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Immigrant entrepreneurship in America: Evidence from the survey of business owners 2007 & 2012[★]



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ABSTRACT

We study immigrant entrepreneurship in 2007 and 2012 using the Survey of Business Owners. First-generation immigrants create about 25% of new firms in America, but this share exceeds 40% in some states. Conditional on basic regression controls, immigrant-owned firms tend to create fewer jobs than native-owned firms, have comparable pay levels, offer fewer benefits, and engage more in international activities. Prominent tech clusters display quite pronounced shares of immigrant entrepreneurs. Our results suggest that most of the impact of immigrant high-tech entrepreneurship for tech centers happens through the quantity dimension: Silicon Valley and similar tech hubs attract many immigrant founders.

1. Introduction

Immigrant entrepreneurship plays an important role in the American economy. Immigrants start about 25% of all U.S. firms in the Survey of Business Owners data during 2008–2012, and this share rises to above 40% in states like California and New York. These immigrant-founded firms provide jobs and innovations, impacting the lives of natives. Immigrant entrepreneurs frequently show up in popular press business narratives, legislation and lobbying discussions, and the founding histories of many prominent firms. Among Fortune 500

companies, about 40% were founded by first- or second-generation immigrants (Partnership for a New American Economy, 2011).

The prominence of immigrant entrepreneurs, aided by expanding economic data sets for research, has yielded a burgeoning academic literature. Many early studies establish that immigrants are more likely to enter self-employment and other forms of entrepreneurship than natives. A few recent studies also identify some important properties of these firms, such as Wang and Liu (2015) showing that U.S. firms with immigrant owners are more likely to export goods and services and have operations abroad. Brown et al. (2018) document a greater

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¹ Examples include (Borjas, 1986; Clark and Drinkwater, 2000; 2006; Fairlie and Meyer, 2003; Fairlie et al., 2010; Kerr and Kerr, 2011; 2017; Lofstrom, 2002; Lofstrom et al., 2014; Schuetze and Antecol, 2007) and Brown et al. (2018). Examples of studies for high-tech immigrant entrepreneurship include (Anderson and Platzer, 2006; Monti et al., 2007; Saxenian, 1999; 2002; Wadhwa et al., 2007), and Hart and Acs (2011).

patenting/innovation rate for immigrant-founded firms.² Yet, this comparison between immigrant- and native-founded firms remains incomplete, and relatively little is known about the broader impacts of immigrant entrepreneurs in terms of job creation and economic growth.³ Given that over a quarter a new firm births are connected to immigrant entrepreneurs—a share that is continually rising—an accurate characterization of these inputs is important for enhanced business and economic analysis.

Such a depiction would be incomplete without a consideration of the vast heterogeneity in immigrant entrepreneurship, which parallels the diversity of entrepreneurship more broadly. Immigrant entrepreneurs range from small "mom and pop" stores in low-tech settings to high-tech start-ups in top clusters like Silicon Valley. These firms are likely to look quite different from each other, and they may also be more or less similar to their closest native peers. We need a better understanding of the range of industries influenced by immigrant entrepreneurs and their impact on U.S. economic regions as diverse as Montana and Florida.

This study quantifies many of these features using a novel data platform—the Survey of Business Owners (SBO) for 2007 and 2012, combined with the Longitudinal Business Database (LBD) for 2007–2011. The SBO allows us to measure the number and quality of jobs created by immigrant entrepreneurs, and we can separate out firms in high-tech vs. low-tech industries. The SBO information spans company payroll per employee, usage of full-time vs. temporary workers, and the provision of various employee benefits such as health insurance and paid time off. We also examine differences between native- and immigrant-founded firms in terms of their international activities and start-up and expansion financing.

To preview some of our results, dependency on immigrant founders varies substantially across regions in America, from less than 5% in Idaho and North Dakota to more than 40% in "gateway" states like California. Immigrant-founded firms tend to have fewer employees than native-founded firms, but they have higher labor productivity (receipts per employee), are more likely to survive to 2011, and grow employment at a slightly faster pace. The jobs created by immigrant-founded firms provide comparable wages, but these firms offer significantly fewer benefits like healthcare or 401k plans. Reflecting the early literature, immigrant-founded firms engage in more extensive international activities.

Regression analyses show that these differences are partly explained by industries in which immigrant-founded startups operate, but a gap persists even with a very stringent set of control variables. With a full set of controls, immigrant-founded firms are economically and statistically less likely to offer employee benefits and are more likely to engage in global activities, with limited differences on other employment conditions like wage levels or employee productivity. High-tech firms founded by immigrants tend to look more like their native peers than those in low-tech industries, but usually the results are of similar qualitative direction regardless of sector. There are also differences by owner ethnicity, but relatively fewer differences by owner education level.

The depth of the survey also allows us to consider entrepreneurship inside vs. outside of prominent tech clusters. We find that immigrant-founded companies account for more than 40% of startups in leading clusters, with modestly higher shares in the high-tech sector compared

to low-tech. As the traits of immigrant-founded companies tend to resemble those of native-founded companies in these clusters, most of their impact appears to come through sheer quantity of immigrant entrepreneurs agglomerating in key hubs.

These results are important given the role of new businesses in generating jobs (Haltiwanger et al., 2013). The United States lacks a systematic program for facilitating the migration of entrepreneurs. Consequently, as most immigrants are under family-based visas or have become permanent U.S. residents, the degree to which immigrants engage in entrepreneurship can only be answered empirically. This study confirms immigrants enter entrepreneurship at a higher rate than natives and begins to describe the distinctive features of their firms.

The rest of this study is organized as follows. Section 2 reviews the literature on immigrant entrepreneurship and presents theories as to why immigrants choose to enter entrepreneurship. Section 3 describes the SBO data platform and provides descriptive tabulation. Section 4 uses regression analyses to formally compare immigrant- and native-owned businesses. Section 5 considers isolating top metropolitan areas. The final section concludes with some discussion of future research opportunities.⁶

2. Theoretical and conceptual background

A growing body of work documents the higher rate at which immigrants enter entrepreneurship in America than natives (Fairlie, 2012). This section explores some of the key findings from this literature and how theoretically we anticipate immigrant entrepreneurship in high-tech vs. low-tech industries to be different. The high rate of immigrant entrepreneurship is broad-based and not simply due to immigrants from one source country or region being particularly entrepreneurial. Fairlie and Lofstrom (2013) use the 2007–2011 Current Population Survey (CPS) and confirm, among other things, that immigrant entrepreneurship is pervasive across ethnic groups. Consequently, as immigration to America is very diverse across education levels, industries, and regions, we anticipate substantial heterogeneity in the entrepreneurial population.

2.1. Root factors for immigrant entrepreneurship

We draw from the literature four factors that contribute directly to immigrant entrepreneurship and interact with each other. Some of these root factors "pull" immigrants into entrepreneurship, emphasizing the personality traits of immigrants, group-level benefits from joint selection into entrepreneurship, and so on. Other factors "push" immigrants into self employment due to weak opportunities for regular employment, discrimination, and similar challenges compared to natives. While our data lack the motivations and context of individual entrepreneurs, a conceptual consideration of the factors helps frame potential differences across sectors.

Entrepreneurial Personality: A substantial literature, reviewed by Astebro et al. (2014), explores the degree to which entrepreneurs have

² Brown et al. (2018) consider the 2007 SBO and 2014 Annual Survey of Entrepreneurs. Their important study finds that immigrant entrepreneurs have distinct motivations for starting a business as compared to natives, and immigrant entrepreneurs are more likely to engage in R&D and innovation. This is especially true among college-educated founders.

³ Immigrant scientists and engineers have received closer study. For example, (Hunt, 2011; Hunt and Gauthier-Loiselle, 2010; Kerr et al., 2015a; 2015b; Kerr, 2010; Kerr and Lincoln 2010; Lofstrom 2011; Peri et al., 2015), and Breschi et al. (2017). Kerr (2017) provides a review.

⁴ In 2019, the United States has the EB-5 visa that targets wealthy immigrants capable of investing a million dollars into a U.S.-based business, but the country lacks a program that facilitates other aspiring migrant entrepreneurs (or graduating students from U.S. schools who wish to create a firm vs. entering paid employment). The appendix provides some examples of policies in other countries and city-level initiatives within the United States.

⁵ The time in America before starting the venture could boost the chances of success. Mata and Alves (2018) show that immigrant firms have lower rate of survival but experience in host countries improves the chances of survival.

⁶The appendix contains additional materials and references considering second-generation immigrants. Interestingly, the firms founded by second-generation immigrants show some evidence of business assimilation, such that their traits sit in between those of native founders and foreign-born founders presented in this paper.

a prototypical personality. On many dimensions of personality, such as the classic Big-5 personality traits (Openness to experience, Conscientiousness, Extraversion, Agreeableness, Neuroticism; see Kerr et al., 2018), the literature finds very limited difference between entrepreneurs and wage workers. The bigger differences instead emerge around factors such as the willingness or ability to tolerate risk and uncertainty, self-efficacy (the belief in one's ability to complete tasks and fill roles), internal locus of control (the belief that one's decisions control the outcomes of life vs. external factors), and the need for achievement. The required tolerance for risk has been closely studied (e.g., Hvide and Panos, 2014; Kihlstrom and Laffont, 1979) and Kerr et al., 2019 find survey and experimental evidence consistent with these personality factors.

There may be a conceptual connection of these personality traits to immigration. Leaving one's home and moving abroad frequently involves uncertainty and risk, and migrants must often believe in themselves and their power to create a life in their new home. The choice to migrate may select on individuals with these traits, and the duration within the new home may further engender them. For example, a young migrant who successfully gets started in America may endogenously acquire a greater tolerance for risk and belief in her capabilities to produce the outcomes she desires. While the empirical verification of these linkages remains incomplete, the act of migration may capture a pool of individuals with personalities more aligned to opening up a business.

Conditional on being an entrepreneur (which will be true throughout our empirical work), we conjecture that these personality forces will have relatively limited differences between high-tech and low-tech industries. One can easily imagine the poorest of migrants being the most selected on these dimensions and overcoming the most adversities (per the classic American dream). Broader population rates of entrepreneurship by immigrant group could be affected but are beyond this study's data scope.

Opportunity-Based Migration: A feature related to the selection to migrate is the opportunity-based nature of much of immigration. While some migration is sadly forced (e.g., refugees), much of immigration occurs when individuals seek opportunities (and much of the missing benefits of migration happen when these intentions are blocked, such as Clemens, 2011). This occurs within regions (e.g., low-skilled migration from India to work in Gulf States) and on global scales (e.g., flocking of bankers to leading financial centers). The United States has long been a favored destination for prospective entrepreneurs due to its open and mostly competitive markets, its complementary service providers (such as financing), and its content-sized product markets and customer bases. For many entrepreneurial immigrants, it is the dream destination.

While we believe this factor promotes immigrant entrepreneurship across the board, the impact for high-tech sectors is likely to be more pronounced. America provides prospective high-tech entrepreneurs access to the scientific frontier, the world's most vibrant talent clusters, deep venture capital markets, and so forth. Akcigit et al. (2016) demonstrate that the most productive immigrant inventors are the most sensitive to higher tax rates, and Kerr (2010) documents how immigrants are particularly fast to migrate to locations experiencing breakthrough inventions. These patterns suggest that high-tech entrepreneurs have the most to gain from migration to America vs. other potential destinations.⁷

Weaker Labor Market Prospects: Entrepreneurship does not happen at equal rates across the education and skill distribution. First,

at a macro level, entrepreneurship exhibits a U-shaped pattern with respect to the full distribution of skills, disproportionately occurring at the upper and lower tails of the distribution (Levine and Rubinstein, 2017; Poschke, 2013). Åstebro et al., 2011 colorfully describe these tails as "stars" and "misfits." Second, Hegde and Tumlinson (2018) provide provocative evidence that within each education rank (grade by grade), individuals are more likely to start their own business if they have high skill levels and abilities compared to others with the same credentials.

Both of these patterns connect into immigrant entrepreneurship. At the macro level, immigrants are more prevalent at the lower and higher ends of the education distribution than natives in America. Among those aged 18 and older, immigrants are 20% more likely than natives to have ended their education with a high school diploma or less, but they are also 40% more likely than natives to have earned a doctorate or equivalent degree (calculated using the 2012 American Community Survey). Immigration at the lower end of the education distribution is connected to both employment-based migration for low-skilled work (e.g., agricultural visas) and family-based migration; these groups arrive disproportionately from Central and Latin America and connect in part to unauthorized inflows. Immigration at the upper end of the education ladder connects more to student and skilled worker visas.

At a more micro level, immigrants can be pushed towards entrepreneurship due to a lack of labor market opportunities commensurate with their skill set. Many immigrants experience downward mobility and underemployment when they first arrive in a destination country. This is often due to an under-recognition of education and experience gained in their home country (e.g., Batalova et al., 2008; Friedberg, 2000; Li, 2001), as it is more difficult for employers to assess foreign school quality or validate credentials compared to a domestic candidate. For some migrants, this temporary setback is rectified by gaining additional experience and/or education after migration (e.g., Creese and Wiebe, 2012), but others look to entrepreneurship as an attractive alternative.

Given the pervasive nature of this factor, it is not theoretically clear if it should impact high-tech or low-tech industries more. The challenges presented by discrimination (e.g., Edo et al., 2013; Oreopoulos, 2011) or a lack of employment authorization may be more acute in low-tech work. The founding entrepreneur may also decide to start a business because of comparative access to underemployed or undocumented individuals, potentially gaining lower labor costs compared to competitors.

For high-tech industries, it is likely that the pathways to wage work are stronger for immigrants and more consistent, due to the greater transportability of technical skills and the deeper pool of the labor markets. According to 2012 ACS statistics, immigrants are twice as likely as natives to be employed in a STEM occupation, and thus employers will have greater incentives to recruit effectively in these markets. On the other hand, small proportionate differences in wage vs. entrepreneurial outcomes become much larger as one gets to the highest end of the skill distribution.

Co-Ethnic Social Bond: Connected to the above factors, immigrant entrepreneurs display a remarkable concentration—varying by ethnic group—in terms of the sectors in which they operate. Prominent low-tech examples include Vietnamese nail care salons, Korean dry cleaners, Gujarti Indian motels, and Punjabi Indian convenience stores. In the pre-Uber days, immigrant groups often drove most of the taxis in a city, with the particular ethnic group varying by city. Studies of this entrepreneurial concentration highlight the benefits obtained by group specialization and shared knowledge when strong social networks undergird the ethnic community, and this concentration becomes a natural pathway to employment and potential entrepreneurship for new arrivals.⁸

⁷ This potential for opportunity-based migration is strong enough to affect early education choices made in sending countries (e.g., Chand and Clemens, 2008; Gibson and McKenzie, 2011). Akee et al. (2013) show that migrants with a history of entrepreneurship in their home country are more likely to be entrepreneurs in their new nation.

⁸ For example, Kalnins and Chung (2006), Roth et al. (2012), Patel and

There is similar evidence in advanced high-tech sectors of this specialization and co-ethnic connection, albeit likely less pronounced. Hegde and Tumlinson (2014) document that venture investors are more likely to invest in a firm run by someone of the same ethnic background, and Gompers et al. (2016) document how venture inventors also co-invest with each other along ethnic lines. These co-ethnic connections are not necessarily efficient choices, as investors may be less careful for example, but speak again to the group-based concentration.

Consistent with this concentration, we later document in the SBO data that roughly half of immigrant-owned startups are in three sectors: accommodation and food services, retail trade, and professional and technical services. Native-owned firms are less concentrated. These group based factors appear strongest among low-tech services and trade segments, compared to the high-tech sector, due to the greater integration of high-tech firms in local markets.

2.2. Combining features and defining business traits

Our discussion highlights how all four of these root factors contribute to immigrant entrepreneurship, but likely to varying degrees for high-tech vs. low-tech industries. We conjecture that immigrant founders of high-tech firms are more likely to select into entrepreneurship due to pull factors, especially opportunity-based migration. Push factors like discrimination or weak labor market prospects are likely to be less important, although early stories of Silicon Valley immigrant entrepreneurs do mention perceptions of glass ceilings on advancement at local tech incumbents.

The greater prevalence of pull factors suggest to us that high-tech immigrant entrepreneurs will be stronger and building better firms overall than their fellow migrants in low-tech settings. Some early confirmation of this selection effect is evident in the 2012 SBO data, where immigrant high-tech founders draw disproportionately from the highest education groups. Hunt (2011) also observes that the highest earning, most innovative, and most entrepreneurial immigrants arrived in the United States through temporary work or education visas, both which require a high level of education. These high-skilled individuals are quite mobile and often select locations where they will have the most opportunities. Indeed, we further conjecture that the strongest of high-tech immigrant entrepreneurs will be found in innovation clusters where firms compete in dynamic markets and diversity rates are high. In these competitive clusters, we further anticipate that the jobs created will need to match to a large degree what is being offered (wages and benefits) by comparable native-founded firms.

Immigrant founders in low-tech sectors are harder to predict. These founders are more likely to have migrated for non-work reasons and to have selected entrepreneurship as a way to build work opportunities for their families and/or communities. These firms will be similar to most small businesses in that few are seeking to disrupt a market or invent a new product or model (Hurst and Pugsley, 2011). The 2012 SBO confirms that low-tech immigrant founders are disproportionately selected from low education groups. In this environment, we expect that greater differences can emerge in terms of employment conditions and pay compared to comparable native-founded firms. This is especially true for family firms or firms who hire other immigrants, connected to lower worker productivity (e.g., learning the language), lack of competing employment offers, or similar.

Two limits to these conceptual remarks are important to note. Jan Koum, an immigrant to America from Ukraine, cofounded WhatsApp in 2009 after being denied for employment at Facebook, later to sell

(footnote continued)

WhatsApp to Facebook in 2014 for \$19.3 billion and join Facebook's board of directors. This wild story humourously shows that both pull-and push-based entrepreneurship can lead to success. It also highlights that measures of firm performance available in administrative data, such as productivity and business survival, do not do justice to every experience. While we do not capture the underlying motivations of entrepreneurs and our outcome metrics imperfectly capture the experiences felt, our work describes empirical regularities that inform the entrepreneurship literature and the broad economic outcomes of immigrant entrepreneurship.

Finally, the SBO data collect information on the global activities of firms. An extensive literature connects migration to trade. ¹⁰ Global engagement could be focused on the exchange of ethnic goods and services, possibly linked to overseas diaspora communities, in ways that extend the product set of their host country. Migrants may also use their connections and global understanding to boost overseas sales of general products without ethnic specific components. We anticipate both lowand high-tech immigrant entrepreneurs to have a comparative advantage towards international engagement than their native peers. We further anticipate the benefits of this advantage to be greater with high-tech industries given the anecdotal and empirical accounts of global ethnic networks within high-tech industries (e.g., Kerr, 2008; Saxenian, 2002) and the typically greater market span for these products.

2.3. Mixed founding teams

While our conceptual background has treated immigrant and native entrepreneurs as separate, there are many firms with mixed founding teams. Accounts of immigrant entrepreneurship show a range of treatments from statistics that focus on the share of firms with an immigrant founder (i.e., declaring WhatsApp as an immigrant-founded company due to Koum's role) while other approaches weight immigrant contributions by number of founders (i.e., apportioning credit between Koum and his cofounder Brian Acton, who was born in Michigan). As each approach carries useful information, we provide most of our descriptive statistics both ways.

The more interesting and challenging question, however, arises when designing our multivariate empirical specifications to isolate traits for immigrant entrepreneurs over and above correlates like founder age, sector, and so on. It is interesting to explore, for example, whether mixed founding teams "split the difference" between pure immigrant and native founding teams or take on immigrant-connected traits so long as any one founder is an immigrant. For example, how of much of the greater global engagement of immigrant-founded firms arise from one founder being an immigrant vs. all of them? While presenting results both ways, our regressions prioritize splitting mixed founding teams from immigrant only teams to help shed light on these questions.

Separating mixed founding teams also requires a careful consideration of founding team size, as, by definition, mixed firms have more than one founder and so tend to be larger than exclusively immigrant or native founding teams. We have considered this question in several ways, and our upcoming work focuses mostly on settings where we control for team size in the regression. In summary, our chosen empirical approach provides an attractive platform to learning about mixed teams compared to those exclusively comprised of immigrants and natives, while also being on guard to not confound team size with its heterogeneity.

Vella (2013), Andersson et al. (2014), Kerr and Mandorff (2015), and Battisti et al. (2016).

⁹ For example, Saxenian (1996, 2000), Florida (2005), Fallick et al. (2006), and Kerr (2019).

¹⁰ Examples include Gould (1994), Head and Ries (1998), Rauch (2001), Rauch and Trindade (2002), Hatzigeorgiou and Lodefalk (2011), Bahar and Rapoport (2018), and Kerr (2018). Docquier and Rapoport (2012) provide a broader review

¹¹ We have also confirmed that our key immigrant vs. native comparisons hold when dropping firms with a single founder or when modelling indicator variables for team size.

3. Data and descriptive tabulations

We use the restricted-access Survey of Business Owners (SBO) data housed in the Federal Statistical Research Data Centers (RDC). We employ the 2007 and 2012 SBOs and merge them with other Census Bureau data sources, including the Longitudinal Business Database (LBD). These data provide a rich and detailed platform to study immigrant entrepreneurship across industries and geographies.

3.1. SBO 2007 And 2012 data

The raw SBO files contain many types of firms, ranging from self-employed individuals who do not hire employees to small and large employer firms, some of which are publicly held. Our SBO analysis considers employer firms given our focus on understanding the quantity and types of jobs created, rather than the self-employment patterns previously discussed in the literature. ¹² We also exclude publicly owned firms from the sample, as it is impossible to accurately separate them into the immigrant- vs. native-owned categories.

In 2007, our baseline sample of private employer firms includes 950 thousand companies. We exclude 1.4 million records for publicly owned firms and firms with no identifiable owner (e.g., estates, trusts, cooperatives, clubs, tribal entities) and 10.4 million records for self-employed incorporated non-employers. In 2012, our baseline sample of private employer firms includes 300 thousand companies. This 2012 sample comes after the exclusion of 224 thousand records for publicly owned companies and firms with no identifiable owner and 8.3 million records for self-employed individuals. The core sample is smaller in 2012 due to the introduction of two separate versions of the SBO survey instrument, one of which lacks detailed questions about the owners of the firm. This change does not impact our work as tabulation weights allow for population-based estimates.

We define new firms to be those entering in the five years prior to each survey. This segment captures the role of immigrants in recent entrepreneurial activity, and we use the term "startups" interchangeably. The number of new firm records that underlie the upcoming analyses is 139 thousand in 2007 and 48 thousand in 2012 (approximately 15% and 16% of the included SBO firms in 2007 and 2012, respectively). We track the new firms that enter prior to the 2007 SBO over time in the LBD, which provides annual employment and payroll information. This link affords measurement of the survival and growth patterns of these young firms during the critical early years of their operations.

The SBO records information on each owner of the firm, and we consider these owners to be the founders or entrepreneurs of the new firms that we study, although in a small share of cases the ownership of the firm will have changed hands by the time of the SBO survey. In some tabulations, we mirror the literature by classifying a firm as immigrant-owned if any of the firm's owners is an immigrant. In our regression analyses, we typically parse into a separate category the firms with mixed immigrant and native ownership teams to allow for exclusively immigrant-owned companies to be compared to exclusively native-owned companies.

We define the high-tech industry based on the company NAICS code being in the list of high-tech industry NAICS codes in Hecker (2005) or Goldschlag and Miranda (2016) or being an NAICS code listed as a patent-intensive industry in Doms et al. (2012). ¹³ The SBO records data

on around 97 thousand high-tech firms in 2007 and 48 thousand in 2012 (approximately 15% and 18% of the included SBO firms in 2007 and 2012, respectively). Among new firms, high-tech firms account for 16 thousand in 2007 and 8 thousand in 2012, or a 12% and 16% share respectively. Of course, a firm can be technologically sophisticated in a low-tech industry, and vice versa. Despite the imperfections of industry-based divisions, the ability to explore entrepreneurship in high-tech settings is a powerful addition to the literature.

We also investigate patterns for Metropolitan Statistical Areas (MSAs), following previous research on the high concentration of hightech firms (e.g., Liu et al., 2014). High-tech MSAs are defined as the top ten areas for housing high-tech firms using combined 2007 and 2012 SBOs: Atlanta, Boston, Chicago, Dallas, Houston, Los Angeles, Miami, New York, San Francisco / San Jose, and Washington D.C. Given the particular interest for Silicon Valley, we will sometimes separate San Jose from San Francisco.

Throughout this paper, Census Bureau disclosure requires observation counts be rounded, and all reported numbers are likewise rounded to four significant digits. We use the SBO tabulation weights in summary tables, and the noise-infused employment, payroll and receipt outcomes in 2007 (and for variables built upon those metrics). As regressions control for or select upon sampling strata (state, NAICS industry, employer firm or not), we do not weight observations in our regression analyses. ¹⁴

3.2. SBO Descriptive analysis

Tables 1a-c describe the SBO sample for new firms, with parallel tabulations for all firms being found in Appendix Tables A1a-c. In Table 1a, 26% of new firms formed in 2012 have an immigrant founder, which is comparable to prior work and other data approaches. ¹⁵ Immigrant-owned firms have fewer employees but slightly higher receipts per employee. ¹⁶ Receipts include the total revenue and business done by domestic establishments of the firm, excluding foreign operations; values are reported in thousands of nominal dollars. Immigrant-owned firms also pay lower wages (measured as payroll divided by employment), with a 12% differential evident in 2012, and begin with more start-up capital.

Looking at the traits of entrepreneurs, female ownership is similar across both firm groups. Immigrant entrepreneurs tend to be younger and are more likely to combine owners of several ages, perhaps indicative of a greater prevalence of family businesses. Education levels are broadly comparable between immigrants and natives. Native-only firms are more likely to have single owners, while firms with immigrant or mixed owners are more likely to report three or more owners.

In addition to paying lower wages, immigrant-owned firms are less likely to offer employee benefits such as health insurance, retirement benefits, and paid leave. These differences across owner types are among the starkest in the SBO data and perhaps indicate less attractive employment. (The provision of these benefits declined among all startups between 2007 and 2012, which we have confirmed in other data

 $^{^{12}}$ Immigrants account for about 15% of self-employed owners in SBO. We later provide complementary evidence using incorporated self-employed statistics from the American Community Survey.

¹³ High-tech industries include NAICS 333, 335, 1131-2, 2111, 2211, 3241, 3251-6, 3259, 3341-6, 3364, 3369, 3391, 3399, 4234, 4861-2, 4869, 5112, 5161, 5171-4, 5179, 5181-2, 5191, 5211, 5232, 5413, 5415-7, 5511, 5612, and 8112.

¹⁴ This choice was confirmed in conversations with the Census Bureau staff regarding treatment of the SBO data and further reflects the efficiency advantages of an unweighted estimation. We have confirmed that weighted regressions identify the same key results described below.

¹⁵ Kerr and Kerr (2017) measure immigrant entrepreneurship through the Longitudinal Employer Household Dynamics (LEHD) database, a very large administrative dataset developed by the Census Bureau. Relative to the SBO, these data cover a much greater number of establishments, but the firm and founder details in the SBO are much richer. Kerr and Kerr (2017) find that the share of immigrant founders steadily increased between 1995 and 2008, reaching 25% by 2008.

¹⁶ Employment, payroll and sales receipts variables are not collected by the SBO but instead merged by the Census Bureau from the economic censuses conducted in parallel to the SBO.

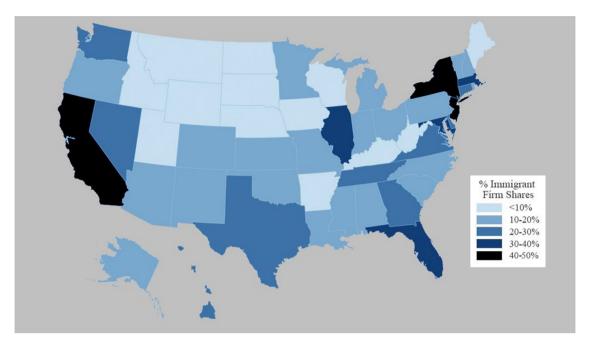


Fig. 1. Immigrant entrepreneur share of SBO employer firms in 2012. Notes: Sample includes non-public employer firms from the 2012 SBO, with entrepreneurship measured through new firms created in the five years prior to the survey. These statistics combine Immigrant only and Mixed teams.

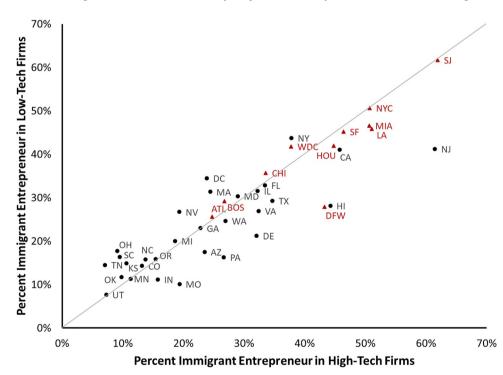


Fig. 2a. Immigrant entrepreneur distribution in high- vs. low-tech sectors in 2012. Notes: See Fig. 1. Sample includes 30 states for which the number of firms is above the Census Bureau's disclosure cut-off for both high-tech and low-tech sectors. The state-level correlation across series is 0.83. In addition, the large tech clusters are presented: Atlanta, Boston, Chicago, Dallas, Houston, Los Angeles, Miami, New York City, San Francisco, San Jose, and Washington D.C. The cluster-level correlation across series is 0.90. These statistics combine Immigrant only and Mixed teams.

sources like the Current Population Survey.)

Immigrant-owned firms are comparable to native-owned firms in terms of hiring temporary vs. full-time workers. Nationally, temporary workers account for just over 2% of private sector jobs (Economics and Statistics Administration, 2015). Temporary employment includes workers from temporary agencies, day laborers, and leased employees; part-time workers are a separate category. Finally, immigrant-owned firms show a much higher rate of international activity as measured by exporting, outsourcing, and maintaining overseas operations.

Table 1b separates purely immigrant-owned start-ups from mixed teams, with Appendix Table A1b providing comparable breakouts for all firms. Immigrant-only teams accounted for 19% and 22% of new

firms in 2007 and 2012, while mixed teams accounted for 5% and 4%, respectively. Start-ups with mixed ownership tend to be larger and begin with more capital, but they are comparable for wages and receipts per employee. Interestingly, the most common number of owners is two for mixed teams, as compared to only one among immigrant- and native-only firms. The greater number of owners allows for mixed teams to show more ownership diversity for age, education, and gender. With respect to benefits, mixed-owner firms are more likely to offer health insurance and paid leave, but not retirement benefits. Related to hiring more employees, mixed-owner firms are more likely than native-only firms to hire both temporary and full-time workers. Lastly, mixed-owner firms report international operations at a higher rate than any

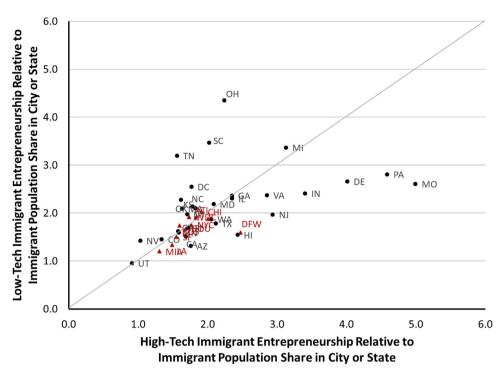


Fig. 2b. Immigrant entrepreneur distribution in high- vs. low-tech sectors in 2012 relative to immigrant population share in city or state. Notes: See Fig. 2a. Immigrant entrepreneurship shares are shown relative to local immigrant population shares. The state-level correlation across series is 0.43. The cluster-level correlation across series is 0.49.

other firm group, including immigrant-only firms.

Table 1c considers new firms in high-tech vs. low-tech industries. Immigrant-owned startups comprised 29% and 26% of high- and low-tech entry in 2012, respectively. This is similar to 2007, but rates among high-tech firms rose faster (the proportions were 25% and 24%, respectively). Among immigrant-owned firms, high-tech firms tend to hire fewer employees and pay almost double the wages of immigrant-owned firms in low-tech settings. Start-up capital amounts are consistently lower among high-tech firms, but higher for immigrant-owned firms among both groups.

High-tech firms often have larger founding teams, despite their lower employment, but are less likely to include women. High-tech founders are also more concentrated in higher levels of education. High-tech firms are substantially more likely to offer benefits and engage in international activities. The earlier differences among immigrant- and native-owned firms remains among both industry groups in regards to international operations; differences in employer-provided benefits remain for low-tech firms but are much smaller for high-tech firms. As noted earlier, this could be due to the prevalence of high-tech firms in more competitive markets for employees.

3.3. Industry, financing and geographic variation

Table 2 lists the most common two-digit NAICS industry codes for immigrant- and native-owned firms. Roughly half of immigrant-owned startups are in three sectors: accommodation and food services, retail trade, and professional and technical services. Native-owned firms show less industrial concentration, as noted earlier. This industry breakdown highlights the concentration of immigrant entrepreneurs at the upper and lower ends of the distribution. Professional and technical services include many high-tech industries, whereas accommodation and food services and retail trade fall into the low-tech category.

The differences in firm traits in Tables 1a-1c could be due to these industry choices, but data from the March 2017 National Compensation Survey conducted by the Bureau of Labor Statistics suggest that industry differences are unlikely to bear full responsibility. Our working paper tabulates in greater depth how the three most prominent sectors for immigrant-owned businesses fall above and below national averages on most dimensions like offering benefit plans. Upcoming regression

analyses control for industry differences in a rigorous manner.

Previous studies document that immigrant-owned businesses start with more funding (e.g., Fairlie, 2012); the 2007 SBO shows that much of this difference comes through firms with mixed ownership teams. Table 3 shows the most common sources of start-up capital for immigrant entrepreneurs.¹⁷ The first panel reports capital sources for all new firms, while the second two separate firms by industry. Firms with mixed owners report a higher use of nearly all funding sources. Personal savings are the most important source of capital for all firms, but this source is especially important for firms with immigrant owners. Firms with native owners are more likely to have bank loans and credit, while those with immigrant owners are more likely to rely on family loans. The use of home equity is highest among mixed owner firms and fell across all groups between 2007 and 2012, reflecting the effects of the Great Recession. These patterns may signal a lower ability by immigrants to obtain bank credit. 18 Venture capital funding is rare but consistently higher for high-tech firms.

Fig. 1 documents the states with the greatest and least reliance on immigrant entrepreneurs, with extreme values tabulated in Table 4. The least dependent states, such as Montana, the Dakotas, and Idaho, have 6% or less of their new firms founded by immigrants in 2012, whereas the shares for California, New Jersey, and New York exceed 40%. These differences are naturally tied to geographic variation in where immigrants make up a large share of the population. The correlation in 2012 between the working age population share and firm owner share for immigrants is 0.85 for new firms and 0.91 for all firms. ¹⁹ Metropolitan areas within states also vary substantially. The most-dependent MSAs in California display immigrant business owner shares in excess of 60%, a 50% increase upon the state average.

Fig. 2a plots the share of immigrant entrepreneurs among high-tech

¹⁷ Appendix Table A2 shows similar patterns for sources of expansion capital, with native-only firms being less likely to expand.

¹⁸ For example, Blanchflower et al. (2003), U.S. Chamber of Commerce (2005) and Bruder et al. (2011).

¹⁹ Between the 2007 and 2012 SBO, Texas (6%), New Jersey (6%), and Alabama (5%) saw the largest gains in immigrant entrepreneur share, while the District of Columbia (-10%), New Mexico (-5%), and South Dakota (-3%) saw the largest declines.

 Table 1a

 Summary statistics for immigrant and native entrepreneurship.

	2007		2012	
	Immigrant/ Mixed 1	Native only 2	Immigrant/ Mixed 3	Native only 4
% of firms	23.7%	76.3%	26.0%	74.0%
Mean: employees	5.26	5.45	5.03	5.88
Mean: employees if > 0	6.57	6.91	6.52	7.70
Mean: receipts (thousands)	\$739	\$729	\$752	\$839
Mean: ln(receipts/employee)	11.44	11.34	11.51	11.38
Mean: payroll/employee	\$27,720	\$31,350	\$28,470	\$32,290
Mean: start-up capital	\$164,900	\$136,900	\$146,800	\$126,800
% 1 owner	48.5%	49.9%	59.7%	61.6%
% 2 owners	37.9%	38.9%	28.8%	29.0%
% 3 or more owners	13.6%	11.2%	11.5%	9.4%
% female owners	48.3%	47.3%	44.1%	44.1%
% owners < 35	12.9%	14.5%	13.0%	15.5%
% owners 35-55	58.9%	54.0%	58.5%	50.9%
% owners > 55	10.1%	14.9%	12.1%	18.7%
% mixed age	18.0%	16.6%	16.4%	14.9%
% high educated	41.9%	42.1%	46.0%	49.1%
% low educated	44.4%	42.6%	42.7%	38.7%
% mixed educated	13.6%	15.4%	11.4%	12.2%
% offer health insurance	24.2%	33.9%	18.6%	26.4%
% offer 401k	9.7%	15.5%	8.4%	12.5%
% offer paid leave	33.1%	38.8%	28.4%	34.6%
% hire temps	10.3%	11.0%	6.8%	5.9%
% hire full-time workers	69.3%	67.1%	62.5%	60.5%
% export	8.3%	4.7%	6.9%	2.6%
% outsource	2.7%	0.9%	3.1%	1.2%
% operations abroad	1.5%	0.5%	2.7%	1.1%
% in high-tech industry	11.8%	11.1%	15.7%	13.7
SBO survey size (rounded)	30,000	109,000	12,000	36,000

Notes: Sample includes non-public employer firms, with entrepreneurship measured as new firms created in the five years prior to the survey. Data for 2007 use noise infusion for employment, receipts, and payroll, as well as variables derived using those measures. Reported numbers use tabulation weighting and are rounded to maximum of four significant digits. Groupings: Immigrant only includes firms with only immigrant owners, Mixed includes firms with both immigrant and native owners, and Native only includes firms with only native owners. Immigrant only and Mixed are combined in this table.

vs. low-tech startups by state in 2012. The included 30 states in the graph are those where a sufficient number of SBO observations pass the Census Bureau's disclosure rules for both industry groups. Most states are clustered around the 45-degree line, reflecting a similar proportion of immigrant entrepreneurship across industries, and the correlation of the two series is 0.83. The main outlier is New Jersey, which had more than 60% of new high-tech firms founded by immigrants in 2012. We also include the top tech clusters, which show a 0.90 correlation. These clusters typically exceed their home state in terms of immigrant entrepreneurship, reflecting the greater rates of immigration into big cities. San Jose / Silicon Valley shows immigrant entrepreneurship in both sectors that just exceeds 60%.

Fig. 2b repeats Fig. 2a but normalizes each immigrant entrepreneur share by the immigrant population share in the cluster or state. In all cases other than Utah, the immigrant entrepreneur shares in both sectors exceed the local immigrant population shares. Most clusters and states fall in between 1x and 3x for high- and low-tech entrepreneurship compared to the local immigrant population. Some states with lower overall immigration shares show more extreme differentials, especially for high-tech entrepreneurship.

4. Regression analysis of immigrant entrepreneurs

Our descriptive tabulations measure sizable differences between immigrant- and native-owned firms in terms of employment, wages, and other job characteristics like employer-provided benefits. This section analyzes the degree to which these differences persist once we control for state and industry choices, along with other observable traits of the owners like age, gender, and race/ethnicity. The background regression takes the form:

$$Y_{f,t} = \beta \cdot \text{Imm.Entr}_{f,t} + \zeta \cdot \text{Mixed.Entr}_{f,t} + \gamma X_{f,t} + \delta_t + \varepsilon_{f,t}, \tag{1}$$

where $Y_{f,t}$ is a measured trait of the firm. Imm.Entr $_{f,t}$ takes a (0,1) value for the founding team being comprised exclusively of immigrants. Mixed.Entr $_{f,t}$ take a (0,1) value for the founding team being comprised of both immigrants and natives. Native-only teams serve as the reference category.

Our regression models combine the 2007 and 2012 SBO data and control for year fixed effects δ_t . Baseline controls $X_{f,t}$ include indicator variables for the firm's state and four-digit NAICS industry and the gender, education and age composition of owners (using the groupings shown in the descriptive tables). As noted earlier, we also control for the number of owners of the firm and consider ethnicity by aggregating baseline SBO categories into three groups: African-American, Hispanic (Mexican, Cuban, Other Hispanic, not Puerto Rican), and Asian (Chinese, Indian, Filipino, Japanese, Korean, Vietnamese, and Other Asian). We then enter for each of these groups the share of founders who are of that ethnic background. In a second regression set, we further add a control for the log of firm employment as a size measure.

Fig. 3 reports the β point estimates and confidence intervals for the indicator variable of an immigrant-only founding team. Regressions are unweighted and use robust standard errors to derive 95% confidence intervals. To facilitate easy comparison, we conduct these regressions separately for high-tech vs. low-tech firms and combine the results into Fig. 3. Circles indicate the coefficients for immigrant founders in high-tech entrepreneurship; triangles indicate the same for low-tech industries. The accompanying table reports the relative economic magnitude of the coefficient for immigrant entrepreneurs. This effect is calculated as the coefficient divided by the mean of the outcome variable. These calculations help evaluate the relative economic magnitudes given that some outcomes are in logs (the first four rows) vs. indicator variables (the rest); they also account for baseline differences across industries. 20

Panel A displays the results without firm size controls. Immigrant entrepreneurs hire fewer employees than native-owned firms, with a sizable relative effect of 16% for low-tech sectors. The immigrant effect is smaller at 5% and not statistically significant for high-tech firms. By contrast, immigrant vs. native founder differences on start-up capital raised, labor productivity (i.e., receipts/employee), and wages tend to be quite modest and with a relative effect of under 1%. The types of employees hired by immigrant-only founders look mostly similar to their native peers.

The more noticeable differences are at the bottom of Panel A. Immigrants in low-tech settings are substantially less likely to have employer-provided benefits, with the relative size ranging from 24% less for paid time off to 66% for 401k plans. As a summary metric, immigrant startups in low-tech sectors are 18% less likely to offer any of the three indicated employer-provided benefits than natives. Within the high-tech industries, the gaps are substantially less, but still reach a 16% relative effect for the offering of 401k plans. In total, immigrant-only high-tech startups are 4% less likely to offer any of the three indicated employer-provided benefits than natives. Thus, the average "job quality," as defined by these metrics, is weaker in immigrant-owned firms, and the earlier analysis shows that the lower provision of these benefits is not being offset in higher wages.

²⁰ Tables A3a-A4n in the online appendix provide our complete estimations. These tables also provide analyses with a full sample combining high-tech and low-tech together, regression variants without control variables, and regression variants where we do not parse out the mixed ownership group. Our NBER working paper also contains additional variations of these regressions.

Table 1b
Table 1a splitting Immigrant only and Mixed founding teams.

	2007			2012		
	Immigrant only	Mixed 2	Native only	Immigrant only	Mixed 5	Native only
% of firms	18.5%	5.2%	76.3%	21.7%	4.3%	74.0%
Mean: employees	4.56	7.77	5.45	4.52	7.63	5.88
Mean: employees if > 0	5.71	9.63	6.91	5.89	9.69	7.70
Mean: receipts (thousands)	\$652	\$1,047	\$729	\$681	\$1,119	\$839
Mean: ln(receipts/employee)	11.45	11.38	11.34	11.50	11.55	11.38
Mean: payroll/employee	\$26,250	\$32,900	\$31,350	\$27,410	\$33,760	\$32,290
Mean: start-up capital	\$147,900	\$222,500	\$136,900	\$133,500	\$212,700	\$126,800
% 1 owner	62.0%	0.0%	49.9%	71.4%	0.0%	61.6%
% 2 owners	30.2%	65.5%	38.9%	21.9%	63.6%	29.0%
% 3 or more owners	7.7%	34.5%	11.2%	6.7%	36.4%	9.4%
% female owners	42.9%	67.9%	47.3%	40.0%	65.1%	44.1%
% owners < 35	14.4%	7.6%	14.5%	14.1%	7.7%	15.5%
% owners 35-55	63.2%	43.5%	54.0%	62.9%	36.4%	50.9%
% owners > 55	10.9%	7.4%	14.9%	13.1%	7.1%	18.7%
% mixed age	11.5%	41.5%	16.6%	10.4%	48.8%	14.9%
% high educated	43.3%	36.8%	42.1%	46.7%	42.5%	49.1%
% low educated	48.4%	30.5%	42.6%	46.2%	24.5%	38.7%
% mixed educated	8.3%	32.7%	15.4%	7.1%	33.0%	12.2%
% offer health insurance	20.2%	38.4%	33.9%	16.3%	30.3%	26.4%
% offer 401k	8.4%	14.2%	15.5%	7.8%	11.0%	12.5%
% offer paid leave	29.6%	45.3%	38.8%	25.4%	43.6%	34.6%
% hire temps	9.6%	12.8%	11.0%	6.5%	8.2%	5.9%
% hire full-time workers	67.9%	74.2%	67.1%	60.8%	71.0%	60.5%
% export	7.9%	9.6%	4.7%	6.7%	8.1%	2.6%
% outsource	2.7%	3.0%	0.9%	2.8%	4.6%	1.2%
% operations abroad	1.5%	1.5%	0.5%	2.6%	3.2%	1.1%
% in high-tech industry	10.9%	14.9%	11.1%	15.3%	17.6%	13.7%
SBO survey size (rounded)	22,500	7,500	109,000	9,800	2,300	36,000

Notes: See Table 1a. Immigrant only and Mixed firms presented separately.

Table 1c
Table 1a splitting high-tech versus low-tech industries.

	High-tech				Low-tech			
	2007		2012		2007		2012	
	Immigrant/Mixed	Native only	Immigrant/Mixed 3	Native only	Immigrant/Mixed 5	Native only	Immigrant/Mixed	Native only
% of firms	24.8%	75.3%	28.6%	71.4%	23.6%	76.4%	25.5%	74.5%
Mean: employees	3.40	3.16	3.50	4.50	5.51	5.73	5.31	6.10
Mean: employees if > 0	4.56	4.24	4.78	6.16	6.82	7.23	6.83	7.93
Mean: receipts (thousands)	\$661	\$569	\$877	\$1,237	\$749	\$749	\$729	\$776
Mean: ln(receipts/employee)	11.67	11.49	11.88	11.66	11.41	11.32	11.44	11.34
Mean: payroll/employee	\$52,430	\$47,110	\$48,510	\$47,780	\$24,670	\$29,510	\$24,960	\$29,950
Mean: start-up capital	\$105,400	\$88,430	\$104,700	\$89,460	\$172,600	\$142,900	\$154,600	\$132,600
% 1 owner	46.7%	53.3%	57.5%	62.0%	48.7%	49.5%	60.1%	61.5%
% 2 owners	37.2%	35.0%	28.7%	27.0%	38.0%	39.3%	28.8%	29.3%
% 3 or more owners	16.2%	11.7%	13.9%	11.0%	13.2%	11.2%	11.1%	9.2%
% female owners	45.3%	39.6%	40.6%	35.1%	48.8%	48.2%	44.7%	45.5%
% owners < 35	14.3%	12.3%	11.9%	12.6%	12.8%	14.8%	13.2%	16.0%
% owners 35-55	57.8%	53.5%	57.9%	50.6%	59.0%	54.1%	58.6%	50.9%
% owners > 55	9.8%	19.2%	12.5%	22.8%	10.2%	14.4%	12.0%	18.0%
% mixed age	18.1%	15.1%	17.7%	14.0%	18.0%	16.8%	16.1%	15.1%
% high educated	71.5%	60.5%	73.6%	63.8%	38.0%	39.8%	40.8%	46.8%
% low educated	14.6%	23.8%	15.9%	25.3%	48.4%	44.9%	47.6%	40.8%
% mixed educated	14.0%	15.7%	10.5%	11.0%	13.6%	15.3%	11.5%	12.4%
% offer health insurance	45.3%	45.0%	37.0%	37.8%	21.3%	32.5%	15.2%	24.6%
% offer 401k	24.8%	26.8%	20.6%	19.6%	7.7%	14.1%	6.1%	11.3%
% offer paid leave	38.6%	38.1%	34.1%	34.3%	32.3%	38.9%	27.3%	34.6%
% hire temps	8.3%	7.2%	6.3%	4.8%	10.6%	11.4%	6.9%	6.1%
% hire full-time workers	66.8%	62.0%	63.9%	56.5%	69.6%	67.7%	62.2%	61.1%
% export	15.3%	8.0%	18.6%	6.6%	7.4%	4.3%	4.8%	2.0%
% outsource	10.2%	2.6%	10.6%	3.4%	1.7%	0.6%	1.7%	0.8%
% operations abroad	4.4%	1.3%	9.0%	3.1%	1.2%	0.4%	1.6%	0.8%
SBO survey size (rounded)	3,800	12,500	2,100	5,700	26,000	96,500	10,000	30,500

Notes: See Table 1a. High-tech is defined as belonging to a high-tech or patent-intensive industry, as described in the main text. These include NAICS 333, 335, 1131-2, 2111, 2211, 3241, 3251-6, 3259, 3341-6, 3364, 3369, 3391, 3399, 4234, 4861-2, 4869, 5112, 5161, 5171-4, 5179, 5181-2, 5191, 5211, 5232, 5413, 5415-7, 5511, 5612, and 8112.

Table 2Most common industries for immigrant and native entrepreneurs.

	2007				2012			
	Immigrant/Mixed		Native only		Immigrant/Mixed		Native only	
	Industry	Share	Industry	Share	Industry	Share	Industry	Share
	1	2	3	4	5	6	7	8
New firms	s							
#1	72 Accomm & food	18.0%	54 Prof, tech services	17.5%	72 Accomm & food	20.1%	54 Prof, tech services	19.4%
#2	44 Retail trade	15.3%	23 Construction	16.9%	54 Prof, tech services	14.8%	62 Health care & social	11.7%
#3	54 Prof, tech services	13.3%	62 Health care & social	9.7%	44 Retail trade	12.6%	23 Construction	10.5%
#4	62 Health care & social	11.5%	44 Retail trade	9.5%	62 Health care & social	12.5%	72 Accomm & food	10.4%
#5	23 Construction	9.4%	72 Accomm & food	7.6%	81 Other services	6.9%	44 Retail trade	6.4%
#6	81 Other services	6.7%	56 Admin etc. services	6.6%	23 Construction	5.8%	81 Other services	6.4%
#7	42 Wholesale trade	5.9%	53 Real estate & rental	6.4%	42 Wholesale trade	5.7%	56 Admin etc. services	6.3%
% firms in	n top 7 industries	80.1%		74.2%		78.4%		71.1%
All firms								
#1	72 Accomm & food	16.3%	54 Prof, tech services	15.1%	72 Accomm & food	16.2%	54 Prof, tech services	17.0%
#2	44 Retail trade	15.5%	23 Construction	14.7%	62 Health care & social	14.3%	23 Construction	13.4%
#3	62 Health care & social	12.3%	44 Retail trade	13.0%	54 Prof, tech services	12.8%	62 Health care & social	11.1%
#4	54 Prof, tech services	11.9%	62 Health care & social	9.4%	44 Retail trade	12.5%	44 Retail trade	7.7%
#5	23 Construction	8.2%	72 Accomm & food	6.4%	81 Other services	7.7%	81 Other services	6.6%
#6	42 Wholesale trade	7.3%	81 Other services	6.2%	23 Construction	7.0%	56 Admin etc. services	6.5%
#7	81 Other services	7.2%	56 Admin etc. services	6.0%	42 Wholesale trade	6.9%	72 Accomm & food	6.1%
% firms ii	n top 7 industries	78.7%		70.8%		77.4%		68.4%

Notes: See Table 1a. Industries are 2-digit NAICS codes.

 Table 3

 Sources of start-up capital for immigrant and native entrepreneurs.

	2007			2012		
	Immigrant only	Mixed 2	Native only	Immigrant only 4	Mixed 5	Native only 6
All firms						
Mean: start-up capital	\$147,900	\$222,500	\$136,900	\$133,500	\$212,700	\$126,800
Personal savings	71.2%	72.7%	70.1%	74.7%	77.1%	71.8%
Bank loan	14.1%	19.0%	18.7%	10.6%	12.2%	14.3%
Credit	14.8%	19.4%	18.1%	11.3%	15.4%	13.9%
Home equity loan	13.1%	17.9%	13.6%	5.1%	7.1%	6.1%
Assets	9.6%	14.1%	12.8%	8.7%	10.9%	10.3%
Family loan	4.9%	6.1%	4.7%	5.6%	5.1%	5.0%
Venture funding	0.5%	2.4%	0.8%	0.5%	2.6%	0.8%
Other financing	2.2%	4.0%	3.2%	1.9%	3.7%	3.2%
High-tech						
Mean: start-up capital	\$67,000	\$210,200	\$88,430	\$86,100	\$187,500	\$89,460
Personal savings	77.3%	73.8%	76.5%	76.4%	77.8%	75.3%
Bank loan	4.0%	7.2%	6.9%	2.1%	2.6%	5.5%
Credit	11.6%	15.5%	15.1%	8.7%	10.8%	11.4
Home equity loan	6.6%	11.9%	8.5%	2.8%	2.4%	3.6%
Assets	7.1%	13.4%	9.9%	6.6%	7.8%	7.8%
Family loan	2.3%	6.9%	2.9%	3.1%	3.9%	2.8%
Venture funding	1.1%	5.6%	1.6%	0.8%	7.3%	1.6%
Other financing	1.6%	3.4%	1.8%	0.6%	3.3%	1.1%
Low-tech						
Mean: start-up capital	\$157,500	\$226,000	\$142,900	\$142,100	\$217,900	\$132,600
Personal savings	70.4%	72.5%	69.3%	74.4%	76.9%	71.2%
Bank loan	15.4%	21.0%	20.1%	12.2%	14.3%	15.7%
Credit	15.2%	20.1%	18.5%	11.8%	16.4%	14.3%
Home equity loan	13.9%	19.0%	14.2%	5.5%	8.2%	6.5%
Assets	9.9%	14.3%	13.2%	9.1%	11.6%	10.8%
Family loan	5.3%	6.0%	4.9%	6.1%	5.4%	5.3%
Venture funding	0.4%	1.8%	0.7%	0.5%	1.5%	0.7%
Other financing	2.3%	4.1%	3.4%	2.1%	3.7%	3.4%

Notes: See Table 1a. Reported figures document the share of firms reporting they used the funding source for start-up capital as a percentage of all surveyed firms. Firms can report using multiple funding sources.

Similarly, but in the opposite direction, immigrant-owned startups show typically 40%-70% increases in international engagement. These international engagement effects are less distinguishable between low-tech and high-tech firms. In aggregate, immigrant founders in low-tech and high-tech sectors are 81% and 57%, respectively, more likely to

engage in one or more of the three forms of international engagement captured by the SBO.

While we do not report the regression coefficients for control variables, a few results are worth noting. Startups with more owners tend to hire more workers, start their firms with more capital, pay higher

 Table 4

 State level dependency on immigrant entrepreneurs .

	2007				2012			
	New firms	Share 2	All firms	Share 4	New firms 5	Share 6	All firms	Share 8
Top 10	California	42.4%	California	33.1%	New Jersey	44.5%	California	33.4%
•	Washington D.C.	42.3%	Washington D.C.	32.6%	New York	43.1%	Washington D.C.	29.7%
	New York	39.6%	New York	27.1%	California	41.9%	New York	29.1%
	New Jersey	38.6%	New Jersey	26.2%	Florida	33.0%	New Jersey	28.3%
	Florida	30.1%	Hawaii	25.3%	Washington D.C.	32.2%	Florida	25.9%
	Connecticut	28.3%	Florida	25.3%	Illinois	31.7%	Hawaii	23.4%
	Maryland	27.9%	Maryland	18.9%	Massachusetts	30.2%	Maryland	21.1%
	Illinois	27.7%	Nevada	18.6%	Texas	30.1%	Illinois	20.2%
	Massachusetts	26.4%	Illinois	17.7%	Maryland	30.1%	Texas	19.8%
	Nevada	26.4%	Connecticut	17.2%	Hawaii	29.8%	Nevada	18.9%
Bottom 10	Montana	5.0%	North Dakota	3.4%	South Dakota	2.4%	South Dakota	2.5%
	West Virginia	5.0%	South Dakota	3.5%	North Dakota	4.7%	North Dakota	3.2%
	South Dakota	5.7%	Iowa	4.5%	Idaho	4.8%	Nebraska	3.4%
	Wyoming	6.3%	Wyoming	4.5%	Montana	5.4%	Montana	3.4%
	Nebraska	6.6%	Montana	4.5%	Iowa	6.1%	Iowa	3.7%
	North Dakota	6.7%	Nebraska	4.6%	West Virginia	6.3%	Idaho	4.7%
	Idaho	7.1%	West Virginia	4.8%	Maine	6.6%	Wyoming	4.8%
	Iowa	8.7%	Mississippi	5.2%	Wyoming	6.8%	West Virginia	5.0%
	Kentucky	9.0%	Arkansas	5.2%	Utah	7.6%	Arkansas	5.4%
	Arkansas	9.0%	Idaho	5.5%	Nebraska	8.0%	Maine	5.4%

Notes: Table shows states with highest and lowest shares of immigrant owners among surveyed SBO firms. These statistics combine Immigrant only and Mixed teams.

wages, and are also more likely to provide employee benefits. Larger firms, in general, are also more likely to pay better and to offer employee benefits. Part of this difference is due to legal mandates imposed upon larger firms, but a long literature has noted the greater general attractiveness of jobs in larger firms (e.g., Brown et al., 1990; Gibson and Stillman, 2009; Moore, 1911). Firms with female owners, younger owners, and lower-educated owners tend to hire fewer employees, pay lower wages and benefits, and engage less in international activities.

In most cases, these estimated coefficients and effects in Fig. 3 resemble what is observed in tabulations of the raw data; we also tend to find similar results (tabulated in the appendix) when excluding all firm controls $X_{f,t}$. One of the more interesting exceptions is that the lower wage rates paid by immigrant firms in the low-tech sector would be more significant at 1%-1.5% in relative terms without the controls, compared to the 0.2% with the controls. State and industry choices account for about half of the difference, and adding ethnicity controls accounts for the rest, with Asian and Hispanic owned firms tending to pay lower wages in the low-tech sector.

Panel B introduces the firm size control. It is debatable whether one should control for the fact that immigrants tend to own different-sized firms than natives, as we use firm size in constructing some metrics (e.g., receipts per employment) and the size of a company is endogenous with other firm outcomes. Nevertheless, the overall picture remains very similar. For most firm traits, this control slightly diminishes the coefficients and relative magnitudes, but the major themes of weaker provision of benefits and greater overseas activity persist.

Fig. 4 plots regression coefficients similar to Fig. 3 for a variant of specification (1) that combines the immigrant only and mixed team indicator variables. Most of themes emphasized above are reproduced, as the number of mixed ownership teams is small compared to the immigrant only count. The most noticeable differences are a moderating effect on the observed lower provision of employer-provided benefits by immigrant owned companies and an expansion of differences compared to native only firms for international engagement.

Finally, Tables 5a and 5b study the survival and growth properties of immigrant- vs. native-owned firms using the subsequent history of 2007 SBO firms to 2011 in the LBD. The sample begins with 139 thousand companies that were founded between 2002 and 2007 and present in the 2007 SBO. Among those firms matched to the 2007 LBD, Table 5a shows that immigrant-only founded firms are somewhat more

likely to survive to 2011 than are native-owned firms (62.8% vs. 60.1%), with this pattern holding true over shorter time intervals as well (e.g., two-year survival rate). Conditional on survival until 2011, immigrant-only firms remain somewhat smaller in size than native-only firm, with immigrant-only startups growing their employment 23% to 2011 vs. 19% for natives. 21

As we parse the sample into high-tech vs. low-tech in Table 5a, interesting differences emerge. The survival rate for immigrant-only high-tech startups tends to be equal to or less than native-only firms, but the growth rate is significantly faster in large part due to a smaller starting size. For low-tech, immigrant-only firms are more likely to survive and again appear to partially catch-up in terms of employment by 2012 to native-only firms.

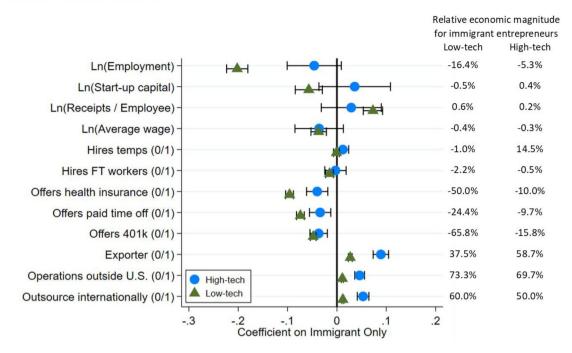
Table 5b tests the stability of these patterns in regression formats that control for geography, industry, and size, using linear probability models with survival until 2011 as the dependent variable. Across the three panels, immigrant-founded firms in the high-tech sector behave in a manner quite similar to native-founded high-tech firms, whereas differences for low-tech remain in Panel C even when conditioning on firm size. The faster growth of immigrant-owned firms in both samples directly connects to their smaller starting size. The 2007–2011 period was, of course, the depths of the Great Recession, and with the future extensions of the LBD it will be important to look at these patterns throughout the subsequent recovery.

5. Spatial differences

We earlier noted that immigrant entrepreneurship is unevenly distributed across the country, with eight-fold or higher differences across states. Florida (2005), Moretti (2012), and other scholars emphasize the growth of powerful high-tech and knowledge centers, with spillover effects onto job creation for other workers. The authors frequently connect these dynamic clusters to immigration and entrepreneurship, and many business press accounts speak of a Silicon Valley exceptionalism. We turn to describing with new data the role of

²¹ We define growth through the log ratio of 2011 employment to 2007 employment, and the patterns are very similar if instead using the Davis et al. (1996) formula with average employment as the baseline.

Panel A: Baseline controls



Panel B: Baseline controls plus firm size control

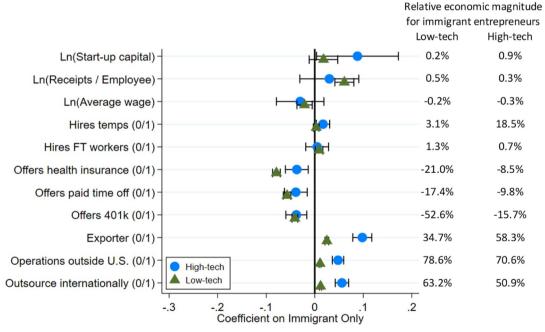


Fig. 3. Estimations for firm traits of immigrant entrepreneurs. **Notes**: See **Fig. 1** and **Table 1a**. Estimations pool 2007 and 2012 data. Coefficients are from an indicator variable for Immigrant only owners. Panel A includes fixed effects for year, state, and industry and controls for the gender, ethnicity/race, age, and number of owners. Panel B further controls for log employment. Regressions are unweighted and show 95% confidence intervals based upon robust standard errors. Appendix Tables A3a-n tabulate results. Relative economic magnitudes are calculated as the ratio of the regression coefficient and the mean of the dependent variable.

immigration entrepreneurs across tech hubs.²²

Table 6 describes how immigrant entrepreneurs are distributed over MSAs. While 29% of new high-tech firms are owned by immigrants or mixed teams, this share is 63% in the San Jose / Silicon Valley area and

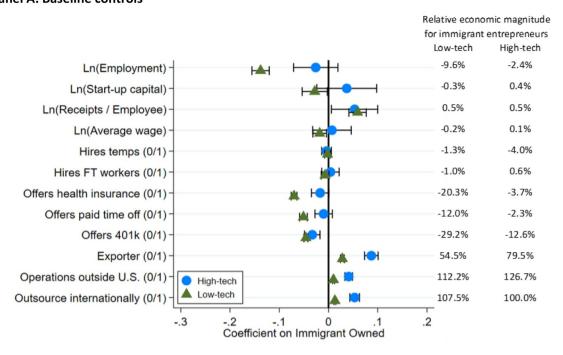
44% in other top tech clusters, compared to 18% elsewhere. Dramatically, about 4% of all high-tech firms owned by immigrants are located in Silicon Valley, compared to 1% for natives. New immigrant-founded

 $(footnote\ continued)$

regional visas for incoming skilled immigrants. Such visas are used, for example, in Canada and are often discussed as a mechanism for building broader policy consensus around expanded migration.

²²In addition to providing an economic portrait of current activity, these distributions can be informative for potential policy changes to encourage

Panel A: Baseline controls



Panel B: Baseline controls plus firm size control

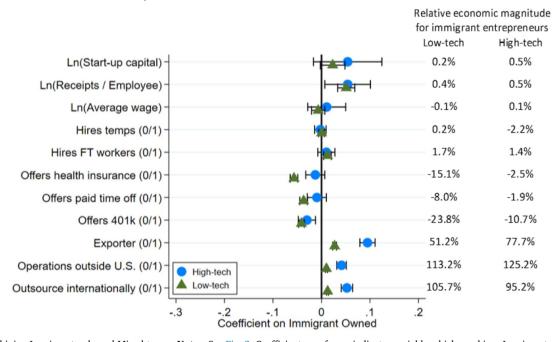


Fig. 4. Fig. 3 combining Immigrant only and Mixed teams. Notes: See Fig. 3. Coefficients are for an indicator variable which combines Immigrant only and Mixed firm ownership. Appendix Tables A4a-n tabulate results.

firms also constitute high shares of low-tech activity in the big tech centers, being in fact equal in Silicon Valley at 63%, but there is overall more mass of immigrant low-tech startups outside of the top tech clusters. This aligns with Figure 2a, where the tech centers show greater rates of both types of immigrant entrepreneurship compared to the states and also a second-order leaning towards high-tech activity (seen visually as tech cluster positions being usually at or below the 45-degree line).

Fig. 5 maps regression coefficients for immigrant-only, mixed, and native-only founding teams by location, with native-only founding teams located outside of the top 10 tech clusters serving as the reference

group. These estimations no longer separate Silicon Valley from the other top regions. Appendix Tables 6a and 6b provide the underlying regressions. Panel A of Fig. 5 shows that high-tech firms founded by immigrants only are modestly under-sized relative to their peers in the top tech clusters, but the bigger differences are in the low-tech sector where immigrant-only startups are smaller within and outside of tech centers.

The remaining panels of Fig. 5 condition on firm size in addition to the other controls. For startup financing, immigrant-only teams raise more seed capital within and outside of the top tech clusters, whereas no real difference exists for low-tech sectors. On receipts per employee,

Table 5aFirm survival and growth summary statistics.

	All industries			High-tech			Low-tech		
	Immigrant only	Mixed 2	Native only	Immigrant only	Mixed 5	Native only	Immigrant only	Mixed 8	Native only
Survival Rate									
Survival until 2008	87.5%	87.8%	86.2%	85.1%	89.7%	86.0%	87.8%	87.4%	86.2%
Survival until 2009	77.4%	76.2%	74.7%	74.0%	79.6%	75.3%	77.8%	75.6%	74.6%
Survival until 2010	69.4%	67.8%	66.7%	65.3%	70.9%	66.9%	69.9%	67.2%	66.7%
Survival until 2011	62.8%	61.2%	60.1%	59.4%	63.8%	60.4%	63.2%	60.8%	60.1%
Conditional on Survival Until 2011									
Mean: Log employment 2007	0.948	1.342	1.047	0.569	0.983	0.674	0.991	1.417	1.094
Mean: Log employment 2011	1.174	1.617	1.238	0.823	1.363	0.885	1.214	1.664	1.281
Mean: Employee growth 2007–2012	22.6%	27.4%	19.0%	25.4%	42.5%	21.1%	22.3%	24.7%	18.1%

Notes: See Table 1a. SBO firms are matched to LBD and followed until 2011.

Table 5bFirm survival and growth regressions.

	All industries		High-tech		Low-tech	
	Alive in 2011	Growth 2007-11 2	Alive in 2011	Growth 2007-11 4	Alive in 2011	Growth 2007-11 6
	N = 139,000	N = 87,000	N = 16,000	N = 10,000	N = 123,000	N = 77,000
1. No controls						
Immigrant only	0.013	0.022	-0.015	0.032	0.017	0.020
-	(0.004)	(0.009)	(0.011)	(0.025)	(0.004)	(0.009)
Mixed	0.008	0.055	0.057	0.153	-0.004	0.031
	(0.006)	(0.015)	(0.014)	(0.042)	(0.006)	(0.018)
Constant	0.623	0.165	0.611	0.216	0.624	0.158
Adj R2	0.0001	0.0002	0.0011	0.0020	0.0002	0.0001
2. State & NAICS Industry						
Immigrant only	0.013	0.017	-0.017	0.011	-0.001	0.018
	(0.004)	(0.010)	(0.011)	(0.026)	(0.004)	(0.010)
Mixed	0.007	0.036	0.054	0.104	-0.002	0.023
	(0.006)	(0.015)	(0.015)	(0.042)	(0.006)	(0.018)
Constant	0.604	0.219	0.630	0.110	0.602	0.225
Adj R2	0.046	0.029	0.015	0.045	0.050	0.028
3. Plus size in 2007						
Immigrant only	0.029	-0.137	-0.003	-0.042	0.333	-0.151
	(0.004)	(0.009)	(0.001)	(0.025)	(0.004)	(0.010)
Mixed	0.002	0.042	0.036	0.159	-0.005	0.022
	(0.006)	(0.014)	(0.014)	(0.025)	(0.006)	(0.016)
Constant	0.520	0.605	0.557	0.370	0.516	0.629
Adj R2	0.076	0.163	0.041	0.126	0.081	0.168

Notes: See Table 5a. Regressions are unweighted.

immigrant-only teams look mostly similar to their native-only counterparts, while wages paid by immigrant-only firms are lower in high tech clusters than peer companies. Lower provision of employer-provided benefits by immigrant-only firms is most pronounced in low-tech sectors, regardless of spatial position, and the gap is erased in mixed teams. By contrast, the greater propensity by immigrant founders towards international activities is strongest in high-tech sectors and independent of a mixed or immigrant-only founding team. ²³

We interpret these results as suggesting that most of the impact of immigrant high-tech entrepreneurship for tech centers happens through the quantity dimension: Silicon Valley and similar tech hubs attract a lot of immigrant founders. Being located in a high-tech cluster demands more of companies: higher receipts per employee and greater wages. Immigrant-founded firms are not very different on these dimensions, providing slightly lower wages and benefits, as we have seen in prior

analyses. This is somewhat to be expected: when representing 40% or more of local startups, it is harder for immigrant founders in tech clusters to behave too differently from peer entrants.

We supplement this SBO analysis with comparable evidence from the publicly available American Community Survey (ACS) data. Within the ACS, the closest metric to business ownership is self-employed individuals in incorporated businesses (SE-I). The primary ACS sample is restricted to individuals who report their place of birth and are aged between 25 and 55. The ACS shows that an increasing share of SE-I entrepreneurs are immigrants, growing from 17% in 2001 to about 24% by 2015. ²⁴

Table 7 again shows immigrant SE-I are disproportionately agglomerated in top tech hubs compared to native SE-I. While the ACS

²³ Appendix Tables 6a and 6b provide for immigrant-only and mixed teams the linear differences between values for being inside and outside of top clusters. In most every case, the linear difference is somewhat smaller than the top cluster coefficient, as the point estimates for those outside of the clusters tend to be in the same direction but smaller, and the differences remain statistically significant.

²⁴ Most states show growing immigrant SE-I shares across this time period, with 14 states exceeding 6% growth, while only three states—West Virginia, Vermont, and Maine—saw declines. Immigrant SE-I has pulled increasingly from individuals coming from Mexico, India, and China since 2001, although no country accounts for more than 4% of the total SE-I stock in 2015. In 2015, immigrant SE-I shares are higher for those with STEM degrees (27%) or Business/Education (22%) compared to other fields (17%). Our NBER working paper provides additional statistics related to this sample.

Table 6 Geographic distribution in 2012.

	Immigrant owned share of firms	Immigrant owned share of group employment	Share of immigrant owned firms over groups	Share of native owned firms over groups
	1	2	3	4
New firms				
High-tech industries				
Overall	28.5%	23.7%		
Outside of Top 10 clusters	17.6%	17.0%	37.0%	69.0%
Top 10 clusters, ex San Jose	43.9%	37.8%	59.1%	30.1%
San Jose / Silicon Valley	62.5%	75.0%	3.9%	0.9%
Low-tech industries				
Overall	25.6%	23.0%		
Outside of Top 10 clusters	18.1%	16.8%	48.9%	76.2%
Top 10 clusters, ex San Jose	42.0%	38.0%	49.6%	23.5%
San Jose / Silicon Valley	62.5%	52.5%	1.5%	0.3%
All firms				
High-tech industries				
Overall	20.0%	13.9%		
Outside of Top 10 clusters	12.2%	9.4%	39.8%	71.4%
Top 10 clusters, ex San Jose	33.6%	26.8%	56.4%	27.9%
San Jose / Silicon Valley	58.6%	36.4%	3.8%	0.7%
Low-tech industries				
Overall	17.4%	14.5%		
Outside of Top 10 clusters	11.8%	10.0%	49.3%	77.8%
Top 10 clusters, ex San Jose	32.3%	27.0%	49.3%	21.8%
San Jose / Silicon Valley	41.6%	40.7%	1.4%	0.4%

Notes: See Table 1a. These statistics combine Immigrant only and Mixed teams. The Top-10 MSAs ex San Jose include Atlanta, Boston, Chicago, Dallas, Houston, Los Angeles, Miami, New York, San Francisco, and Washington D.C.

collected fewer data fields, we can look at income levels reported for the individual and household. Interestingly, immigrant SE-I in high-tech industries report mostly comparable income to native SE-I in all geographic settings. By contrast, low-tech immigrant SE-I report lower incomes than native SE-I and these differences become more pronounced in leading tech hubs, as the incomes for native SE-I rise faster. These intriguing patterns suggest that immigrants engaged in high-tech entrepreneurship in the prominent tech hubs are quite similar to their native peers, but that these larger cities also have a more expansive low-tech immigrant entrepreneurship sector that behaves differently from native-led startups nearby in these sectors.

6. Discussion and future research

We explored the 2007 and 2012 Survey of Business Owners records to learn more about how the businesses created by immigrants resemble and differ from those owned by natives. To summarize a few key findings: immigrant-owned firms are somewhat smaller than nativeowned firms in terms of employee counts but have comparable or greater sales per employee; the jobs created by immigrant firms have mostly comparable salaries but lower provision of health, retirement, and paid time off benefits; and the firms owned by immigrants show a substantially higher rate of engagement in international activity like exporting and the launch of overseas facilities. These patterns are present in both high- and low-tech sectors, with immigrant-founded firms in high-tech sectors tending to look more like their nativefounded peers than they do in low-tech sectors. This partial convergence is consistent with a potentially greater share of pull factors being responsible for immigrant high-tech entrepreneurship and/or greater levels of competition shrinking the potential differences.

The biggest differences are spatial, with ten-fold differences across states in terms of the share of businesses owned by immigrants. A Silicon Valley effect exists in that a staggering 63% of high- and low-tech startups in 2012 had an immigrant founder, with elevated rates of immigrant entrepreneur shares evident in other top tech centers, too. A sub-investigation of firm traits across geographies suggest most of the impact of immigrant entrepreneurs for top tech centers happens via

their large numbers, a quantity aspect, versus different behavior compared to native firms in these locations.

There are several important directions future research can take. We have provided novel evidence on the quality of jobs generated by immigrant-owned firms in terms of compensation and benefits, but there are many other dimensions worth pursuing. Merging onto the SBO the Longitudinal Employer Household Dynamics (LEHD) database would allow researchers to look at the duration of jobs and the evolution of earnings over tenure for workers in immigrant- vs. native-owned firms. The LEHD's mostly universal nature would also allow a greater characterization of ethnic enclaves within regions and how immigrant entrepreneurs function inside vs. external to them.

Uniting the long-form Decennial Census files with the SBO data would provide greater information on the countries of origin and dates of arrival of immigrants. These extra data would allow researchers to examine more sharply differences over groups. As immigrant entrepreneurship rates differ somewhat by nationality, one could learn more about how much of these patterns follow from group-wide preferences to be one's own boss (Hurst and Pugsley, 2011) and how the concentration of immigrant groups into specific occupations for entrepreneurship (Kerr and Mandorff, 2015) shifts their behavior. Such extensive margin evidence would better highlight the mechanisms behind perceived differences in job quality.

The evidence regarding greater overseas activity of immigrant-owned businesses also deserves more consideration. These contributions may be more quantitative and model-based: what are the general equilibrium implications of a rising share of U.S. entrepreneurs being immigrants and therefore being more likely to engage in global activities? As the period of time covered by these surveys includes some countries expanding and others contracting, the relative value of these overseas connections will provide nice variation to tease out their empirical effects.

Finally, we have provided some basic evidence on the jobs created within immigrant firms, but more of the job creation and job destruction machinery (e.g., Davis et al., 1996) and growth analysis (e.g., Puri and Zarutskie, 2012) could be applied to these groups. This would be especially powerful when combined with information on the

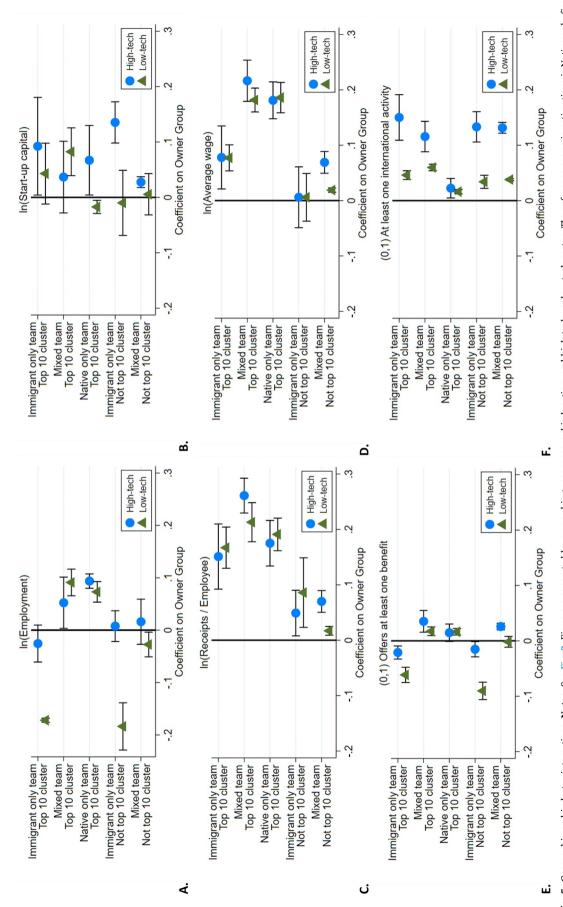


Fig. 5. Geographic and industry interactions. Notes: See Fig. 3. Firms are separated by ownership types, geographic location, and high-tech vs. low-tech sector. The reference group in estimations is Native only firms located outside of Top 10 clusters. Panel A includes all controls except firm size. Firm size is added as a control for Panel B-F. Appendix Tables A6a and A6b provide detailed results.

Geographic distribution for immigrant and native self-employed, 2012-2015.

	Immigrant share of self-employed		Share of native self-employed	Average individual income for	Average individual income for native	Ratio of Column 4 to Column 5	Average household income for	Average household income for native	Ratio of Column 7 to
		employed over groups	over groups	immi grant self-employed	self-employed		immigrant self-employed	self-employed	Column 8
	1	2	3	4	2	9	7	8	6
High-tech industries									
Overall	19.9%			\$99,532	\$104,636	95.1%	\$163,918	\$160,784	101.9%
Outside of Top 10 clusters	11.7%	35.5%	%6.99	\$91,844	\$96,169	95.5%	\$147,648	\$147,559	100.1%
Top 10 clusters, ex San Jose	31.4%	55.8%	30.4%	\$100,541	\$120,542	83.4%	\$166,199	\$186,265	89.2%
San Jose / Silicon Valley	45.1%	8.7%	2.6%	\$124,389	\$135,824	91.6%	\$215,592	\$202,175	106.6%
Low-tech industries									
Overall	21.9%			\$64,993	\$81,876	79.4%	\$110,920	\$130,900	84.7%
Outside of Top 10 clusters	14.0%	44.0%	75.5%	\$62,185	\$76,128	81.7%	\$105,625	\$121,704	86.8%
Top 10 clusters, ex San Jose	38.8%	52.3%	23.1%	\$66,979	\$98,403	68.1%	\$113,462	\$157,393	72.1%
San Jose / Silicon Valley	43.5%	3.7%	1.3%	\$70,329	\$120,730	58.3%	\$138,142	\$192,168	71.9%

Notes: See Table 6. Data from American Consumer Survey, pooling 2012–2015. Sample restricted to incorporated self-employed respondents aged 25–55.

individuals hired. Immigrant owners may show different employment adjustment patterns for immigrant employees from their home country than immigrants from other countries or native employees. Given the heavy geographic and industrial clustering of immigrant entrepreneurs, this could in turn influence regional business cycles.

Authors contributed

Both authors contributed equally to all aspects of the work.

Declaration of Competing Interest

None.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.respol.2019.103918.

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