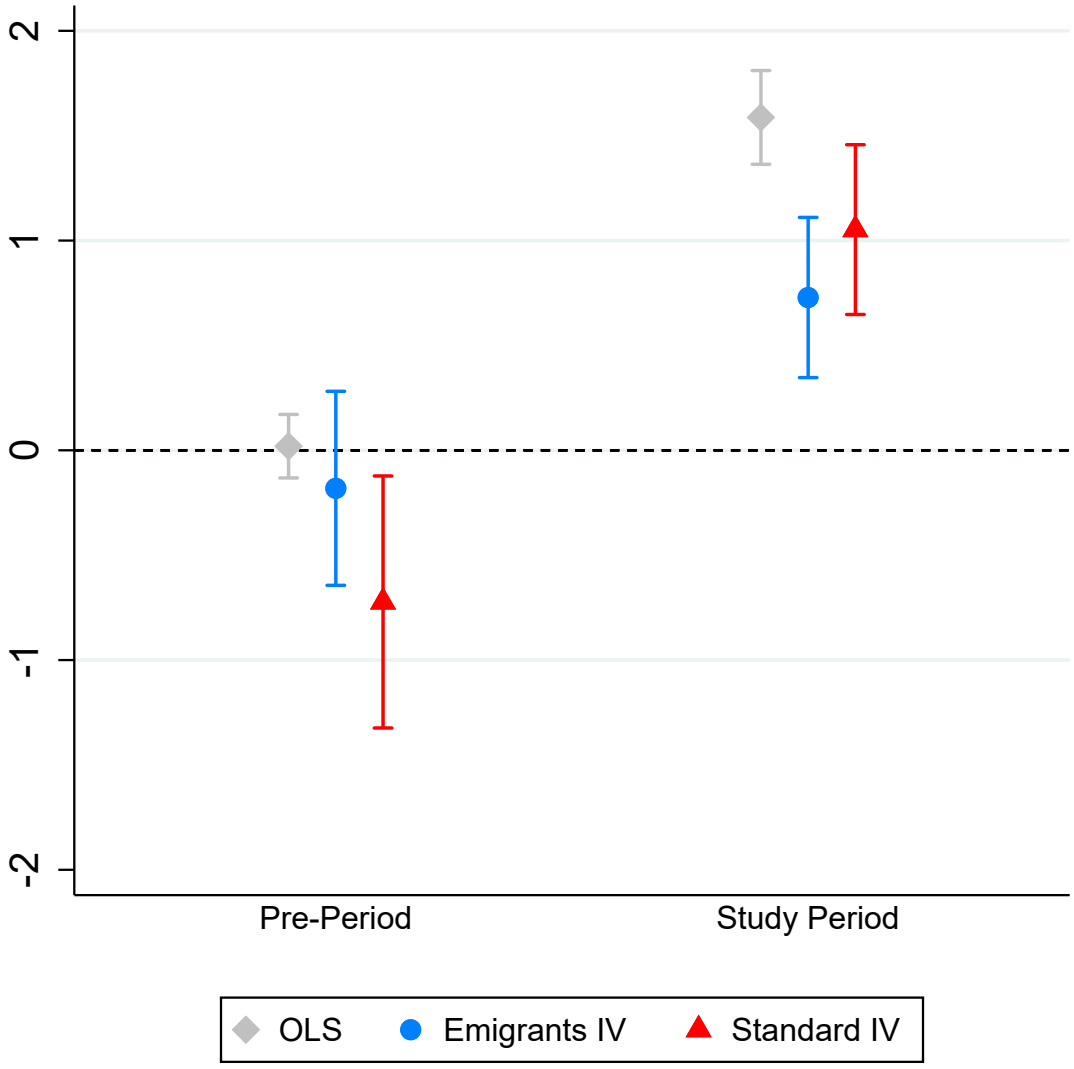
A.2.5 Confounding Short and Long-Run Responses (Jaeger et al., 2018)

Jaeger et al. (2018) broach a concern that arises from serial correlation in the "shift" component of "shift-share" instruments—one that is particularly concerning with regards to the standard immigration shift-share instrument. When this shift component is excessively serially correlated over time, estimated parameters like β in in Equation (3.1) can confound short- and long-run responses to immigrant inflows. Though this concern is particularly deleterious when wages are the primary outcome variable of interest, it merits consideration in any setting where prior shocks may affect current outcomes.

Jaeger et al. (2018) propose a data-demanding procedure to both test for and account for such concerns, which is to include both the independent variable and its lag, and to instrument for both (i.e., here, include ΔI_{gkt} and $\Delta I_{gk,t-10}$ and use both $\Delta z_{gkt}^{\text{Emigrants}}$ and $\Delta z_{gk,t-10}^{\text{Emigrants}}$ as instruments. Table 2 already demonstrates that $\Delta z_{gkt}^{\text{Emigrants}}$ passes this rigorous test, and additionally provides evidence that the effect of immigrant inflows on firm presence is largely confined to the decade of the inflow, at least when comparing across industries within commuting zones. Here, I present evidence that this robustness applies to employment as an outcome as well and is a unique feature of $\Delta z_{gkt}^{\text{Emigrants}}$ relative to $\Delta z_{gkt}^{\text{Standard}}$.

Table A4 presents the relevant results. While $\Delta z_{gkt}^{\text{Emigrants}}$loses a substantial amount of first stage relevance, it retains enough of a first stage to make reasonable inferential statements about estimated coefficients. On the other hand, the specification with $\Delta z_{gkt}^{\text{Standard}}$ breaks down in terms of first stage relevance, rendering it uninterpretable. In line with Jaeger et al. (2018), I hypothesize that the reason is that emigrant outflows to non-U.S. locations are less serially correlated across time across origin countries o than are immigrant inflows to the U.S., which are dominated by Mexico.

Figure A2: Jobs Created per Immigrant—Pre-Trends Test and Effect Estimates



Notes: See Equation (3.1) for specification. Data obtained from IPUMS-USA. All specifications include control variables for 1980 log employment, 1980 establishments per worker, 1980 self employment share, 1980 college share, and 1980 under-40 share in the local industry interacted with year fixed effects, region-industry group-year fixed effects, and commuting zone-year fixed effects. Observations weighted by 1980 local industry workforce size. Standard errors clustered at the commuting zone-sector level.

Table A4: Results Across Instruments, with Double Instrumentation (Publicly-Available Data)

	Outcome: Change in Employees per Initial Worker					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔI_{gkt}	1.587***	1.476***	0.728***	0.770***	1.052***	3.158
	(0.114)	(0.105)	(0.195)	(0.285)	(0.207)	(6.119)
$\Delta I_{gk,t-10}$		-0.308***		-0.243		-2.754
		(0.0644)		(0.302)		(7.585)
Instrument	None—OLS	None—OLS	Emigrants	Emigrants	Standard	Standard
1st Stage F Statistic	—	—	48.52	14.33	47.07	0.0640
Within R^2	0.143	0.158	0.101	0.122	0.127	-0.318
α_{gt}, α_{kt}	✓	✓	✓	✓	✓	✓
Region × Industry Group × Year FE	✓	✓	✓	✓	✓	✓
1980 Controls × Year FE	✓	✓	✓	✓	✓	✓
Observations	29,091	19,394	29,091	19,394	29,091	19,394

Notes: See Equation (3.1) for specification. All specifications include control variables for 1980 log employment, 1980 establishments per worker, 1980 self employment share, 1980 college share, and 1980 under-40 share in the local industry interacted with year fixed effects. Observations weighted by local industry 1980 workforce size. Standard errors clustered at the commuting zone-sector level. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

A.2.6 Correlated Shocks Across gk with Similar Shares (Adao et al., 2019)

Adao et al. (2019) find that regression residuals can be substantially correlated across areas with similar "share" components in shift-share instruments, invalidating standard inference procedures. Importing their concerns to the current study, any industry-country level shocks that affect outcomes through the presence of base year shares $\pi_{go,1980}$, even if not related to immigration itself, can generate correlated outcomes across areas with similar $\pi_{go,1980}$.

A simple example that could apply here would be a sector-specific trade shock in a given origin country. For example, if Syria experiences a positive trade shock that is independent of Syrian emigration forces, this can affect firm presence in areas heavily populated by Syrians in the U.S.—e.g., Detroit and Boston—through trade linkages, but it is unlikely to have any affect on firm presence in areas like Atlanta or Miami with low Syrian populations. These correlated shocks would not create a bias in β, but would require a modification of standard errors beyond clustering at the commuting zone-industry level, since Detroit and Boston are not even in the same region.

Adao et al. (2019) illustrate this issue by conducting placebo tests in which they replace the "shift" component with white noise and assessing the resulting false rejection rate after multiple simulations of the reduced form regression model. Here, the analogous placebo exercise uses instruments of the form

$$z_{gkt}^{\text{Placebo}} \frac{1}{E_{g,1980}} \sum_{o} \pi_{go,1980} \times \rho_{o(-r(g))kt} \times \omega_{okt}$$

where ω_{okt} is a random draw from a normal distribution . Each placebo instrument is then used in the reduced form estimating equation:

$$\Delta y_{gkt} = \alpha + \beta^{\text{Placebo}} \left[\Delta z_{gkt}^{\text{Placebo}} \right] + \Gamma X_{gkt} + \alpha_{gt} + \alpha_{r(g)kt} + u_{gkt}$$

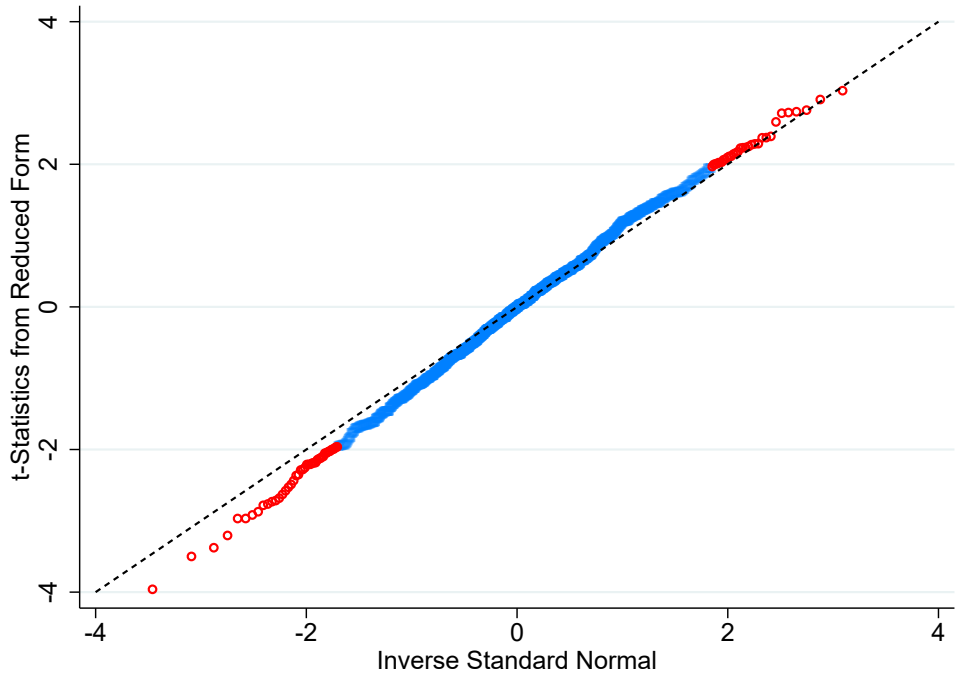
with publicly-available (IPUMS-USA) change in employees per initial worker from IPUMS-USA as the outcome and errors clustered at the local industry (commuting zone-industry) level, as in the main analysis.

Results from 1,000 placebo simulations are summarized in Table A5 and Figure A3. There is evidence of a small bias in the standard errors when clustering at the local industry level. The false rejection rate at the 95% confidence level is 0.0592 (should be 0.05) and the false rejection rate at the 99% confidence level is 0.0121 (should be 0.01). In Figure A3, I present a Q-Q plot that does not portend any signs of non-standardness in the asymptotic distribution—other than being slightly fatter tailed (as implied in Table A5. I hypothesize that the rich fixed effects structure $\alpha_{gt} + \alpha_{r(g)kt}$ removes much of the correlation across geographies found in Adao et al. (2019) when they study the standard immigration instrument at the gt (rather than gkt) level, but the remaining over-rejection will be addressed in future drafts.

Table A5: Summary Characteristics of 1,000 t-Statistics from Adao et al. (2019) Placebo Simulations (Publicly-Available Data)

	Simulation Result	Target
Mean	-0.035	0
Standard Deviation	1.118	1
False Rejection Rate: 90% Confidence Interval	0.136	0.1
False Rejection Rate: 95% Confidence Interval	0.077	0.05
False Rejection Rate: 99% Confidence Interval	0.022	0.01

Figure A3: Q-Q Plot from Adao et al. (2019) Placebo Simulations (Publicly-Available Data)



Notes: Data obtained from IPUMS-USA. Red circles represent a simulation that resulted in a false rejections whereas blue squares represent simulations that did not result in false rejections.

A.3 Evidence from Case Studies

In order to establish a causal empirical relationship between immigration and business presence, I separately analyze, then pool together, two well-known case studies from the immigration literature—the 1980 Mariel Boatlift in Miami and the 2008 enactment of the Legal Arizona Workers Act (LAWA). The structure of the analyses presented in this sub-section can be thought of as mimicking an indirect least squares approach to instrumental variable estimation. In each case, I establish a "first stage," in which an event spurred a large inflow (or outflow) of immigrants into (or out of) a local geography, either using existing estimates in the literature or through my own estimation. I then estimate "reduced form" effects of these events on the counts of establishments in those geographies using the Synthetic Control Method (SCM) (Abadie et al., 2010). Finally, using a pooling method proposed by Dube and Zipperer (2015), I combine the case studies and generate harmonized estimates of the dynamic effects of immigration on net firm presence. The case studies that I focus on broadly represent two distinct push factors for immigration that are common in the U.S.—shocks originating in sending countries and policies meant to deter undocumented immigration. Continuing the analogy to instrumental variables, these case studies will thus estimate different local average treatment effects, and pooling them together will generate an average of these different effects.

Despite its numerous benefits, because of the wide range of covariates that can be used in a given SCM model, the methodology can be susceptible to cherry-picking (Ferman et al., 2016). In order to circumvent these concerns, I choose the predictor variables for each synthetic control model for establishments per worker using a cross-validation procedure, also proposed by Dube and Zipperer (2015). Briefly, the procedure selects the set of control variables that best predicts donor unit outcomes in the post-treatment period.[38] The utility of this methodology can be seen in selection of sector shares for inclusion in the model. Geographic areas, including Arizona, that had high concentrations in the construction industry because of the housing bubble were harder hit by the Great Recession. These shares, then, serve as key control variables because they ensure that Arizona and its metropolitan areas are compared to other areas that were hard-hit by the Great Recession for the same underlying reason. Additional outflows of immigrants that occurred in Arizona after 2008, relative to these other hard-hit areas, are then more credibly claimed to be the result of LAWA rather than the Great Recession. The cross-validation procedure selects sector shares for inclusion precisely because they help accurately predict post-recession (post-2008) local economic paths in donor geographies. Section A.4.1 provides a more detailed overview of SCM, while Section A.4.2 provides additional details of the cross-validation procedure.

A.3.1 Background and Data

The first case study I examine is the Mariel Boatlift, representing variation generated by push factors that occur abroad. The Mariel Boatlift saw roughly 125,000 Cubans immigrate to Miami between May and September of 1980 after Fidel Castro announced that he would open the ports of Mariel, Cuba to those seeking to leave the country. Beginning with the seminal work of Card (1990), the literature has gone back and forth regarding the consequences of this labor supply shock on the wages of substitutable workers in Miami, where a majority of "Marielitos" ended up settling (Peri and Yasenov, 2015; Borjas, 2017; Clemens and Hunt, 2017). Taking advantage of this

[38] "Donor" units are all geographies other than the treated unit. Each receives a non-negative weight. The weighted sum of donor unit outcomes, using these weights, is the "synthetic control" outcome.

existing literature, I rely on previous estimates of the size of the Mariel inflow shock rather than estimating it myself: the "first stage" effect of the Mariel Boatlift was to increase Miami's foreign-born workforce by 6.6 percent relative to initial employment (Card, 1990). However, I follow a more recent literature in examining how the Mariel Boatlift affected alternate adjustment channels, beyond wage changes (e.g., Anastasopoulos et al., 2018). I seek to extend this work by examining its effect on establishment presence in the Miami metropolitan statistical area.

The second case study I consider is the introduction of the Legal Arizona Workers Act (LAWA) in 2008, representing variation generated by sub-national legislation meant to curb the presence of undocumented immigrants in local areas. LAWA attempted to achieve this aim by requiring all employers to verify the eligibility of their new hires using the national E-Verify system. Bohn et al. (2014) previously studied LAWA, and found that it produced a robust and statistically significant drop in the number of Hispanic residents with less than a high-school degree in Arizona—the group most likely to contain undocumented immigrants. Unlike the Mariel case, I estimate the "first stage" affect of LAWA on overall immigrant presence since direct analogs have not been previously estimated.[39] This first stage model is estimated using the same covariates selected for the "reduced form," establishment outcome. In order to keep geographies consistent across cases, I specifically study Arizona's largest metropolitan statistical area, Phoenix-Mesa-Scottsdale, and drop the remaining Arizona cities from the analysis. Full results for the Arizona case at the state level can be seen in Section A.4.4.

The data for the case study analyses come from IPUMS-USA and the County Business Patterns. Using IPUMS-USA (Ruggles et al., 2019), I construct measures of immigrant presence for 1980, 1990, and 2001 through 2004 at the state level and 2000 and 2005 through 2014 for both the state and MSA level. Data for the years 1980, 1990, and 2000 are from public-use Decennial Long-Form Census microdata, while data for 2005 onward are from public-use American Community Survey microdata. The County Business Patterns (CBP) contains counts of establishments by industry and size at the county level going back to the 1960s. For consistent coverage, I use the CBP from 1970 forward. The CBP also generates key control variables: log employment as a proxy for market size and sector shares. These data were accessed directly from the Census Bureau and from the Inter-university Consortium for Political and Social Research (ICSPR). These counts, divided by employment in the year before treatment ($t^* - 1$) serve as the outcomes in the analysis described below.

A.3.2 Individual Case Results

Figure A4 shows standard SCM results for the two events examined in this paper. Along with plotting the treated unit's outcome ($y_{gt,\text{treated}}$ for a given outcome variable y and treated geography g) and the synthetic control outcome ($y_{gt,\text{synthetic}}$) in the top row, the bottom row also shows the evolution of the difference-in-differences estimates between the two ($[y_{gt,\text{treated}} - y_{gt,\text{synthetic}}] - [y_{g,t^*-1,\text{treated}} - y_{g,t^*-1,\text{synthetic}}]$, where $t^* - 1$ is the year before treatment) compared to this same difference for each potential donor unit, after constructing a "placebo" synthetic control for each donor unit in its bottom row. Comparing the thick black line (which plots the evolution of the treated unit) to the gray lines (one for each donor unit) generates a visual test of how unique the treated unit is in its behavior both before and after the event. The predictor variables include

[39] Bohn et al. (2014) study the change in the proportion of residents that are Hispanic with less than a high-school degree—a proxy for the proportion of residents that are undocumented. In order to retain consistency with the Mariel case and with the independent variable studied in Section 3, I study the change in the overall immigrant workforce relative to 2007 employment in Arizona. Nonetheless, the results of this exercise are wholly consistent with Bohn et al. (2014)—both find that LAWA generated a severe drop in immigrant presence.

every-five-year pre-treatment averages of the outcome[40], along with log employment, sector shares, the under-40 year-old share, the self-employed share, and the college share at time $t^* - 1$. These variables were selected using the cross-validation procedure described above.

As found in Bohn et al. (2014) for Arizona, Phoenix shows a stark decrease in its immigrant workforce after the passage of LAWA in Figure A4. This is true both for the state as a whole and for its largest metropolitan area, Phoenix-Mesa-Scottsdale.[41] Note that immigrant workers can be employees or self-employed, so this outflow captures actual decreases in the number of immigrants relative to the counterfactual, not just the also-sizable response of switching to self-employment documented in Bohn and Lofstrom (2012).

For the Phoenix cases, I define

$$\delta^{1S} \equiv (I_{\text{treated},t^*+5} - I_{\text{synthetic},t^*+5}) - (I_{\text{treated},t^*-1} - I_{\text{synthetic},t^*-1})$$

where I_{gt} is the immigrant worker count in year t and geography g divided by the overall year $t^* - 1$ worker count in g. I use five years later as a benchmark to define permanent changes to the labor force induced by LAWA and to retain consistency with similar estimates for the Mariel Boatlift in Card (1990). For Phoenix, Table A6 shows these estimates along with "empirical" p-values, generated after conducting exact inference based on the rank of the δ^{1S} for the treated unit relative to the rank of the same parameter estimated after creating a synthetic control for all donor units (see Abadie et al., 2010 for details of this inference procedure). This manner of inference formalizes the aforementioned visual placebo tests in the bottom rows of Figures A4.

Table A6: "First Stage" Scaling Factors δ^{1S}

Case	Treatment Start (t^*)	Variation Source	Δ_I^{DD}	Empirical p-value
Phoenix-Mesa-Scotsdale, AZ	2008	Arizona LAWA	-0.052	0.056
Miami-Fort Lauderdale-West Palm Beach, FL	1980	Mariel Boatlift	0.066	—

Source: First row—author's calculations from IPUMS-USA and County Business Patterns. Second row—Card (1990) p. 248 and Table 1.

Miami's first stage is not included in Figure A4 because the Mariel Boatlift occurred before yearly estimates of immigrant populations are available for the U.S.[42] However, as mentioned above, the number of Marielitos and total employment in Miami in 1979 are well-documented in Card (1990). These allow me to construct an estimate of δ^{1S} for Miami, shown in Table A6. As a numerator, I use Card's estimate that the Mariel Boatlift generated a permanent increase in the Miami foreign-born workforce of 45,000. As a denominator, I use his tabulated estimate of the 16-61 year-old Miami labor force in 1979, 678,200.[43] Comparing the first column in Figure A4 to the second two columns reveals that both Miami and Phoenix appear to feature a positive relationship between firm presence and immigrant inflows. This is despite the fact that the origins of these inflows are substantively different, as described above.

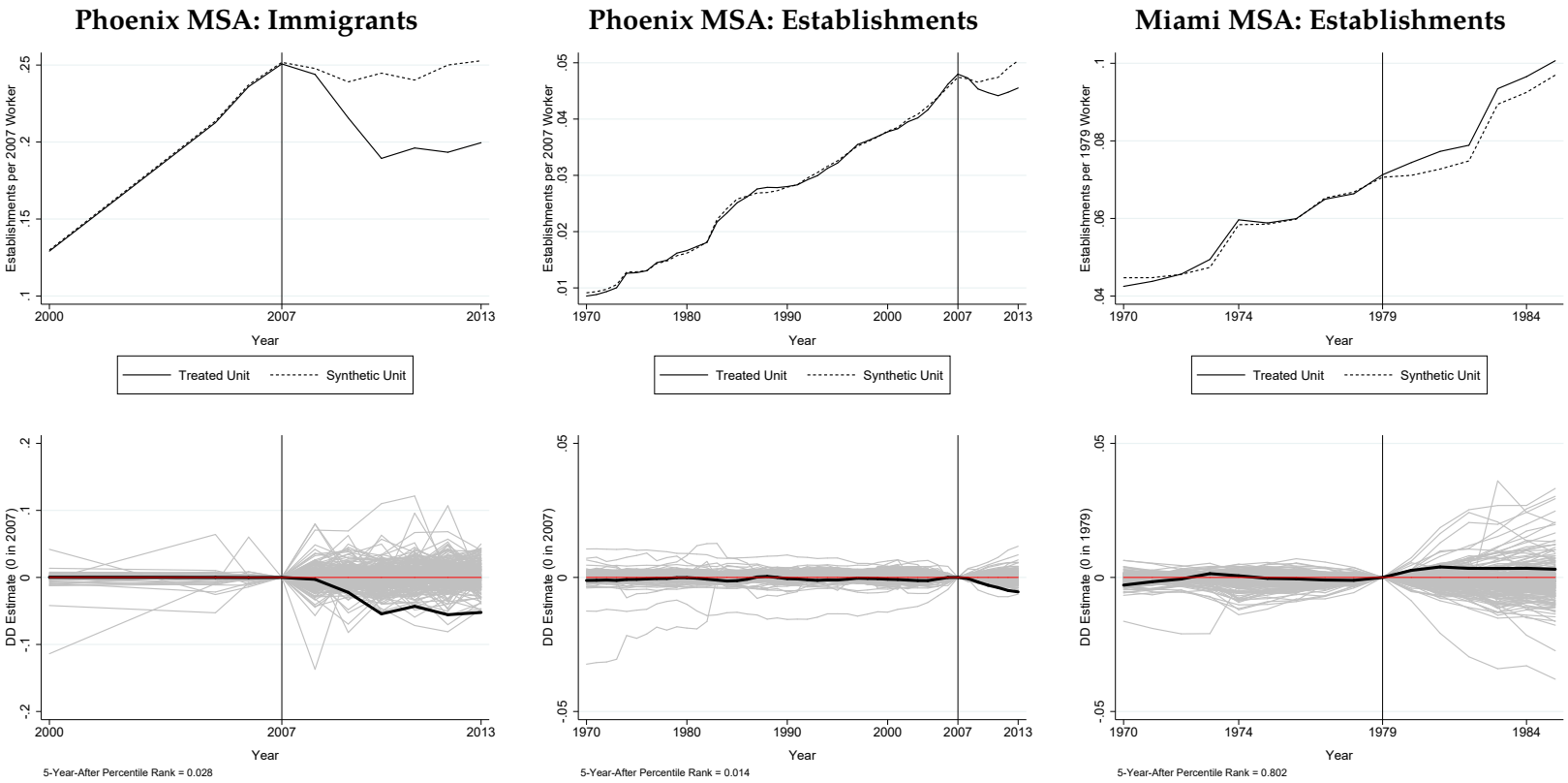
[40] i.e., 1970-1974 and 1975-1979 for Miami and 1970-1974, 1975-1979,...,1995-1999, and 2000-2007 for Phoenix/Arizona.

[41] See Figure A6 for Arizona as a whole. Results do not change qualitatively when considering Phoenix compared to Arizona as a whole. From this point forward, I will use "Phoenix" and "Phoenix-Mesa-Scottsdale" interchangeably.

[42] Peri and Yasenov (2015), for example, use the "Hispanic" variable in the CPS to get around this.

[43] Note that in Card (1990), Miami is only defined as Miami-Dade County, and both the numerator and denominator here reflect that county only. My outcome and control variables include Ft. Lauderdale and West Palm Beach—the entire Miami commuting zone.

Figure A4: Individual Synthetic Control Results—Measures per Initial (t^* – 1) Worker



Source: Author's calculations from IPUMS-USA and County Business Patterns.

A.3.3 Pooling Cases

Despite the suggestive nature of the point estimates, the reduced form results presented in the second and third columns Figure A4 come from distinct first stages—both in terms of size and sign. In order to harmonize these analyses and double my statistical power, I pool cases and conduct an exercise similar to two-stage least squares. This approach is motivated by Dube and Zipperer (2015), who pool SCM cases to study the effects of minimum wage changes. As a first and aforementioned step, I focus on the largest metropolitan area in Arizona—Phoenix—rather than the state as a whole and drop the other Arizona cities from the analysis.[44] This harmonizes the geographies being studied to the MSA level while keeping the number of events being studied to two.

I then define

$$\delta_t^{RF} \equiv (y_{\text{treated},t} - y_{\text{synthetic},t}) - (y_{\text{treated},t^*-1} - y_{\text{synthetic},t^*-1})$$

where y_{gt} stands for the number of establishments in year t and geography g divided by year $t^* - 1$ employment in g. Where δ^{1S} can be thought of as a "first stage" in instrumental variable parlance—the causal effect of a given event on immigrant inflows five years after—we can similarly think of δ_t^{RF} as a "reduced form"—the causal effect of that same event on net establishment entry in year t.

I can then utilize the indirect least squares formula and define

$$\beta_t^e \equiv \frac{\delta_t^{RF}}{\delta^{1S}}$$

where e stands for a given event (i.e., $e \in \{\text{Mariel Boatlift,LAWA}\}$). Then, following Dube and Zipperer (2015), I estimate an average across events to recover a single estimate of the effect of immigrant inflows on net firm creation in year t

$$\beta_t \equiv \frac{1}{E} \sum_e \beta_t^e$$

where E is the total number of events ($E = 2$ here). I estimate β_t for $t \leq 5$ to retain consistency with δ^{1S} and to avoid confounding factors that can arise over longer horizons. The interpretation of β_5 is then the number of firms associated with each exogenously pushed, permanent immigrant over the five year period after the initial shock. β_1 through β_4 show us how the generation of β_5 evolves.

As described above, individual SCM results generally utilize exact inference based on the rank of the difference-in-difference estimator for the treated unit relative to the rank of the same parameter estimated after creating a synthetic control for all donor units. This percentile rank has a uniform distribution, enabling simple calculation of empirical p-values. Dube and Zipperer (2015) extend this concept to pooled case studies, where inference of the mean of these difference-in-difference estimates (such as β_t) estimated by SCM is facilitated by the fact that the sum of uniform random variables has a known (Irwin-Hall) distribution. Further details on inference used in this section can be seen in Appendix Section A.4.3 and Dube and Zipperer (2015).[45]

[44] An alternate strategy is to expand our focus from Miami to the state of Florida and pool case studies at the state level. The results from this pooling exercise can be seen in Section A.4.4.

[45] Note that I only use δ^{1S} as a scaling factor here—I do not account for variance in its estimation in the pooling exercise. The confidence intervals should be understood as only applying to the reduced form.

The primary result of this harmonized, pooled SCM exercise at the metropolitan level can be seen in Figure A5. Pooled estimates from Miami and Phoenix in pre-treatment years hover around and are not statistically distinguishable from zero, passing the standard event study pre-trends test. Five years after the immigration shock, the estimated effect of immigrant inflows on establishment presence is roughly 0.08. This number is economically meaningful: if we were to apply it to overall immigrant inflows into the U.S. between 1980 and 2010, it would indicate that immigrants were responsible for 40 percent of net establishment creation in that period despite only being responsible for 30 percent of net workforce growth. As expected, this number is also greater than the estimated effects found below in Section 4, where any effects of consumer demand are limited by comparing across industries within commuting zones. However, it is strikingly similar to estimates in Section 4 that do not control for consumer demand. Unlike the decade-by-decade analysis featured in Section 3, however, Figure A5 also sheds light on the dynamic responses of local labor markets to immigration shocks. These responses start relatively rapidly, but continue to show an upward trend throughout the analysis window.

A.3.4 Discussion

The results in this section imply a causal link between immigrant inflows and establishment presence. They also raise a new set of questions regarding its nature. In particular, that more immigrants lead to more firms may be the result of increased overall consumer demand, immigrant-specific consumer demand, general labor cost reductions, or immigrant-specific characteristics from the supply side of the product market. Due to data limitations, they are also unable to shed light on whether the link between immigration and firm presence comes from firm entry, the prevention of firm exit, or a combination of the two.[46] Thus, while the results contained in this section provide clear identification, they ultimately serve more as a proof of concept. The rest of this section, then, utilizes detailed data to probe 1) whether the effect found here is broad-based beyond the specific cases of Arizona and Miami; 2) whether some of it can be accounted for by the effect immigrants have on the production side of the economy, as workers and entrepreneurs as opposed to as consumers; 3) its heterogeneous nature in terms of firm age, size, and other characteristics; and 4) how much it matters for immigrant absorption.

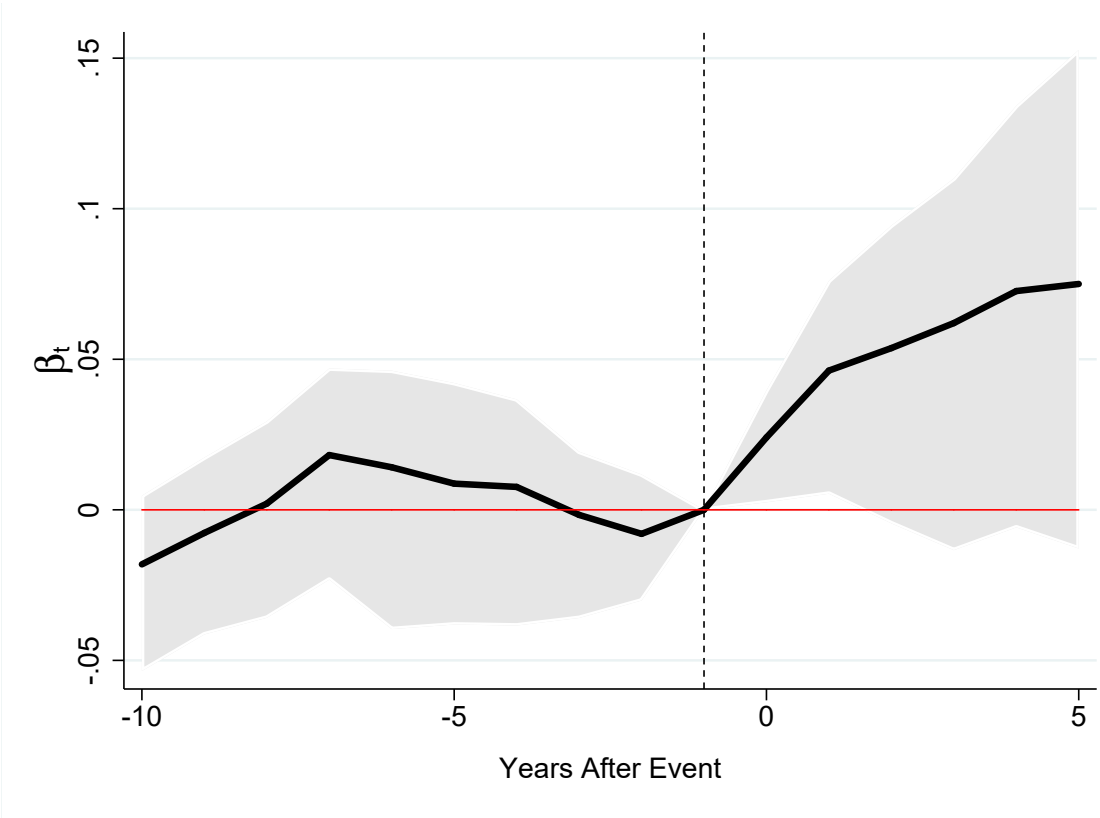
A.4 Case Studies: Further Details

A.4.1 Synthetic Control Method: an Overview

The Synthetic Control Method (SCM) is a data driven approach for constructing control groups when treatments occur in specific geographies. By incorporating elements of matching, it relaxes the traditional difference-in-differences assumption that confounding factors must be time invariant in order to estimate unbiased treatment effects. It allows common shocks across regions to

[46] Previous drafts of this paper used the U.S. Census Bureau's Business Dynamics Statistics (BDS) at the metropolitan statistical area (MSA) level for this analysis. The BDS has substantial advantages over the CBP: it counts firms as well as establishments, and counts firm entry and exit separately, allowing researchers to study the flows that change the firm stock. However, two disadvantages regarding the Miami case study render it currently ill-suited for use here. First, the synthetic control method is suited for cases with many pre-treatment years, whereas the Mariel Boatlift occurred in 1980 and the BDS starts in 1977. Second, the BDS appears to have a significant discrepancy with the CBP regarding establishment and employment counts for the Miami MSA. In 1980, the BDS measures 524,350 employees, whereas the Decennial Census measures 1,057,240 and the CBP measures 982,983. Future drafts plan to resolve this discrpenacy and combine information from the CBP and BDS to both give the SCM enough pre-treatment years to properly find a synthetic control unit for Miami, and to be able to take advantage of the rich data contained in the BDS.

Figure A5: Pooled SCM Results, Establishments per Immigrant (β_t)



Source: Author's calculations from IPUMS-USA and County Business Patterns.
Notes: 95% confidence intervals represented by gray area around point estimates indicated by solid black line. These confidence intervals only apply to the "reduced form"—"first stage" only used as a scaling factor. Combined estimates reflect the cases of Phoenix-Mesa-Scottsdsale, AZ with 2008 as year 0 and Miami, FL with 1980 as year 0.

affect different regions differently. In short, SCM utilizes the information at its disposal, including pre-event outcomes, to generate a control group most similar to the treated unit in its pre-treatment behavior. Specifically, given a set of untreated, "donor" geographies, D, a set of M control variables for each of these donors, $X_{M\times 1}$, and a year of treatment t^*, SCM solves

$$W^*(V) = \arg\min_{\boldsymbol{W}} ||X_{\text{treated},m} - \mathbf{X}'W||_{v_m}$$

where $\mathbf{X}_{D\times M}$ stacks the vectors of control variables over donors. $W^*(V)_{(D\times 1)}$ is a set of weights for donor units that minimizes the distance between the control variables in the treated and donor units. Like with matching, X can and should include pre-treatment outcomes, but should not include the full set of pre-treatment outcomes (Kaul et al., 2015). Denoting y_t as the outcome of interest and y_{Dt} as the $(D \times 1)$ vector of outcomes in the donor units at time t,

$$W^*(V)' \times y_{Dt} \equiv y_{t,\text{Synthetic}}$$

gives the synthetic control value at each time t. In order to trace out year-over-year dynamic responses to shocks, the parameters of interest for a given outcome y take the form

$$\delta_{yt} \equiv (y_{\text{treated},t} - y_{\text{synthetic},t}) - (y_{\text{treated},t^*-1} - y_{\text{synthetic},t^*-1}) \tag{A.2}$$

For $t < t^* - 1$, δ_{yt} serves as a test for parallel trends and for $t \geq t^*$, δ_{yt} is akin to an event study treatment effect estimate. At $t^* - 1$, the estimate is normalized to 0.

A.4.2 Choosing Predictors Using Cross-Validation

Because of the wide range of covariates that can be used in a given SCM model, the methodology can be susceptible to cherry-picking in terms of which variables go into X (Ferman et al., 2016). In order to circumvent these concerns, I choose each synthetic control model using a cross-validation procedure proposed by Dube and Zipperer (2015). The procedure is essentially a pseudo-out-of-sample test of how well a given candidate set of predictors does in forecasting *post-treatment* outcomes for donor (untreated) geographies. It creates these forecasts by constructing a synthetic control for each of the donor units. That is, in order to select X, the following procedure is implemented:

1. Choose a candidate X
2. Run the synthetic control method for each donor unit d and each event e
3. Choose the X^* such that $X^* = \arg\min_X \sum_e \sum_{d=1}^{D} \sum_{t\geq t^*} \left(Y_{dt} - \sum_{q\neq d} w_q^*(X) Y_{qt}(X)\right)^2$

where the term $\sum_{q\neq d} w_q^*(X) Y_{qt}(X)$ represents the synthetic control constructed for donor unit d. The treated units are excluded from this entire process. Additionally, I only run this process on the reduced form outcome establishments per $t^* - 1$ worker. The first stages for Phoenix and Arizona are estimated using the chosen X^* from the cross-validation procedure run on the reduced form.

The chosen X^* for SCM estimation were: sector shares, the under-40 year-old share, the self-employed share, and the college share, all in $t^* - 1$. I include log employment in the year before the

event and five-year pre-treatment averages of the outcome, establishments per time $t^* - 1$ worker, in all models. Note that the under-40 year-old share, the self-employed share, and the college share are only able to be included for Phoenix and Arizona. The chosen donor units and their weights can be seen below, in Table A7.

Table A7: Synthetic Control Weights

Geography	Weight
Panel A: Phoenix MSA, Immigrants per Initial Worker*	
Cape Coral-Fort Myers, FL	0.280
Daphne-Fairhope-Foley, AL	0.159
Santa Fe, NM	0.105
Merced, CA	0.057
Madera, CA	0.023
Port St. Lucie, FL	0.010
Salinas, CA	0.010
Panel B: Phoenix MSA, Establishments per Initial Worker	
Austin-Round Rock-Georgetown, TX	0.595
Salisbury, MD-DE	0.094
Cape Coral-Fort Myers, FL	0.089
Port St. Lucie, FL	0.066
Ocala, FL	0.053
San Diego-Chula Vista-Carlsbad, CA	0.047
Riverside-San Bernardino-Ontario, CA	0.036
Barnstable Town, MA	0.021
Panel C: Miami MSA, Establishments per Initial Worker	
San Diego-Chula Vista-Carlsbad, CA	0.381
San Francisco-Oakland-Berkeley, CA	0.205
New York-Newark-Jersey City, NY-NJ-PA	0.145
Houston-The Woodlands-Sugar Land, TX	0.132
Sacramento-Roseville-Folsom, CA	0.084
Ocean City, NJ	0.052

*The Phoenix MSA has several other donor units with weights of less than 0.01 that are not listed here.

A.4.3 Inference

In order to conduct inference and construct confidence intervals for the pooled SCM case studies, I harmonize the analysis to a set of 214 metropolitan statistical areas delineated by the Office of Management and Budget in 2013. Note that all Arizona cities are excluded from the SCM estimates for Miami and all other Arizona cities and Miami are excluded from the SCM estimates for Phoenix. I then once again follow procedures laid out in Dube and Zipperer (2015).

First, for each event e, I calculate δ_t^{RF} for the treated unit as well as a "placebo" version of this estimator for each donor unit as if the donor unit was treated in the same year, $\delta_{t,\text{donor}}^{RF}$.[47] I then divide all of these estimates by the δ^{1S} from the treated unit. The result is an actual estimate of the effect of immigrant inflows on firm presence in the treated unit, β_t^e as well as a set of placebo estimates, $\beta_{t,\text{donor}}^e$ that are used to construct an empirical distribution for inference.

The first step in the inference process involves ranking the estimates of β_t^e among the 212 estimates of $\beta_{t,\text{donor}}^e$. The estimated rank percentile is this rank divided by 213. The test statistic for combined inference is then simply the average of these percentile ranks. The critical values needed

[47] I exclude the treated unit when calculating the placebo estimates.

to conduct inference are given in Table A1 of Dube and Zipperer (2015) for $N = 2$. Inverting this hypothesis test to generate confidence intervals, like those shown in Figure A5, simply involves finding the mean of the empirical distributions at these critical values, $\frac{1}{E}\sum_e \beta^e_{t,\text{donor}}(crit)$. For example, the lower bound of the 95 percent critical value is the estimate β_t plus this mean at the 2.5 percent critical value (0.111) from the aforementioned Table A1 of Dube and Zipperer (2015).

A.4.4 Results from State-Level Case Studies

As described in Section A.3, one way to pool the Mariel and Arizona cases is to focus on Arizona's largest city, Phoenix, and Miami. The other alternative is to consider Arizona and Florida together. This section conducts this alternative for completeness.

Interestingly, Florida shows a stronger relationship in the state case study than Miami did in the individual city case study. This somewhat aligns with previous evidence stemming from the Mariel Boatlift case study. Card (1990), for example, documents that Florida as a whole experienced less population decline than did Miami in the years following the Boatlift. Indeed, most previous Mariel Boatlift studies find that the absorption of Marielitos was only accompanied by a short run increase in population, wholly consistent with net emigration to (or less inmigration to Miami from) the rest of Florida (see, e.g., Figure 2 in Peri and Yasenov, 2015). These relative expansions in the rest of the state could mean that it was really the state of Florida that more completely absorbed the Marielitos rather than Miami itself (see here for anecdotal evidence that the whole state was affected). This, in turn, would lead to larger establishment presence in the rest of the state. Relative to the rest of this paper, this provides moderate caution regarding the magnitudes of the effects found in Section 4. Given the possibility population displacement, particularly when immigration shocks are large, these estimates should be viewed as a lower bound. Smaller shocks that are most likely used for identification from the instrumental variable are less likely to create these issues (see, e.g., Card and DiNardo, 2000).

Table A8: Synthetic Control Weights

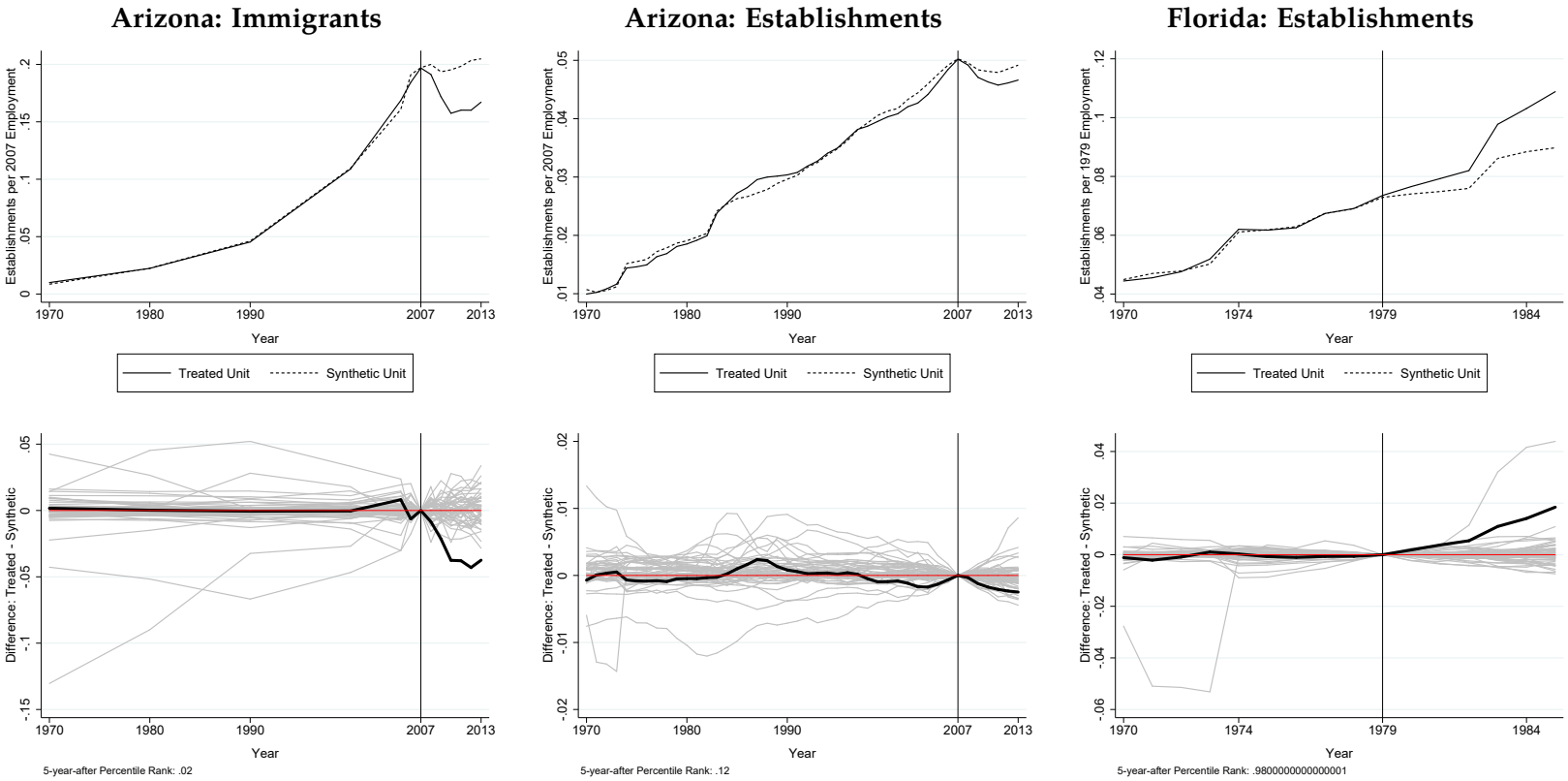
Geography	Weight
Panel A: Arizona, Immigrants per Initial Worker	
Alaska	0.066
Delaware	0.025
Florida	0.05
Georgia	0.111
Maryland	0.043
Nevada	0.566
Utah	0.138
Panel B: Arizona, Establishments per Initial Worker	
Alaska	0.088
Maryland	0.155
Nevada	0.613
Tennessee	0.01
Utah	0.134
Panel C: Florida, Establishments per Initial Worker	
Alaska	0.035
Arizona	0.057
Hawaii	0.230
Maine	0.002
Maryland	0.086
Nebraska	0.008
Rhode Island	0.272
Wyoming	0.300

Table A9: Synthetic Control First Stage Δ_I^{DD}

Case	Treatment Start (t^*)	Variation Source	Δ_I^{DD}	Empirical p-value
Arizona	2008	Arizona LAWA	-0.043	0.038
Florida	1980	Mariel Boatlift	0.036	—

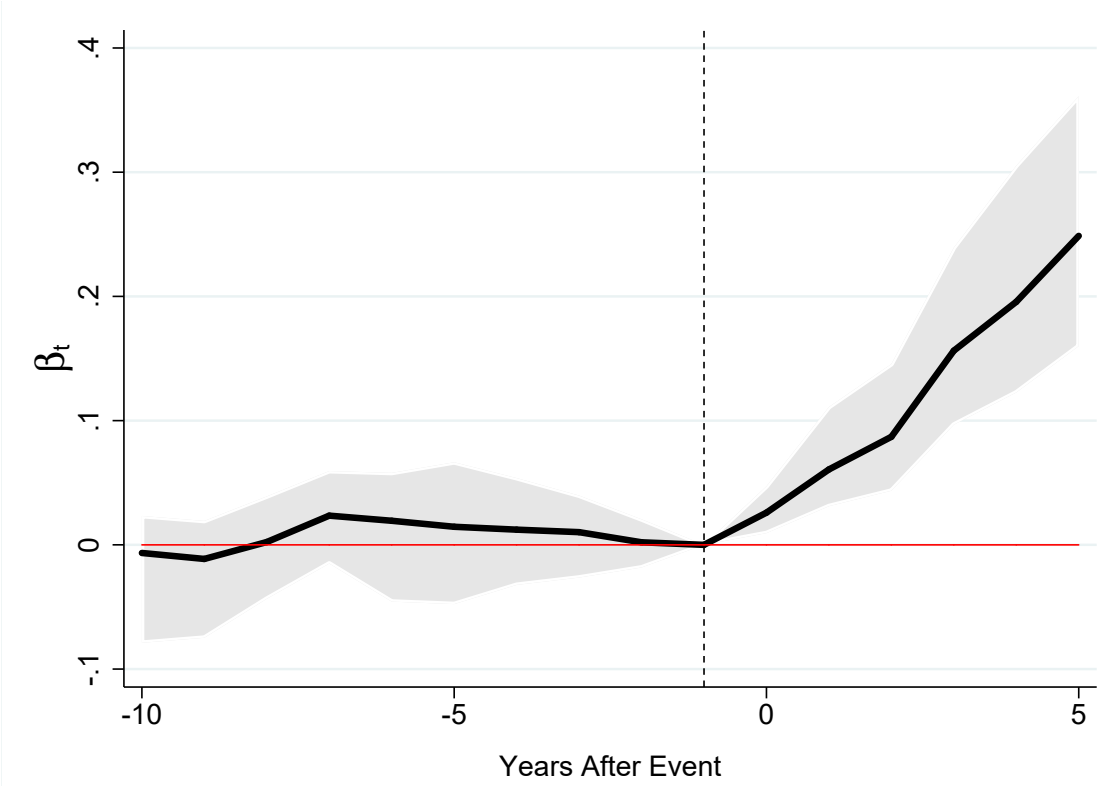
Source: First row—author's calculations from IPUMS-USA and County Business Patterns. Second row—Card (1990) p. 248 and author's calculations from Current Population Survey (CPS) Merged Outgoing Rotation Group accessed using IPUMS-CPS; assumes all 125,000 Marielitos stayed in Florida in order to be conservative.

Figure A6: Individual Synthetic Control Results—Measures per Initial ($t^* - 1$) Worker



Source: Author's calculations from IPUMS-USA and County Business Patterns.

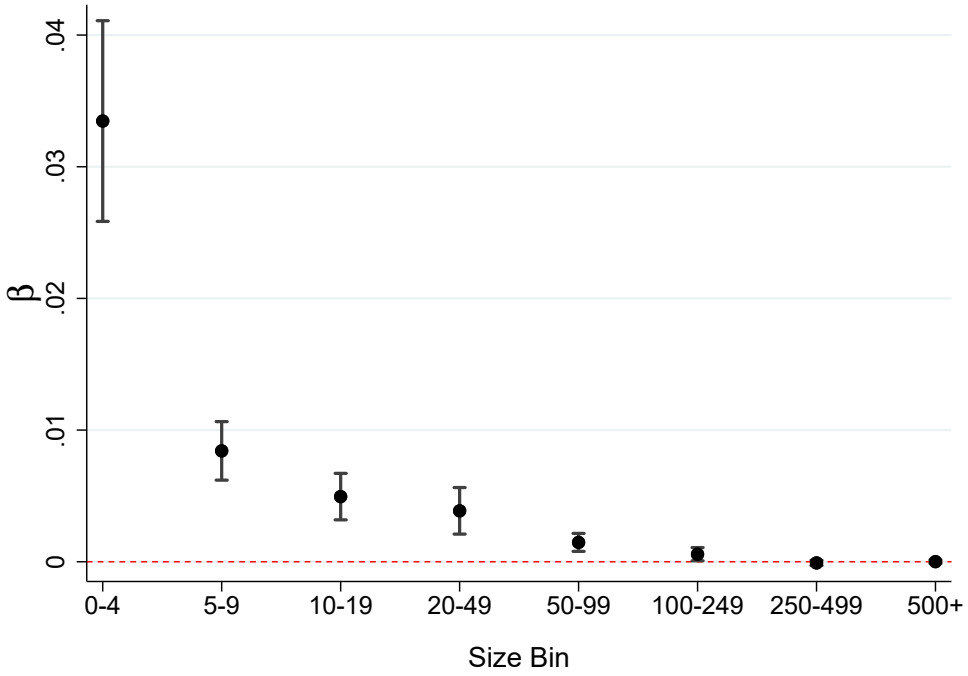
Figure A7: Pooled SCM Results, Establishments per Immigrant (β_t)



Source: Author's calculations from IPUMS-USA and County Business Patterns.
Notes: 95% confidence intervals represented by gray area around point estimates indicated by solid black line. These confidence intervals only apply to the "reduced form"—"first stage" only used as a scaling factor. Combined estimates reflect the cases of Arizona with 2008 as year 0 and Florida with 1980 as year 0.

A.5 Firm Size Results in Levels

Figure A8: The Effect of Immigration on Firm Presence—Size Decomposition



Notes: See Equation (3.1) for specification. Data accessed and analyzed in Michigan Census Research Data Center.

A.6 Model Additions and Extensions

A.6.1 Comparing the Immigrant Surplus in a Representative Firm Model to a Model with Firm Heterogeneity

As a starting point, consider the following, constant elasticity of substitution (CES), model of production for a representative firm[48] in a local economy:

$$Q = \bar{z}\left(aI^{\frac{\sigma_I - 1}{\sigma_I}} + \bar{N}^{\frac{\sigma_I - 1}{\sigma_I}}\right)^{\frac{\sigma_I}{\sigma_I - 1}} \tag{A.3}$$

where I represents immigrant labor, $\bar{N}$ represents a fixed stock of native labor, $\bar{z}$ is total factor productivity, and σ_I is the elasticity of substitution between immigrant and native employees. While a more realistic version of the production function would start with nests for education and eventually work its way down to nativity (see, e.g., Ottaviano and Peri, 2008), this model delivers much of the intuition for the rest of this section in a simple way. In this context, σ_I can be thought of as a reduced form parameter that aggregates all the different reasons why an average immigrant worker may be different than an average native worker (including average educational attainment (see Figure 3).

Let native wages, w_N, be the numeraire. There is only one good, so consumer welfare is simply a function of its price and wages. When I increases in this model, the economy expands automatically (we can think of this as long run capital adjustment with a fixed rental rate in the background), but what matters to native workers is how it affects the price of the good. Denoting immigrant wages as w_I, P as the price of the good, taking first order conditions, and rearranging yields the following expression:

$$\mathcal{W}_I \equiv -\frac{d\log(P)}{dI} = -\frac{d\log(c)}{dI} \tag{A.4}$$

where

$$c \equiv (a^{\sigma_I} w_I^{1-\sigma_I} + 1)^{\frac{1}{1-\sigma_I}}$$

are labor costs to the firm. $\mathcal{W}_I$ is proportional to the immigrant surplus—the surplus accruing to the native workers as a result of immigrant inflows. Here, it is directly tied to the labor cost savings that occur as immigrant wages decline in response to I rising. Using similar, CES production function models, both Borjas (2014) and Ottaviano and Peri (2008) find that $\mathcal{W}_I$ is small and positive.

Sections 4 and 5 will show that immigrants have large and heterogeneous effects on extensive margin decisions by firms. This suggests accounting for these effects in our theoretical analysis of immigration. This point has been made explicitly by di Giovanni et al. (2014), who feature gains from variety in their global welfare analysis of immigration. Melitz (2003) offers a simple way to incorporate extensive margin firm responses in long-run, steady state, general equilibrium analysis. The key features of this model are 1) consumer taste for variety, 2) a non-degenerate total factor productivity distribution across firms, and 3) a fixed cost of production. Combined, these features generate monopolistic competition that results in a non-trivial, but finite, firm mass, with heterogeneity across each firm's total factor productivity level.

We can gain simple insights into how our analysis of immigration may change when we account for these features by placing the production function from (A.3) into the closed economy Melitz

[48] Or, the aggregation of many, small, identical firms.

(2003) framework, where each firm is indexed by its own total factor productivity, z:

$$q(z) = zL(z)$$
$$L(z) = \left[a\left(I(z)\right)^{\frac{\sigma_I - 1}{\sigma_I}} + \left(N(z)\right)^{\frac{\sigma_I - 1}{\sigma_I}} \right]^{\frac{\sigma_I}{\sigma_I - 1}}$$

Consumers have elasticity of substitution μ across firms, leading to a conventional pricing rule for each firm:

$$p(z) = \left(\frac{\mu}{\mu - 1}\right)\left(\frac{c}{z}\right) \tag{A.5}$$

where w_I is the immigrant wage and we once again set native wages w_N to be the numeraire. The overall price index is given by

$$P^{1-\mu} = n_e \int_{z^*}^{\infty} p(z)^{1-\mu} g(z) dz$$

where n_e is the entrepreneur mass and z^* is the cutoff productivity, below which these entrepreneurs suffer losses and therefore exit in the long run. $g(z)$ is the distribution of productivity across firms in the local economy. I follow convention in assuming it is Pareto:

$$g(z) \equiv \phi m^{\phi} z^{-\phi - 1}$$

The mass of firms in the local economy is simply $F \equiv n_e \int_{z^*}^{\infty} g(z)dz = n_e m^{\phi} \left(z^*\right)^{-\phi}$.

With these simple ingredients in place, we can derive the following expression:

$$\mathcal{W}_I \equiv \underbrace{-\frac{d\log(c)}{dI}}_{\text{Same as above}} + \underbrace{\left(\frac{1}{\mu - 1}\right)\frac{d\log(F)}{dI}}_{\text{Increased variety through more firms}} + \underbrace{\frac{d\log(z^*)}{dI}}_{\text{Productivity pass-through to prices}} \tag{A.6}$$

In this setup, the immigration surplus has two additional terms compared to the representative firm model, in Equation (A.4). The first represents welfare gains in the form of increased consumer variety. The second represents welfare gains that arise from an increase in the productivity bar that entrepreneurs must cross in order to operate in the market. As seen in Equation (A.5), firms with higher z charge lower prices to consumers in order to compete away market share from their competitors. Thu\phi-(\mu-1)s, when z^* rises and lower productivity firms exit the market, consumers benefit through lower prices. The signs of each of these additional reduced form parameters are explored in detail in the empirical analyses of this paper. Section 4 finds that increased exposure to immigrant workers generates an increase in firm presence in local labor markets, while Section 5 finds that low productivity firms are culled from the market—in the language of this model, the latter indicates an increase in z^*.

A.6.2 Derivation of Labor Market Equilibrium

In this section, I derive labor market equilibrium for low-education immigrant labor. An analogous derivation gives us labor market equilibrium for low-education native labor. Skilled labor's price is set to be the numeraire, as described in the text. Firm's maximize the following expression for profits:

$$\pi_j(z) = p_j(z)q_j(z) - \sum_i \sum_e w_{ie} i_e - c_j \kappa_j^f$$

where $i \in \{I, N\}$ and $e \in \{U, S\}$. They take their demand curves, $q_j(z) = p_j(z)^{-\mu} P^{\mu-1} Y$ and their production functions $q_j(z) = z L_j(z)$ as given. Thus, first order conditions yield:

$$\begin{aligned} w_{IU} &= c_j L^{1/\sigma_E} a U_j^{1/\sigma_I - 1/\sigma_E} b_{Uj} I_{Uj}^{-1/\sigma_I} \\ w_{NU} &= c_j L^{1/\sigma_E} a U_j^{1/\sigma_I - 1/\sigma_E} N_{Uj}^{-1/\sigma_I} \end{aligned} \tag{A.7}$$

So, we have the familiar relative wage expression among low-education immigrant and native workers:

$$\frac{w_{IU}}{w_{NU}} = \left(\frac{I_{Uj}}{N_{Uj}} \right)^{-1/\sigma_I} b_{Uj}$$

Solving for N_{Uj} and plugging into the low-education aggregate U_j then yields the following expression for U_j in terms of I_{Uj}:

$$U_j = I_{Uj} b_{Uj}^{-\sigma_I} w_{IU}^{\sigma_I} c_{Uj}^{-\sigma_I}$$

Plugging this expression back into (A.7) yields the following expression for I_{Uj} in terms of wages and L_j:

$$I_{Uj} = w_{IU}^{-\sigma_I} b_{Uj}^{\sigma_I} c_j^{\sigma_E} c_{Uj}^{\sigma_I - \sigma_E} a^{\sigma_E} L_j \equiv I_{Uj}^{\text{unit}} L_j$$

Firms use L_j to produce output and to cover their fixed costs. Thus, integrating across firms yields the following expression that equates low-education immigrant labor supply, I_U, with labor demand:

$$I_U = n_e \left[\int_{z_0^*}^{z_1^*} I_{U0}^{\text{unit}} \left(\frac{q_0^*(z)}{z} + \kappa_0^f \right) g(z) dz + \int_{z_1^*}^{\infty} I_{U1}^{\text{unit}} \left(\frac{q_1^*(z)}{z} + \kappa_1^f \right) g(z) dz \right]$$

where $q_0^*(z)$ and $q_1^*(z)$ are optimal output choices—plugging in the pricing rule $p_j(z) = \left(\frac{\mu}{\mu - 1} \right) \left(\frac{c_j}{z} \right)$ into the demand expression. After some algebra, the final expression for I_U becomes:

$$\begin{aligned} I_U = a^{\sigma_E} w_{IU}^{-\sigma_I} c_0^{-1} Y \Bigg\{ & b_{U0}^{\sigma_I} c_0^{\sigma_E} c_{U0}^{\sigma_I - \sigma_E} \left[\left(\frac{\mu}{\mu - 1} \right)^{-1} (\theta)^{-1} \left(1 - R_z^{-(\phi - (\mu-1))} \right) + \left(\frac{\phi - (\mu - 1)}{\phi \mu} \right) \left(1 - R_z^{-\phi} \right) \right] + \\ & b_{U1}^{\sigma_I} c_1^{\sigma_E} c_{U1}^{\sigma_I - \sigma_E} \left(\frac{c_1}{c_0} \right)^{-\mu} \left[\left(\frac{\mu}{\mu - 1} \right)^{-1} (\theta)^{-1} \left(R_z^{-(\phi - (\mu-1))} \right) + \tau \left(\frac{(\phi - (\mu - 1))}{\phi \mu} \right) \left(R_z^{-\phi} \right) \right] \Bigg\} \end{aligned}$$