Entrepreneur Experience & Success: Causal Evidence from Immigration Wait Lines*

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Abstract

This paper investigates the causal impact of entrepreneurs' prior experience on startup success. Employing within-country changes in Green Card wait lines to instrument for immigrant first-time entrepreneurs' experience, we uncover that startups led by more experienced founders demonstrate superior funding, patenting, and employee growth. Specifically, each additional year of founder experience leads to a 0.6 p.p. (1 p.p.) increase in the likelihood of a startup undergoing an IPO (growing to over 1000 employees), over the subsequent decade. The larger initial team size, facilitated by the improved ability to recruit former colleagues, explains the observed startup success. Our findings imply that each extra year of experience is worth $170,000, underscoring a critical consideration for policymakers in the design of startup incubators.

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1 Introduction

What makes a successful entrepreneur? The question holds paramount significance as new enterprises propel economic growth through the introduction of innovative products and processes (Schumpeter, 1942), as well as by reallocating talent toward more productive endeavors (Lucas, 1978; Baumol, 1990; Murphy et al., 1991; Gennaioli et al., 2013). Nonetheless, entrepreneurship inherently carries substantial risk, with approximately 75% of venture-backed startups ultimately culminating in failure (Pollman, 2023). Unraveling the key attributes that forecast startup triumph has become a central question in academic and policy circles.

Previous literature has extensively examined both inherent traits, such as personalities (Kerr et al., 2018; Levine and Rubinstein, 2017), and mutable characteristics, such as skill sets (Lazear, 2004), as potential predictors of entrepreneurial success. In this paper, we delve into the influence of one such characteristic: the founder's prior experience before embarking on their *first* startup. The founder's initial experience holds particular significance from a policy standpoint, as it can often be shaped by the design of incubators and startup fellowships. The prevalence of such incubators is on the rise, with 1400 incubators in the US alone as of 2016[1]. These incubators can adopt very different policies, ranging from Thiel fellowships[2] which require founders to drop out of college, to Venture for America[3], which trains and staffs budding entrepreneurs into startups to gain experience. Consequently, quantifying the impact of prior job experience on startup success is vital for designing incubators.

There exists considerable disagreement on the impact of prior experience on entrepreneurship. Some argue that experience entrenches entrepreneurs in existing paradigms, impeding the introduction of groundbreaking ideas (Azoulay et al., 2020). Anecdotal evidence further reinforces these assertions, with figures like Bill Gates and Mark Zuckerberg serving as prominent examples of college dropouts who went on to establish

[1] https://inbia.org/wp-content/uploads/2018/08/NumberofECsimage.jpg?x62369

[2] https://thielfellowship.org/

[3] https://ventureforamerica.org/

multi-billion dollar enterprises. Conversely, numerous studies indicate that greater market knowledge (Gruber et al., 2008; Chatterji, 2009; Agarwal et al., 2004), technical prowess (Klepper and Sleeper, 2005; Agarwal et al., 2004), and expansive social networks (Singh et al., 1999; Honig and Davidsson, 2000; Kerr and Kerr, 2019; Kerr and Mandorff, 2023), are indicative of entrepreneurial success. It stands to reason that relevant experience should bolster successful entrepreneurship by enhancing these traits. Given the disagreement in predictions from theory, the impact of experience on entrepreneurship ultimately becomes an empirical question.

Previous literature has established a correlation between higher entrepreneur age (Azoulay et al., 2020) and experience (Chatterji, 2009; Klepper and Sleeper, 2005; Gompers et al., 2005; Agarwal et al., 2004) with improved startup outcomes. However, interpreting the findings of these studies causally presents challenges. Entrepreneurs self-select the number of years of experience they acquire, raising the possibility that these results may also be attributed to higher-quality entrepreneurs actively seeking relevant work experience. An ideal setting would involve randomly assigning years of experience to each startup founder and subsequently examining the differential outcomes across the firms they establish. While achieving this ideal scenario may be challenging, we come close to it by exploring the idiosyncrasies of the US immigration system.

Over 70% of legal immigrants enter the US annually utilizing employment-based visas such as H1-B and L1 (Jasso et al., 2010). A prerequisite for these visas is that the immigrant must serve as an employee for a qualified firm, one they do not themselves control[4]. These immigrants must secure legal permanent residency, colloquially known as Green Cards (GCs), to establish and work full-time in their own startups. US immigration regulations restrict employment-based GCs to an annual quota of 140,000, with a maximum of 7% allocated to any single country per year. This cap has proven restrictive for countries with high demand, notably India, China, and Philippines, where demand for GCs far surpasses the 9,800 limit.

[4]Control here refers to the ability to make managerial decisions or exert significant influence over the operations of the firm.

Immigrants from these high-demand countries queue in first-come-first-served wait lines to obtain their GCs. While across country GC wait time differences are large and persistent[5], forecasting wait times within a country is exceedingly challenging. Within cohort wait times can fluctuate due to a number of unpredictable factors such as policy implementation[6], and errors within the United States Citizenship and Immigration Services (USCIS)[7]. For instance, wait times for GCs varied from eight years to eleven years for India, and two years to five years for China, across the 2010–2017 cohorts. The within-country variation in these GC wait times serves as our instrumental variable for founder experience prior to their first startup.

The availability of data has posed a significant obstacle in examining the impact of immigration policies on entrepreneurship in the United States. While previous studies have successfully identified immigrant entrepreneurs using census data (Azoulay et al., 2022; Kerr and Kerr, 2016, 2020; Brown et al., 2019; Burchardi et al., 2020) or name-based algorithms (Saxenian, 2002), estimating the specific GC wait times faced by an individual has been impossible, as the USCIS does not publicly release person-level immigration data. To address this gap, we compile the first dataset correlating the exact date of the Green Card (GC) application (and consequently, the GC wait line) with each immigrant founder. We construct this dataset by obtaining individual PERM filings (the initial step toward employment-based GCs) from the DOL website. These filings contain detailed information on the employee's country of origin, current employment, location, work history, and education. We merge this data with founders' profiles from LinkedIn, which provide comprehensive educational and career histories. Each match is manually verified to ensure accuracy. Furthermore, we merge this data with Crunchbase to acquire funding and startup outcomes, and with patent databases through fuzzy name matching. Our dataset encompasses 2,531 startup founders,

[5]For instance, the average wait time for India is 8.5 years, 3.4 years for China, and 1.5 years for the Philippines in our sample.

[6]Some administrations have chosen to recapture surplus GCs to surpass the 7% cap.

[7]USCIS occasionally misjudges the number of petitions, leading to applications for GCs exceeding the limit (Shen, 2021; Gupta, 2023)

with an average GC wait time of 3.5 years and an average experience of 10.7 years before their first startups. Of these founders, 49% identify as white, and 21% as female. The information technology and service industry and California account for 29% and 20% of the startups in our sample, respectively.

Focusing on immigrants inherently biases our sample toward high-growth startups. Thus our results may not apply to general small businesses in the US. Nonetheless, immigrant-led high-growth startups represent a crucial area of interest. High-growth startups generate 10 percent of new jobs annually, despite accounting for less than one percent of all firms[8]. Immigrant entrepreneurs found about a quarter of these high-growth startups in the US (Kerr and Kerr, 2020; Azoulay et al., 2022). This outsized impact renders immigrant entrepreneurs an interesting setting for addressing our research question.

We begin by confirming the relevance condition of our instrumental variable. Specifically, we investigate whether founders who endure longer Green Card (GC) wait time start their first firm with more experience under their belt. Our analysis reveals an exceptionally robust relationship, wherein each additional year of GC wait time corresponds to an increase of approximately 9 to 10 months in founder experience. The F-statistic surpasses 60, significantly exceeding conventional thresholds for weak instruments. Additionally, the balance of panels tests demonstrates that our instrument effectively captures as-if-random variation in founder experience, remaining uncorrelated with any employee characteristics.

Our analysis reveals that greater founder experience improves startups across various metrics. Specifically, each additional year of experience corresponds to a 12% increase in funding compared to the mean. This surge in funding results from both a greater frequency of funding rounds and a heightened likelihood of securing exceptionally large rounds exceeding $100 million. Additionally, startups led by founders with an extra year of experience issue 4% more patents and garner more citations than the mean, while also experiencing a 12% higher growth rate in their workforce. These benefits significantly elevate the likelihood

[8]https://www.cga.ct.gov/2016/rpt/2016-R-0003.htm

of startup success. Notably, founders possessing one additional year of experience exhibit a 1-percentage-point (p.p.) higher probability of expanding their startups to over 1000 employees and a 0.6-p.p. higher probability of participating in an IPO.

The exogeneity condition of our instrumental variable hinges on the premise that the founder's Green Card (GC) wait times exclusively influence startups through the founder's experience. Two identification concerns merit consideration. Firstly, GC wait times may vary depending on the founder's country of origin and the cohort of application. Confounding variables correlated with these factors could directly impact startup outcomes without affecting the founder's age. We address this concern by incorporating country-fixed effects into our model and demonstrating the robustness of our results to controlling for founder cohort effects. Secondly, longer wait times may alter the quality of immigrants entering the US, thereby influencing the quality of immigrant-led startups. We show our analyses to be robust to using unanticipated wait times, the difference between actual and expected wait times at the time of entry, greatly alleviating any such concern.

Our findings indicate that the positive impact of experience is more pronounced for certain demographic groups, including females, and minorities. Notably, experience appears to be particularly valuable for founders who can leverage it to establish a greater number of social connections. These results align with the notion that job experience plays a pivotal role in reducing informational friction.

In our subsequent analysis, we explore various mechanisms to understand why founder experience improves startup outcomes. We examine three potential pathways: industry-specific knowledge accumulation, financing ability, and ability to attract talent. Our findings suggest strong support for the last mechanism. We observe no significant changes in the probability of entrepreneurs entering the same industry as their prior experience or in securing funding earlier due to increased experience. However, entrepreneurs with more experience start larger firms with a greater number of co-founders, with a notable increase in the initial employees and co-founders sourced from the founder's previous colleagues.

Additionally, our results indicate that startups with larger initial sizes and founding teams drive the observed improvements in startup outcomes. These findings are consistent with experience leading to better startup performance by facilitating team formation.

Back-of-the-envelope calculations estimate that each additional year of experience is valued at approximately 170,000 dollars[9]. This figure holds significant importance as it provides insight into the trade-off that policymakers must consider this valuation when designing scholarships and initiatives aimed at fostering new firm formation directly out of college.

Related Literature

This paper adds to three main strands of literature. First, this paper contributes to existing studies exploring the drivers of entrepreneurship. Existing work has thoroughly explored various predictors of entrepreneurial success, focusing on both inherent traits, such as personalities (Kerr et al., 2018; Levine and Rubinstein, 2017) and mutable characteristics, such as skill sets (Lazear, 2004), location choices (Dahl and Sorenson, 2012), founding experience or serial entrepreneurship (Lafontaine and Shaw, 2016; Gompers et al., 2010; Wright et al., 1997; Hsu, 2007; Zhang, 2011). Specifically, several studies have established a correlation between improved startup outcomes and higher entrepreneur age (Azoulay et al., 2020) or experience at incumbent firms (Chatterji, 2009; Klepper and Sleeper, 2005; Gompers et al., 2005; Agarwal et al., 2004), which is associated with the inheritance of both technological and marketing know-how. However, it is challenging to draw causal conclusions from these studies as founders endogenously choose experience based on their quality. We instrument for founder experience using GC wait times and find strong positive effects of prior work experience on startup success. To our knowledge, this is the first study to establish the causal impact of experience on the success of the first startup founded by an entrepreneur.

[9]See Table A11 for calculation details.

Second, this paper contributes to the literature on the impact of immigration policy on US startups. Existing work has focused on the impact on the supply of immigrants due to exogenous shifts in H1-B visa caps (Kerr and Lincoln, 2010; Ghosh et al., 2014; Ashraf and Ray, 2017; Mayda et al., 2018; Xu, 2018), design of the visa lottery (Clemens, 2013; Doran et al., 2022; Dimmock et al., 2022; Chen et al., 2021), or spatial settlement patterns of immigrants (Kerr et al., 2015; Peri et al., 2015) on startups. Studies examining GC restrictions have focused on the impact of restricted employee mobility on firm monopsony power (Gupta, 2023), investment (Shen, 2021), and family life (Vijayakumar and Cunningham, 2019). Our paper is the first to study the impact of GC restrictions on startup success. Although we cannot directly comment on the welfare implications of GC wait times, our research uncovers an unintended positive outcome resulting from limitations on GC availability: the additional experience gained by immigrants at incumbent firms while awaiting GC processing contributes to the success of their startup ventures.

Finally, this paper adds to the literature on the role of social connections in entrepreneurship. Existing work has examined the impact of different types of social networks on entrepreneurial success, including family networks (Dunn and Holtz-Eakin, 2000; Fairlie and Robb, 2007), friendship networks (Honig and Davidsson, 2000), community networks (Kerr and Kerr, 2019; Kerr and Mandorff, 2023), and general social networks (Singh et al., 1999). We document that experienced founders bring in ex-colleagues to enlarge the initial team, ultimately contributing to better startup performance. Our paper adds to the literature by identifying the importance of professional social ties as a key contributor to startup success.

2 Institutional Setting

Over 70% of legal immigrants enter the US annually utilizing employment-based visas (Jasso et al., 2010). Employers sponsor high-skilled workers for H1-B visas and managers for

L-1 visas. Employees are not allowed to have any ability to make managerial decisions or exert significant operational influence, in firms that sponsor these visas. As a result, immigrants entering the US on employment-based visas must secure legal permanent residency, colloquially known as Green Cards (GCs), to establish and work full-time in their own startups.

A typical GC (Green Card) application involves three sequential steps, each adjudicated independently (Figure B1). First, the worker obtains labor certification (PERM) from the Department of Labor (DOL), with the date of the PERM application serving as the employee's priority date. Second, the employer submits an immigrant petition for the employee (I-140). Finally, the worker can apply for Adjustment of Status (I-485) to receive their GC. The U.S. system sets a fixed cap of 9,800 on the number of Adjustment of Status applications that can be filed annually by any country and employment category.[10] The total annual cap for GCs is 140,000, with any single country and category eligible for a maximum of 7% of the annual cap. Employees from countries and categories where the demand for GCs exceeds the cap are not permitted to apply directly. Instead, they must join first-come-first-served lines and can only apply for Adjustment of Status once their priority date becomes current, as indicated in a monthly visa bulletin[11] released by the Department of State. This system has resulted in significant wait times for high-demand countries, with an average wait of 8.5 years for India, 3.4 years for China, and 1.5 years for the Philippines, in our sample.

Green Card (GC) wait times demonstrate two distinct types of variation - across and within country and category. There are significant differences of five to eight years observed across countries and categories. Within-country and category variations exhibit smaller fluctuations of upto four years across different cohorts. While across-country-category variation is persistent, it is exceedingly difficult to forecast across cohort variations, as they are often influenced by various unpredictable factors. These include policy nuances

[10] There are three GC categories (EB-1, EB-2, EB-3), categorized based on worker education.
[11] https://travel.state.gov/content/travel/en/legal/visa-law0/visa-bulletin.html

(different administrations may apply GC recapture differently, with some even recapturing unused surplus from previous years), and errors within the United States Citizenship and Immigration Services (USCIS), such as occasional misjudgments leading to an excess of GC applications beyond the limit (Shen, 2021; Gupta, 2023). Figure 1 shows this within country-category variation. In numerous instances, wait times across consecutive cohorts separated by just a month, fluctuate by more than 2 years. These fluctuations do not appear to be correlated across country categories within the same cohort. The within-country variation in GC wait time serves as our instrumental variable for founder experience prior to their first startup.

3 Data

The availability of data has posed a significant obstacle in examining the impact of immigration policies on entrepreneurship in the United States. USCIS does not publicly release person-level immigration data, creating a huge challenge in estimating the individual-level GC wait times. We surmount this hurdle by creating a dataset matching the individual-level priority dates (from PERM filings), to different founder and startup-level databases. The next section details the main datasets used in our analysis. We then detail the data-matching process and summary statistics of the data.

3.1 Main Datasets

LinkedIn: LinkedIn, established in 2003, has become the largest global platform for professional networking online, boasting more than 900 million members worldwide. The platform allows users to create profiles that function as an extensive online resume, showcasing their educational background (including the institutions attended, programs completed, and graduation dates) and work experience (detailing the companies worked for, job locations, titles, seniority, salaries, and dates of employment). We use LinkedIn data for over 484 million users extracted from public profiles. The dataset is a 2022 snapshot. We obtain LinkedIn data from Revelio Labs.

Most founder characteristics used in our analysis are from LinkedIn. We define the founder's length of experience at the time of founding the startup as time in years from the highest degree graduation to the startup's founding. Revelio Labs predicts each founder's gender and race based on the name. For education, we define a person with an advanced degree if his or her highest degree level is a master's or higher. We additionally predict country of origin based on name and merge in the 2010 ARWU world rankings[12] of all universities in the education history of the founders. The granular nature of this data allows us to track the entire job history of founders, i.e., which and what types of companies they worked for before founding their startups. We also leverage seniority[13] and salary for each position is imputed based on the position title, firm, and location by Revelio Labs. The number of social connections is also available in one's LinkedIn profile. We also get the industry classification and locations of the startups from their LinkedIn pages.

CrunchBase: Established in 2007, CrunchBase is a global repository of information on companies, investors, and significant people connected to these entities within the startup ecosystem. It covers over 675,000 firms tracking firm names, addresses, industries, founders, and firm events, such as funding, IPOs, and acquisitions. The URLs for the company LinkedIn pages and individual LinkedIn pages available in the CrunchBase database allow us to link the companies and people to the LinkedIn data easily.

We obtain the IPO and funding information of the startups from the CrunchBase database, including timing, amount, and source of funding, as well as the time of listing and valuation price for those that went public. The number of funding rounds and the funding

[12]The Academic Ranking of World Universities (ARWU), also known as the Shanghai Ranking, is one of the annual publications of world university rankings. ARWU is regarded as one of the three most influential and widely observed university rankings, alongside QS and Times.

[13]Revelio Labs breaks positions into 5 equal buckets based on the level or rank of the job title. The seniority of a position can range from 1 to 5, from lowest to highest.

amount are cumulative. Funding values are deflated to be in 2015 dollars.

PatentsView: PatentsView is a platform developed by the United States Patent and Trademark Office (USPTO) aimed at promoting the accessibility and exploration of U.S. patent data. It covers over 4 million U.S. patents tracking patent specifics, inventors, assignees, technology classifications, and citation networks. We use PatentsView to construct patent-related outcomes for startups.

All patent-related outcomes are obtained by summing over all patents filed by the firm as the assignee in that year and eventually granted. Equal weights are assigned when there is more than one assignee.[14] In addition to the number of patents, we count citations within three years from the grant date. We calculate the adjusted number of citations by normalizing each patent's three-year citation count by the average citation count for all other patents granted in the same year and Cooperative Patent Classification (CPC) class (Bernstein et al., 2022). Patents with the top 10% of citations in the same year and CPC class are considered top patents. The data source for KPSS values of patents is Kogan et al. (2017). KPSS values are deflated to be in 2015 dollars.

PERM Data: Obtaining a labor certification (PERM) from the Department of Labor (DOL) is the first step of any GC filing. These filings contain detailed information on an employee's country of origin, current employment, location, work history, and education, and can be downloaded from the DOL website[15]. The PERM filings case number allows us to infer the date of filing, which serves as the priority date for each individual's GC wait line. This priority date information allows us to estimate the exact GC wait line faced by each individual.

[14] For example, if there are two patent assignees, it contributes 0.5 to the patent count for both.

[15] https://www.dol.gov/agencies/eta/foreign-labor/performance

3.2 Data cleaning & matching process

Identifying founders The data sources for the founder sample used in our analysis are LinkedIn and CrunchBase. We filter out the sample of founders from the data in two ways. First, we screen the CrunchBase people dataset for individuals in the U.S. who joined the startups no later than two years after the companies' founding. We match each person on CrunchBase to LinkedIn based on individual and company LinkedIn page URLs. Second, we screen the positions on LinkedIn for individuals working for U.S. companies with job titles that explicitly contain "founder", "cofounder" or "founding". We combine the individuals screened in both ways as our overall sample of founder LinkedIn profiles.

Match between founder profiles and PERM We match the LinkedIn profiles of the founders with their PERM filings to identify the immigrants and determine the priority date and thus the green card wait time of each individual. While PERM filings do not mention an individual name, we are able to uniquely identify and match individuals on other granular characteristics present in both datasets including education institute, education degree, graduation date, firm at the time of PERM filing, employee location at the time of PERM filing, and job title at the time of PERM filing.

We do the matching in two steps. First, we filter founders who established their startups after 2005 to match the sample period of the PERM data. We do fuzzy matching based on school names in education information in PERM filings and LinkedIn profiles. We also require that the degree levels be the same and the difference in graduation dates be no more than one year in the two datasets. For the LinkedIn profiles matched with PERM filings based on education, we additionally do fuzzy matching between the company name of each job position in the profile and the employer firm name in the PERM filing. We also require that the start date of the matched position is no later than one year after the priority date and the end date is no earlier than the priority date. Finally, we manually examine all the potential matches from the first step based on (predicted) countries of origin, school names, majors, graduation dates, company names, job titles, and locations. Credible matches are selected and kept. In the end, our procedure yields a sample of 2,531 immigrant founders.

We also link the founders to the corresponding companies and their employees on LinkedIn. We count the number of active employees in each firm for each year since establishment from the position-level data of LinkedIn. Among employees, we identify previous colleagues of the founder by matching their work history on LinkedIn. Employees who joined the company in the same year as the founding of the company are considered as initial employees. Employees with job titles that explicitly contain "founder", "cofounder" or "founding" are considered cofounders.

Match to CrunchBase & PatentView Founders screened from CrunchBase are already linked to companies within CrunchBase. For those founders screened only from LinkedIn, we match their startups on LinkedIn with CrunchBase companies based on URLs of company LinkedIn pages and fuzzy matching on company names.

We match the founders and their startups with the patent assignees in PatentsView based on fuzzy matching on company names, location match, and time match[16]. We then obtain the patent information of each firm from the PatentsView database.

3.3 Summary Statistics

We present summary statistics of key variables for the sample of immigrant founders and their startups in Table 1, including means, standard deviations, 10%, 50%, and 90% quantiles. Founder characteristics in Panel A and initial startup characteristics in Panel B are at the firm level with 2,531 observations, while startup outcomes in Panel C are at the firm-year level with 20,395 observations. We also present summary statistics for the sample of all founders in Table A2 for comparison. On average, immigrant founders have 10.7 years of experience before founding their first startups, while the average across all founders is lower at 7.8 years. 49% of immigrant founders are white compared to 71% in the overall founder population. A higher percentage of immigrant founders have advanced degrees (72%)

[16] We require the first patent to be filed after the company is founded.

compared to all founders (49%). Similarly, a higher proportion of immigrant startup founders come from the top 500 universities in the world (74%) compared to all founders (56%). Startups of immigrant founders are likely to receive more funding in terms of rounds and amounts. Immigrant founders are more likely to start their firms in tech-centric industries like information technology and computer software as presented in Table A3. They are also more likely to concentrate in certain states like California as presented in Table A4. These patterns are generally consistent with the conclusion that focusing on immigrants biases our sample toward high-growth startups.

4 Empirical Design

We estimate the relationship between the length of experience of the founder and their first startup outcomes using the following empirical framework:

$$\text{OLS: } Y_{i,t} = \beta \ \text{Exp}_i + \boldsymbol{X}'_{i,t}\Gamma + \varepsilon_{i,t} \tag{1}$$

$$\text{First Stage: } \text{Exp}_{i(,t)} = \alpha \ \text{WaitTime}_i + \boldsymbol{X}'_{i,t}\mu + \epsilon_{i,t} \tag{2}$$

$$\text{Second Stage: } Y_{i,t} = \tilde{\beta} \ \widehat{\text{Exp}}_{i,t} + \boldsymbol{X}'_{i,t}\tilde{\Gamma} + \tilde{\varepsilon}_{i,t} \tag{3}$$

In Equation (1), the coefficient β denotes the OLS estimate of the effect of Exp_i, the length of experience of the founder at the time of founding the startup i, on $Y_{i,t}$, the outcome of the startup i in the year t. On the equation's right-hand side, we control for calendar-year fixed effects, founder citizenship fixed effects, founder degree-level fixed effects, firm founding-year fixed effects, firm industry fixed effects, and firm state fixed effects in the baseline, encapsulated by the vector $\boldsymbol{X}_{i,t}$. Equation (2) details the first-stage regression that estimates the relationship between our instrument WaitTime_i, the length of GC wait time of the founder of the startup i, and the length of experience of the founder, Exp_i. Equation (3) presents the second-stage regression, where the coefficient $\tilde{\beta}$ quantifies the 2SLS estimate of the effect of the founder's experience on startup outcomes.

We also implement the same two-stage least squares design in the cross-section for some time-invariant dependent variables, e.g., initial startup characteristics, by estimating the following equations:

$$\text{OLS: } Y_i = \beta \ \text{Exp}_i + \boldsymbol{X}_i' \Gamma + \varepsilon_i \tag{4}$$

$$\text{First Stage: } \text{Exp}_i = \alpha \ \text{WaitTime}_i + \boldsymbol{X}_i' \mu + \epsilon_i \tag{5}$$

$$\text{Second Stage: } Y_i = \tilde{\beta} \ \widehat{\text{Exp}}_i + \boldsymbol{X}_i' \tilde{\Gamma} + \tilde{\varepsilon}_i \tag{6}$$

where Y_i is some time-variant dependent variable of the startup i, and $\boldsymbol{X}_i$ includes founder citizenship fixed effects, founder degree-level fixed effects, firm founding-year fixed effects, firm industry fixed effects, and firm state fixed effects. Other notations and the interpretation of the coefficients are the same as for the panel regression above.

Identifying Assumption and Validity Checks

To identify the causal impact of the founder's experience on startup performance, the exclusion restriction for the 2SLS estimator is that the instrument. i.e., GC wait time, must be orthogonal to omitted founder characteristics that are correlated with startup outcomes, conditional on the controls. Consistent with this assumption, Figure 3 shows results of balancing regressions that our instrumental variable does not correlate with ex-ante founder characteristics conditional on the fixed effects that we control for in the baseline specification. In particular, the instrument does not correlate with whether the founder has degrees from the top 500 universities, whether the seniority of the first job is above the median, the log of the salary of the first job, whether the founder is female, and whether the founder is white. Furthermore, in Table A6, utilizing the full sample of PERM filings, we show that the length of GC wait time does not significantly affect the probability of green card applicants becoming founders on the extensive margin. These results alleviate concerns that longer GC wait time could be correlated with higher-quality founders or the probability of becoming an entrepreneur and underscore that our findings are unlikely driven by the difference in ex-ante founder characteristics.

In contrast, we find that short-experienced founders are more likely to come from highly-ranked universities, even conditional on the fixed effects. This may be because high-quality entrepreneurs are likely to receive higher returns from their ventures, so they tend to start their businesses earlier. High school ranking serves as a proxy for one's high quality here. Although the quality channel may also play a role in the relationship between experience and initial job seniority or salary, the positive correlation suggests that this is more likely because better deals as an employee, possibly due to randomness in job search, make the opportunity cost of starting one's own business increase.

First Stage Results

Our instrument is strongly predictive of the founder's length of experience. The first stage results by estimating Equation (2) are reported in Table 2. Column 5 presents the estimates from our preferred specification. Each additional year of GC wait time corresponds to an increase of approximately 9 to 10 months in founder experience. The F-statistic surpasses 60, significantly exceeding conventional thresholds for weak instruments. The relationship is robust to different fixed effect specifications as presented across columns. We also present the corresponding binned scatter plot that visualizes the relationship between GC wait time and the founder's length of experience in Figure 2.

5 Results

Impact of Experience on Startup Outcomes

We find economically large and statistically significant benefits of founder experience on startup performance across various metrics. Tabel 3, Panel A reports the 2SLS estimates of the effects of founder experience on their first startup outcomes by estimating Equation (3). Following prior literature, our first measure of startup performance is the likelihood and amount of VC financing (Gompers, 1995). In Column (2), we find during our sample period of 2005 to 2022,[17] one additional year of experience increases the total funding amount received from VCs by 12%. In Columns (1) & (3), we further investigate what is driving the higher funding received. We find one additional year of experience leads to 0.16 additional rounds of funding received (7.6% increase relative to the mean), and a 1.45 percentage points (p.p.) higher chance of securing a total funding amount exceeding $100 million (26% increase). Given more than 50% of the immigrant-founded startups in our sample are in tech-centric industries such as IT, Software, and the Internet, a common set of metrics for startup performance are measures of patenting productivity (Bernstein et al., 2016; Chen et al., 2021; Galasso and Schankerman, 2015; Griffith and Macartney, 2014). In Column (4), we find one additional year of founder experience increases the number of patents granted by 3.9%. In Column (5), we measure the quality of patents granted using the number of citations received. One additional year of experience increases the patent citations by 4.9%. One issue with the patent citation measures is citation rates vary significantly across fields and years. Following Bernstein et al. (2022), in Column (6), we normalize the number of citations by the average number of citations for all other patents granted in the same year and the Cooperative Patent Classification (CPC) class. One additional year of experience leads to 4.2% higher adjusted citations. Our third dimension of startup performance is the firms' growth in employment (Azoulay et al., 2020; Kerr and Kerr, 2020). First-time founders with one additional year of experience benefit from a 12% higher growth in employment in Column (7), and 1 p.p. higher chance of expanding over 1000 employees in Column (8). Our last performance measure is the likelihood of undergoing an initial public offering (IPO), which increases by 0.6 p.p. per one additional year of experience. We show effects on additional startup outcomes related to employment and patents in Table A8, which

[17] On average, we observe a startup for 8 years since its founding in our sample.

also provides consistent results. These results suggest that more experience before the first attempt of entrepreneurship helps startups to grow faster on average and also significantly increases startups' chance of achieving right-tail outcomes.

Figure 3 illustrates that founders with higher-quality backgrounds, such as those from esteemed universities, are considerably more inclined to establish firms without prior experience. Consequently, we anticipate a negative selection effect, which may downward bias OLS estimates. Our analysis confirms this expectation, as observed in our OLS estimates derived from Equation 1 and detailed in Table 3, Panel B. While the OLS estimates generally exhibit statistical significance, their magnitudes are notably smaller in comparison to the 2SLS estimates. These findings affirm the negative correlation between founder quality and experience and underscore selection as a significant factor contributing to the perceived association between less experienced founders and success.

Identification Concerns & Robustness Checks

Figure 1 indicates that GC wait time depends on the founders' country of origin and their cohort applying for a green card. Unobservables correlated with these two factors could directly impact startups. To address this concern, in Table 4, Panel A, we control for both the founder's origin country fixed effects and the founder's cohort or graduation year fixed effects, so we are comparing startups founded by immigrants from the same country and the same cohort of application. Results are robust across different performance measures.

We also show in Panel B in Table 4 that the results are robust to using more flexible fixed effects, i.e., firm-industry-by-year fixed effects and firm-state-by-year fixed effects instead of imposing them separately, in addition to the founder controls.

Longer wait time for a green card may alter the composition and thus the quality of immigrants coming to the US over time. For example, talented Indian or Chinese immigrants may be deterred from coming to the US after observing an increasing wait time for a green card over time, which could induce compositional shifts across immigrant cohorts that affect the quality of immigrant-founded startups systematically. To mitigate this concern, in Table 4, Panel C, we replace the instrument with the unanticipated green card wait time, which is the difference between the actual GC wait time of the founder and the wait time of the cohort appearing in the Visa Bulletin when the founder starts the first US job. While one can predict the GC wait time based on the Visa Bulletin's monthly current application dates at the time of filing for a green card, the actual wait time could be longer or shorter due to idiosyncratic reasons that are completely unpredictable. Our unanticipated wait time measure captures the random component of the realized wait time. We find our 2SLS estimates are generally robust using the alternative instrument, though the statistical powers are reduced for some outcomes. The results alleviate the concerns that potential shifts in immigrants' quality due to longer GC wait time also affect startup performance.

Chen and Roth (2023) point out problems with log-like transformation when there are 0 values for the outcome variable. We follow their suggestion and show in Table A7 that our results for logarithmic outcomes are robust to using Poisson regression.

Heterogeneous Effects

Table 7 assesses whether the positive effects of experience on first-time startup performance are more pronounced for certain founder characteristics. Panel A reports the impact of experience by gender. We find a larger positive impact of one additional year of experience on the number of VC funding rounds (0.4 vs. 0.1 for males), total funding amount (33% vs. 12% for males), and employment level (61% vs. 17%) that is statistically significant at the 5% level. The effects of experience on other outcomes are also generally larger albeit not statistically significant. Panel B tests for the differences in impacts by race. We find a larger economic impact of experience on almost all performance metrics for minority founders relative to white founders that are statistically significant at least at the 10% level. For example, one year of experience increases the total VC funding by 21.5% (vs. 5.3% for White), 24.2% higher employment growth (vs. 1.9% for White), 2.3 p.p. higher chance of expanding over 1000 employees (vs. -1 p.p. for White). Panel C documents that experience appears to be more valuable for founders who form more social connections on LinkedIn. Specifically, we find that founders with more social connections raise 0.24 additional rounds of VC funding with one additional year of experience (vs. 0.13 additional rounds for founders with below median social connections) which is significant at the 5% level, and generates both more and better patents, with differences significant at the 10% level.

All three results are consistent with prior experiences in improving startup outcomes by reducing information asymmetries. Females and minorities are thought to have worse startup formation and success rates due to segmented networks from other co-founders and VCs (Cook et al., 2022; Rosenthal and Strange, 2012). Experience can help improve these networks by exposing these entrepreneurs to other potential co-founders and investors. Notably, we find even more direct evidence for this channel as experience appears to be particularly valuable for founders who leverage it to establish a greater number of social connections.

Table A10, reports some additional heterogeneity results by founder education and type of experience. We find that experience is helpful for all candidates regardless of their school rankings, and that both experience in startups and incumbent firms is valuable for future firm success. Figure B4 reports the heterogeneity of one additional year of experience by prior experience level. Consistent with our expectations, we find the largest results for people with the least experience, for whom the additional year may be most valuable.

Mechanism

We investigate different mechanisms to clarify how a founder's previous experience contributes to improved outcomes for their startups in this subsection. We examine three potential pathways that have been explored by the literature: ability to attract talent (Cheraisi and Busolo, 2020; Musharaf and Hussain, 2023), financing availability (Lerner, 2000; Hsu, 2007; Cohen and Wirtz, 2018), and industry-specific knowledge accumulation

(Agarwal et al., 2004; Klepper and Sleeper, 2005; Chatterji, 2009).

Table 5 details tests for the effects of the founder's experience on several potential intermediate variables associated with different mechanisms. Panel A, Columns (1) & (2) document that an additional year of experience increases the number of initial employees by 4.6%. and the number of co-founders by 5.1%. Panel B further demonstrates that these increases result from the founder's former professional connections with previous colleagues. An additional year of experience leads to a 3.0 p.p. higher chance of having any of the founder's previous colleagues as initial employees and increases the number of them by 3.4%. An additional year of experience leads to a 2.7 p.p. higher chance of having any of the founder's previous colleagues as co-founders and increases the number of them by 3.2%. Taken together, these results provide direct evidence of experienced founders bringing in ex-colleagues as co-founders and employees to enlarge the initial team.

Panel A, Column (3) tests for changes in financing ability by looking at the time to receive the first funding. More wealthy founders may delay initial funding rounds. On the other hand, founders more connected to VCs may be able to time the market better and raise initial funding earlier. We do not find any change in the time to funding, reducing the probability of differential funding ability explaining our results. In Column (4), we test if founders join the same industry as their prior work experience. Founders seeking to take advantage of industry-specific knowledge would seek to start firms in similar industries. However, we observe no statistically significant impact.

Table 6 now checks if these intermediate variables drive our results. We should observe our results driven by the sample of firms with larger initial employees if the ability to attract talent is our main driving mechanism. Indeed, we find that this is the case. In Panel A, we measure the size of the startups by the initial employment level. For founders with above median initial employees, one additional year of experience corresponds to a 12% increase in total VC funding (vs. -1.9% for founders with below median initial employees), 1.8 p.p. higher chance of exceeding $100 million in VC funding (vs. -0.5%), 1.5 p.p. higher chance of reaching 1000 employees (vs. -0.05%). These effects are statistically significant at the 10% level. Further, one additional year of experience also enhances the number of patents granted by 8.3% and the patent citations received by 8.8% to 10.5%. These effects are significant at the 5% level. In contrast, these effects are much more muted for founders with below-median initial employees. In Panel B, we measure size by the number of cofounders instead. We again see more outsized effects of experience on startup performance across a range of outcomes that are statistically significant at least at the 10% level. We also do not see any differences in results by year to the first funding round, and experience in the same industry in Table A9, consistent with improved financing ability, or industry-specific knowledge, not driving our results.

6 Conclusion

We conclude by performing some back-of-the-envelope calculations to estimate the value of each additional year of experience. We multiply our estimate for an increase in IPO probability by the average IPO proceeds for a founder. Table A11 reports the assumptions. We find that each additional year of experience can be valued at approximately 170,000 dollars. These results imply that each extra year of experience is indeed very valuable for a startup founder. This figure also provides insights into the monetary trade-offs that incubators/ scholarship designers should consider when designing scholarships and initiatives aimed at fostering new firm formation directly out of college. Thiel Fellowship offers students $100,000 a year to drop out of college and start their own firm. Our estimates imply that the expected value of experience for these students might be higher on average compared to the money offered.

	Mean	S.D.	P10	P50	P90
Panel A: Founder Characteristics					
Experience (years)	10.7	5.58	4.00	11.0	18.0
Green Card Wait Time (years)	3.46	3.71	0.17	2.08	9.51
$\mathbb{1}\{$Female$\}$	0.21	0.41	0.00	0.00	1.00
$\mathbb{1}\{$White$\}$	0.49	0.50	0.00	0.00	1.00
$\mathbb{1}\{$Advanced Degree$\}$	0.72	0.45	0.00	1.00	1.00
$\mathbb{1}\{$Top 500 Universities$\}$	0.74	0.44	0.00	1.00	1.00
Num. of Social Connections	452	110	279	500	500
Seniority of the First Job	2.10	1.22	1.00	2.00	4.00
Salary of the First Job	74,641	30,493	38,305	72,058	119,440
Observations			2,531		
Panel B: Initial Startup Characteristics					
Initial Emp. Size	4.93	8.93	1.00	2.00	11.0
Num. of Cofounders	2.82	2.17	1.00	2.00	6.00
Num. of Previous Colleagues	2.61	4.57	0.00	1.00	9.00
Num. of Previous Colleagues in Initial Employees	0.78	1.99	0.00	0.00	2.00
Num. of Previous Colleagues in Cofounders	0.45	0.70	0.00	0.00	2.00
Years to the First Funding Round	1.21	1.82	0.00	1.00	3.00
$\mathbb{1}\{$Experience in the Same Industry$\}$	0.35	0.48	0.00	0.00	1.00
$\mathbb{1}\{$Experience in Firms with Emp. ≥ 1000 $\}$	0.69	0.46	0.00	1.00	1.00
$\mathbb{1}\{$Experience in Firms with Age $\geq$10ys$\}$	0.37	0.48	0.00	0.00	1.00
Observations			2,531		
Panel C: Startup Outcomes					
Employment Size	154	1,905	0.00	4.00	107
IPO	0.01	0.09	0.00	0.00	0.00
Num. of Funding Rounds	2.11	2.22	0.00	1.00	5.00
Amount of Funding (2015 M$)	14.9	40.1	0.00	0.88	41.7
Num. of Patents	0.15	1.38	0.00	0.00	0.00
Num. of Citations	0.99	20.3	0.00	0.00	0.00
Adjusted Num. of Citations	0.20	2.97	0.00	0.00	0.00
Num. of Top Patents	0.03	0.39	0.00	0.00	0.00
KPSS Value (2015 M$)	7.37	39.1	0.00	0.00	0.00
Observations			20,395		

Table 1: Summary Statistics

Notes: This table presents descriptive statistics for key variables used in the analysis. Panel A presents descriptives on individual-level data for characteristics of immigrant founders. Panel B presents firm-level data for initial startup characteristics. Panel C presents firm-year-level data for time-varying startup outcomes. Columns 1-5 present means, standard deviations, 10%, 50%, and 90% quantiles. We obtain founder characteristics from LinkedIn and PERM. We obtain employment information of the startups from LinkedIn. We obtain the IPO and funding information of startups from CrunchBase. We obtain the patent information of startups from PatentsView.

	(1) Experience	(2) Experience	(3) Experience	(4) Experience	(5) Experience
Wait Time	0.883***	0.861***	0.841***	0.855***	0.825***
	(0.135)	(0.118)	(0.102)	(0.105)	(0.105)
Founder Citizenship FE	Y	Y	Y	Y	Y
Founder Degree Level FE	Y	Y	Y	Y	Y
Year FE		Y	Y	Y	Y
Firm Cohort FE			Y	Y	Y
Firm Industry FE				Y	Y
Firm State FE					Y
Obs.	20,175	20,175	20,175	20,175	19,893
R-squared	0.0782	0.238	0.597	0.632	0.643
F stat	42.88	53.51	67.64	66.94	62.21

Table 2: First Stage

Notes: This table presents estimates of the relationship between green card wait time and the experience of immigrant entrepreneurs. The cells present the coefficients α obtained by estimating Equation (2) from the panel. The independent variable is the green card wait time of the founder, calculated based on time in years from the priority date until the priority date is earlier than the application date in the visa bulletin for 3 consecutive months. The dependent variable is the founder's experience at the time of founding the startup, calculated based on time in years from the highest degree graduation to the startup's founding. Column 1 controls for founder citizenship FEs and founder degree-level FEs. Column 2 adds controls for year FEs. Column 3 adds controls for firm cohort or founding year FEs. Column 4 adds controls for firm industry FEs. Column 5 adds controls for firm-state FEs. Standard errors are clustered by firm. ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.1.

	Funding			Patents			Employment		IPO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Num. of Rounds	Log(Funding Amount)	Funding Amount ≥100M	Log(Patents)	Log(Citations)	Log(Adjusted Citations)	Log(Emp.)	Emp.≥1000	IPO
Panel A: 2SLS									
Experience	0.161**	0.117**	0.0145**	0.0387**	0.0491**	0.0415**	0.118**	0.0102**	0.00617**
	(0.0759)	(0.0504)	(0.00658)	(0.0188)	(0.0240)	(0.0205)	(0.0588)	(0.00486)	(0.00302)
Panel B: OLS									
Experience	0.0328**	0.0358**	0.00399**	0.00447*	0.00612	0.00537*	0.0554***	0.00161**	0.000696
	(0.0163)	(0.0144)	(0.00184)	(0.00270)	(0.00372)	(0.00312)	(0.0109)	(0.000750)	(0.000493)
Founder Citizenship FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Founder Degree Level FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	7,843	7,843	7,843	20,110	20,110	20,110	18,341	18,341	14,792
First-stage F	30.66	30.66	30.66	62.21	62.21	62.21	59.43	59.43	36.82
Mean Outcome	2.11	14.9	0.06	0.15	0.99	0.20	154.1	0.04	0.01
Magnitude(%)	7.63	11.7	26.2	3.87	4.91	4.15	11.8	24.2	73.3

Table 3: Baseline Results

Notes: This table presents estimates of the relationship between the experience of immigrant entrepreneurs and startup performance. Panel A presents 2SLS results and each cell presents the coefficient $\tilde{\beta}$ obtained by estimating Equation (3) from the panel. The independent variable is the founder's experience at the time of founding the startup, calculated based on time in years from the highest degree graduation to the startup's founding. The instrumental variable is the green card wait time of the founder, calculated based on time in years from the priority date until the priority date is earlier than the application date in the visa bulletin for 3 consecutive months. We present effects for the cumulative number of funding rounds, the log of the cumulative funding amount, whether the cumulative funding amount is over 100M$, the log of the number of patents filed in the year of observation and eventually granted, the log of the number of 3-year citations of those patents, the log of the adjusted number of citations normalized by the average in the same year and Cooperative Patent Classification (CPC) class, the log of employment size, whether the employment size is over 1000, and whether the firm went public. Panel B presents the coefficient β for the same outcomes obtained by estimating Equation (1) by OLS from the panel. All the regressions include founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. Magnitude refers to the effect of an additional year of experience relative to the mean of the outcome in percent terms. Standard errors are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.1.

	Funding			Patents			Employment		IPO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Num. of Rounds	Log(Funding Amount)	Funding Amount ≥100M	Log(Patents)	Log(Citations)	Log(Adjusted Citations)	Log(Emp.)	Emp.≥1000	IPO
Panel A: Founder Cohort FEs									
Experience	0.251*	0.185*	0.0291**	0.0786**	0.0992**	0.0867**	0.213**	0.0207**	0.00926*
	(0.151)	(0.102)	(0.0134)	(0.0352)	(0.0459)	(0.0386)	(0.105)	(0.00922)	(0.00478)
First-stage F	14.75	14.75	14.75	38.22	38.22	38.22	33.44	33.44	22.21
Panel B: Firm State × Year FEs + Firm Industry × Year FEs									
Experience	0.171**	0.130**	0.0154**	0.0384*	0.0477*	0.0407*	0.123**	0.00954*	0.00597*
	(0.0827)	(0.0548)	(0.00716)	(0.0197)	(0.0250)	(0.0214)	(0.0612)	(0.00511)	(0.00316)
First-stage F	28.27	28.27	28.27	57.60	57.60	57.60	54.62	54.62	34.57
Panel C: Unanticipated Wait Time									
Experience	0.179*	0.131	0.0215**	0.0556**	0.0743**	0.0637**	0.114	0.0123*	0.00531
	(0.107)	(0.0795)	(0.0109)	(0.0281)	(0.0367)	(0.0309)	(0.0844)	(0.00726)	(0.00363)
First-stage F	22.77	22.77	22.77	47.32	47.32	47.32	46.90	46.90	31.87
Obs.	7,709	7,709	7,709	19,764	19,764	19,764	18,014	18,014	14,521
Mean Outcome	2.11	14.9	0.06	0.15	0.99	0.20	154.1	0.04	0.01

Table 4: Robustness Tests

Notes: This table presents results from specification checks on the relationship between the experience of immigrant entrepreneurs and startup performance, corresponding to results in Panel A in Table 3. The independent variable is the founder's experience at the time of founding the startup, calculated based on time in years from the highest degree graduation to the startup's founding. We present effects for the cumulative number of funding rounds, the log of the cumulative funding amount, whether the cumulative funding amount is over 100M$, the log of the number of patents filed in the year of observation and eventually granted, the log of the number of 3-year citations of those patents, the log of the adjusted number of citations normalized by the average in the same year and Cooperative Patent Classification (CPC) class, the log of employment size, whether the employment size is over 1000, and whether the firm went public. In Panel A, We control for founder citizenship FEs, founder degree-level FEs, firm age FEs, founder cohort or graduation year FEs, firm industry FEs, and firm state FEs. In Panel B, we control for founder citizenship FEs, founder degree-level FEs, firm cohort or founding year FEs, firm industry × year FEs, and firm state × year FEs. In Panel C, we replace the instrumental variable with the unanticipated green card wait time, which is the difference between the actual wait time of the founder and the wait time of the cohort appearing in the visa bulletin when the founder starts the first US job. We control for founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. Standard errors are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.1.

Panel A: Effects on Intermediate Variables				
	(1) Log(Initial Emp.)	(2) Log(Cofounders)	(3) Years to First Funding	(4) $\mathbb{1}${Same Industry}
Experience	0.0460**	0.0511**	0.0266	0.00862
	(0.0220)	(0.0247)	(0.0461)	(0.0101)
Founder Citizenship FE	Y	Y	Y	Y
Founder Degree Level FE	Y	Y	Y	Y
Firm Cohort FE	Y	Y	Y	Y
Firm Industry FE	Y	Y	Y	Y
Firm State FE	Y	Y	Y	Y
Obs.	2,135	2,103	931	2,249
First-stage F	83.37	81.99	38.45	81.40
Mean Outcome	4.43	2.65	1.21	0.35

Panel B: Effects on Previous Colleagues				
	Previous Colleagues in Initial Emp.		Previous Colleagues in Cofounders	
	(1) $\mathbb{1}${Num.>0}	(2) Log(Num.)	(3) $\mathbb{1}${Num.>0}	(4) Log(Num.)
Experience	0.0295***	0.0338***	0.0266**	0.0317***
	(0.0112)	(0.0130)	(0.0110)	(0.0117)
Founder Citizenship FE	Y	Y	Y	Y
Founder Degree Level FE	Y	Y	Y	Y
Firm Cohort FE	Y	Y	Y	Y
Firm Industry FE	Y	Y	Y	Y
Firm State FE	Y	Y	Y	Y
Obs.	2,135	2,135	2,135	2,135
First-stage F	83.37	83.37	83.37	83.37
Mean Outcome	0.33	0.71	0.30	0.41

Table 5: Effects on Intermediate Variables

Notes: This table presents estimates of the relationship between the experience of immigrant entrepreneurs and several intermediate variables of startups. Each cell presents the coefficient $\tilde{\beta}$ obtained by estimating Equation (6) from the cross-section. The independent variable is the founder's experience at the time of founding the startup, calculated based on time in years from the highest degree graduation to the startup's founding, instrumented by the green card wait time of the founder. We present effects for the log of initial employment size, the log of the number of cofounders, whether the startup has the founder's previous colleagues in initial employees, the log of the number of previous colleagues in initial employees, whether the startup has the founder's previous colleagues in cofounders, the log of the number of previous colleagues in cofounders, years to the first funding round, and whether the founder worked in the same industry before. Employees who joined the company in the same year as the founding of the company are considered as initial employees. Employees with job titles that explicitly contain "founder", "cofounder" or "founding" are considered cofounders. All the regressions include founder citizenship FEs, founder degree-level FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. Standard errors are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.1.

	Funding			Patents			Employment		IPO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Num. of Rounds	Log(Funding Amount)	Funding Amount ≥100M	Log(Patents)	Log(Citations)	Log(Adjusted Citations)	Log(Emp.)	Emp.≥1000	IPO
Panel A: by Initial Employment Size									
Initial Employment Size < Median									
Experience	-0.0178	-0.0187	-0.00519	-0.0117	-0.0162	-0.0133	0.0747	-0.000520	0.000814
	(0.0992)	(0.0600)	(0.00762)	(0.00957)	(0.0140)	(0.0126)	(0.0557)	(0.000439)	(0.00474)
Initial Employment Size > Median									
Experience	0.178	0.120*	0.0179*	0.0826**	0.105**	0.0878**	0.0923	0.0145*	0.00849**
	(0.113)	(0.0726)	(0.00992)	(0.0371)	(0.0464)	(0.0397)	(0.0812)	(0.00822)	(0.00416)
Diff.									
	0.196	0.139	0.0231*	0.0943**	0.121**	0.101**	0.0176	0.0150*	0.00767
	(0.150)	(0.0941)	(0.0125)	(0.0383)	(0.0485)	(0.0417)	(0.0985)	(0.00823)	(0.00631)
Panel B: by Number of Cofounders									
Number of Cofounders < Median									
Experience	-0.000983	0.0130	-0.00555	-0.0134	-0.0176	-0.0140	0.0597	-0.000494	0.00128
	(0.0963)	(0.0647)	(0.00801)	(0.00934)	(0.0135)	(0.0122)	(0.0536)	(0.000418)	(0.00466)
Number of Cofounders > Median									
Experience	0.183	0.117	0.0189*	0.0920**	0.115**	0.0968**	0.0849	0.0147*	0.00869**
	(0.122)	(0.0794)	(0.0108)	(0.0412)	(0.0515)	(0.0440)	(0.0879)	(0.00884)	(0.00423)
Diff.									
	0.184	0.104	0.0245*	0.105**	0.133**	0.111**	0.0252	0.0152*	0.00741
	(0.156)	(0.102)	(0.0135)	(0.0423)	(0.0532)	(0.0456)	(0.103)	(0.00885)	(0.00629)

Table 6: Heterogeneity Tests on Intermediate Variables

Notes: This table presents how the relationship between experience of immigrant entrepreneurs and startup performance depends on some intermediate variables using subsample analysis, corresponding to results in Panel A in Table 3. The independent variable is the founder's experience at the time of founding the startup, calculated based on time in years from the highest degree graduation to the startup's founding, instrumented by the green card wait time of the founder. The intermediate variables include initial employment size and the number of cofounders. Employees who joined the company in the same year as the founding of the company are considered as initial employees. Employees with job titles that explicitly contain "founder", "cofounder" or "founding" are considered cofounders. All the regressions include founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. Standard errors are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.1.

	Funding			Patents			Employment		IPO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Num. of Rounds	Log(Funding Amount)	Funding Amount ≥100M	Log(Patents)	Log(Citations)	Log(Adjusted Citations)	Log(Emp.)	Emp.≥1000	IPO
Panel A: by Gender									
Male									
Experience	0.100	0.122**	0.00822	0.0415*	0.0519*	0.0423*	0.170**	0.0159***	0.00648*
	(0.0642)	(0.0573)	(0.00690)	(0.0226)	(0.0287)	(0.0246)	(0.0675)	(0.00582)	(0.00375)
Female									
Experience	0.410**	0.334**	0.0222	0.129	0.151	0.134	0.611**	0.0297	0.0132
	(0.177)	(0.134)	(0.0176)	(0.111)	(0.136)	(0.117)	(0.309)	(0.0234)	(0.0142)
Diff.									
	0.309*	0.213	0.0140	0.0879	0.0987	0.0919	0.441	0.0138	0.00671
	(0.183)	(0.142)	(0.0185)	(0.112)	(0.137)	(0.118)	(0.312)	(0.0238)	(0.0144)
Panel B: by Race									
Non-white									
Experience	0.276*	0.215**	0.0144	0.0661*	0.0777*	0.0644*	0.242***	0.0233***	0.00955*
	(0.140)	(0.0915)	(0.0117)	(0.0340)	(0.0423)	(0.0367)	(0.0812)	(0.00741)	(0.00511)
White									
Experience	0.0503	0.0528	0.00568	-0.00599	-0.00427	-0.00175	0.0194	-0.00993	0.00817
	(0.0997)	(0.0869)	(0.0106)	(0.00469)	(0.00605)	(0.00442)	(0.0974)	(0.00649)	(0.00595)
Diff.									
	-0.225	-0.162	-0.00877	-0.0720**	-0.0819*	-0.0662*	-0.223*	-0.0332***	-0.00138
	(0.172)	(0.126)	(0.0158)	(0.0343)	(0.0428)	(0.0370)	(0.127)	(0.00985)	(0.00783)
Panel C: by Number of Social Connections									
Number of Social Connections < Median									
Experience	0.132*	0.152*	0.00684	-0.00144	-0.00341	0.00174	0.210*	0.0183**	0.0149
	(0.0716)	(0.0866)	(0.0108)	(0.00606)	(0.00792)	(0.00518)	(0.123)	(0.00931)	(0.00965)
Number of Social Connections > Median									
Experience	0.241**	0.144**	0.0112	0.0534*	0.0650*	0.0549*	0.142**	0.0103**	0.00528
	(0.101)	(0.0680)	(0.00851)	(0.0273)	(0.0340)	(0.0294)	(0.0642)	(0.00517)	(0.00401)
Diff.									
	0.110	-0.00775	0.00433	0.0549**	0.0684*	0.0531*	-0.0687	-0.00802	-0.00961
	(0.124)	(0.110)	(0.0137)	(0.0279)	(0.0349)	(0.0299)	(0.138)	(0.0106)	(0.0104)

Table 7: Heterogeneity Tests on Founder characteristics

Notes: This table presents how the relationship between experience of immigrant entrepreneurs and startup performance depends on founder characteristics using subsample analysis, corresponding to results in Panel A in Table 3. The independent variable is the founder's experience at the time of founding the startup, calculated based on time in years from the highest degree graduation to the startup's founding, instrumented by the green card wait time of the founder. The founder characteristics include gender, race, and the number of social connections on LinkedIn. All the regressions include founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. Standard errors are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.1.

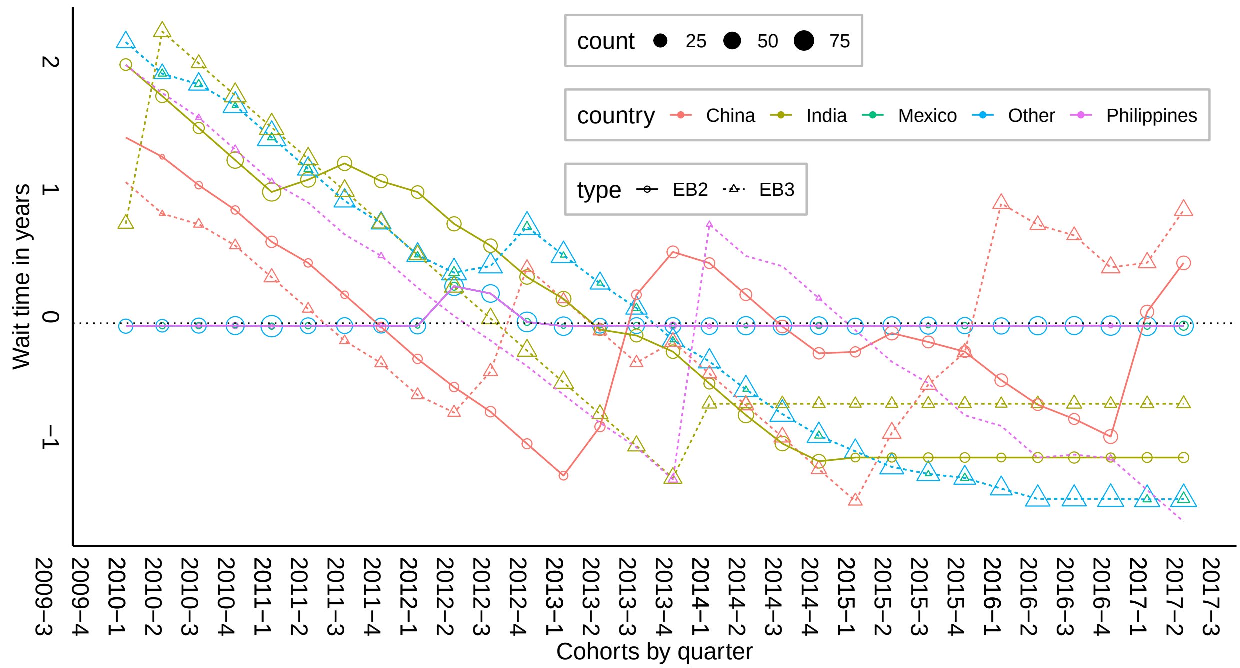

Figure 1: Green Card Wait Time across Cohorts

Notes: This figure presents the average green card wait time across cohorts for different countries of origin and visa types. The colors of the dots and lines stand for countries. Solid lines and round dots stand for EB2, while dashed lines and triangular dots stand for EB3. The size of the dot stands for the number of individuals in the cohort. Cohorts are defined by the year-quarter in which the applicant's priority date falls. The green card wait time is the time in years from the priority date until the priority date is earlier than the application date in the visa bulletin for 3 consecutive months. The wait time is de-meaned within each line.

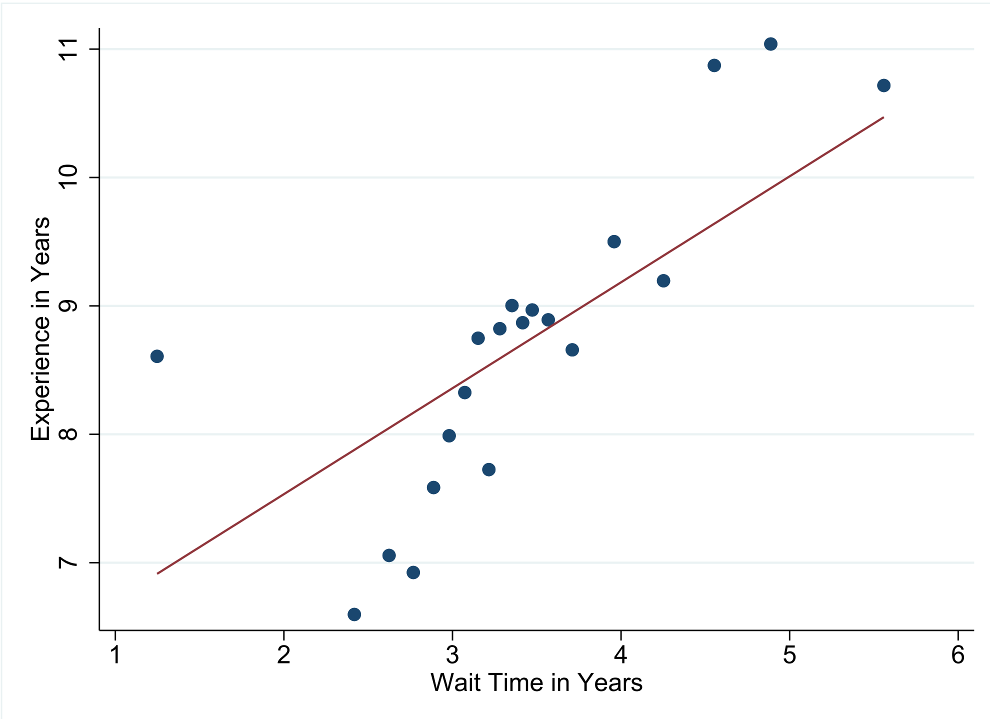

Figure 2: Binned Scatterplot of First Stage Regression
(Slope = 0.825 ± 0.105, F=62.2)

Notes: This figure presents the binned scatterplot that visualizes the relationship between green card wait time and experience of immigrant entrepreneurs, controlling for founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. The independent variable is the green card wait time of the founder, calculated based on time in years from the priority date until the priority date is earlier than the application date in the visa bulletin for 3 consecutive months. The dependent variable is the founder's experience at the time of founding the startup, calculated based on time in years from the highest degree graduation to the startup's founding.

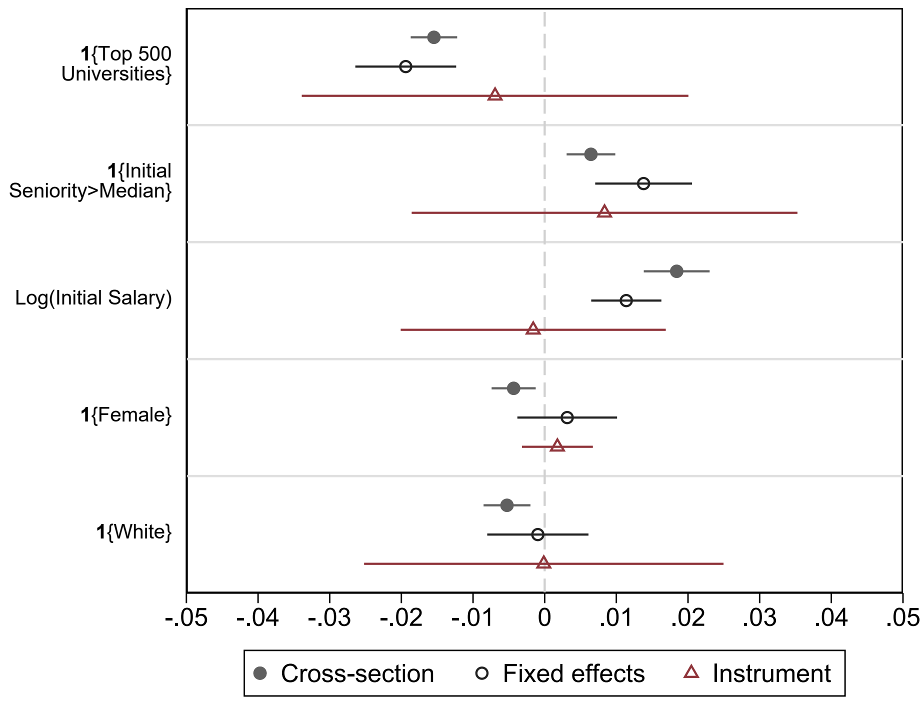

Figure 3: Balancing Regressions

Notes: This figure presents coefficients of balancing regressions for a range of covariates in the cross-section, denoted in the y-axis. Cross-section refers to OLS regressions of covariates on experience without the inclusion of fixed effects. Fixed effects refer to OLS regressions of covariates on experience with the inclusion of founder citizenship FEs, founder degree-level FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. Instrument refers to OLS regressions of covariates on GC wait time with the inclusion of founder citizenship FEs, founder degree-level FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. We present effects for whether the founder has degrees from the top 500 universities, whether the seniority of the first job is above the median, the log of the salary of the first job, whether the founder is female, and whether the founder is white. 95% confidence intervals are shown along with point estimates. Standard errors are clustered by firm.

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Appendix For Online Publication

A Additional Tables

	Mean (Exp. < Med.)	Mean (Exp. > Med.)
Panel A: Founder Characteristics		
Experience (years)	6.40	15.2
Green Card Wait Time (years)	2.91	4.03
$\mathbb{1}\{\text{Female}\}$	0.22	0.20
$\mathbb{1}\{\text{White}\}$	0.51	0.48
$\mathbb{1}\{\text{Advanced Degree}\}$	0.76	0.68
$\mathbb{1}\{\text{Top 500 Universities}\}$	0.81	0.67
Num. of Social Connections	443	460
Seniority of the First Job	2.06	2.15
Salary of the First Job	70,577	79,872
$\mathbb{1}\{\text{Experience in the Same Industry}\}$	0.27	0.43
$\mathbb{1}\{\text{Experience in the Startups with Emp.} \geq 1000\}$	0.64	0.74
$\mathbb{1}\{\text{Experience in Firms with Age} \geq \text{10ys}\}$	0.32	0.42
Panel B: Initial Startup Characteristics		
Initial Emp. Size	4.78	5.07
Num. of Cofounders	2.92	2.72
Num. of Previous Colleagues	2.41	2.81
Num. of Previous Colleagues in Initial Employees	0.64	0.92
Num. of Previous Colleagues in Cofounders	0.37	0.52
Years to the First Funding Round	1.43	0.99

Table A1: Summary Statistics by Experience

Notes: This table presents descriptive statistics for founder characteristics and initial startup characteristics used in the analysis separately on the two subsamples divided based on the length of experience. Column 1 presents means of characteristics on the subsample with experience lower than the median. Column 2 presents means of characteristics on the subsample with experience higher than the median. We obtain founder characteristics from LinkedIn and PERM. We obtain employment information of startups from LinkedIn. We obtain the IPO and funding information of startups from CrunchBase.

	Mean (Immigrant Startups)	Mean (All Startups)
Panel A: Founder Characteristics		
Experience (years)	10.7	7.8
$\mathbb{1}\{\text{Female}\}$	0.21	0.23
$\mathbb{1}\{\text{White}\}$	0.49	0.71
$\mathbb{1}\{\text{Advanced Degree}\}$	0.72	0.49
$\mathbb{1}\{\text{Top 500 Universities}\}$	0.74	0.56
Obs.	2,531	77,366
Panel B: Startup Outcomes		
IPO	0.01	0.01
Num. of Funding Rounds	2.11	1.96
Amount of Funding (2015M$)	14.9	10.2
Obs.	20,395	725,576

Table A2: Summary Statistics of Immigrant Startups and All Startups

Notes: This table presents descriptive statistics for founder characteristics and startup outcomes separately on the sample of immigrant startups and all startups. Column 1 presents means of characteristics on the sample of immigrant startups. Column 2 presents means of characteristics on the sample of all startups. We obtain founder characteristics from LinkedIn. We obtain the IPO and funding information of startups from CrunchBase.

Industry	Percentage (Immigrant Startups)	Percentage (All Startups)
Information technology and services	29.0	19.7
Computer software	13.5	9.1
Internet	6.8	8.4
Marketing and advertising	3.6	6.8
Financial services	3.2	5.0
Hospital and health care	2.6	5.2

Table A3: Top 5 Industries

Notes: This table presents the union of the five industries with the highest number of startups in our sample of immigrant startups and all startups. Industry categories are based on self-reported industries on the firms' LinkedIn pages with some standardization.

State	Percentage (Immigrant Startups)	Percentage (All Startups)
California	39.2	28.6
New York	12.5	14.4
Washington	8.9	2.9
Illinois	4.6	3.9
Texas	4.4	6.5
Massachusetts	4.3	5.9
Florida	2.5	4.2

Table A4: Top 5 States

Notes: This table presents the union of the five states with the highest number of startups in our sample of immigrant startups and all startups. The data sources are LinkedIn and CrunchBase.

	(1) 1{Top 500 Universities}	(2) 1{Seniority>Median}	(3) Log(Salary)	(4) 1{Female}	(5) 1{White}
Panel A: Cross-section					
Experience	-0.0155***	0.00646***	0.0184***	-0.00433***	-0.00526***
	(0.00165)	(0.00173)	(0.00235)	(0.00157)	(0.00167)
Panel B: Fixed effects					
Experience	-0.0194***	0.0138***	0.0114***	0.00315	-0.000954
	(0.00359)	(0.00345)	(0.00250)	(0.00355)	(0.00360)
Panel C: Instrument					
Wait Time	-0.00692	0.00836	-0.00160	0.00178	-0.000121
	(0.0138)	(0.0137)	(0.00944)	(0.00252)	(0.0128)
Founder Citizenship FE	Y	Y	Y	Y	Y
Founder Degree Level FE	Y	Y	Y	Y	Y
Firm Cohort FE	Y	Y	Y	Y	Y
Firm Industry FE	Y	Y	Y	Y	Y
Firm State FE	Y	Y	Y	Y	Y
Obs.	2,444	2,444	1,496	1,933	1,933

Table A5: Balancing Regressions

Notes: This table presents presents coefficients of balancing regressions for a range of covariates in the cross-section. Cross-section refers to OLS regressions of covariates on experience without the inclusion of fixed effects. Fixed effects refers to OLS regressions of covariates on experience with the inclusion of founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. Instrument refers to OLS regressions of covariates on wait time with the inclusion of founder citizenship FEs, founder degree-level FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. We present effects for whether the founder has degrees from the top 500 universities, whether the seniority of the first job is above the median, the log of the salary of the first job, whether the founder is female, whether the founder is white, and whether the founder has 500 or more social connections on LinkedIn. Standard errors are clustered by firm. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

	(1) $\mathbb{1}\{\text{Founder}\}$	(2) $\mathbb{1}\{\text{Founder}\}$
Wait Time	0.00118	0.000367
	(0.00155)	(0.00155)
Individual Cohort FE	Y	Y
Individual Citizenship FE	Y	Y
Individual Degree Level FE		Y
Obs.	57,672	57,672

Table A6: Effect of GC Wait Time on Probability of Becoming a Founder

Notes: This table presents estimates of the relationship between green card wait time and the probability of being a founder. The cells present the coefficients obtained by regressing the indicator of whether an immigrant is a founder on the GC wait time in the cross-section. The independent variable is the green card wait time of the founder, calculated based on time in years from the priority date until the priority date is earlier than the application date in the visa bulletin for 3 consecutive months. The dependent variable is the indicator of whether an immigrant is identified as a founder in our sample. Column 1 controls for individual cohort FEs and individual citizenship FEs. Cohorts are defined based on the year of the immigrant's priority date. Column 2 adds controls for individual degree level FEs. Standard errors are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.1.

	(1) Funding Amount	(2) Num. of Patents	(3) Num. of Citations	(4) Adjusted Num. of Citations	(5) Emp.
Panel A: Poisson					
Experience	0.0343**	0.0547**	0.0925***	0.0845***	0.0469***
	(0.0155)	(0.0220)	(0.0330)	(0.0274)	(0.0141)
Panel B: IV Poisson					
Experience	0.115**	0.278**	0.468**	0.371**	0.0114
	(.0578)	(0.131)	(0.209)	(0.172)	(0.103)
Founder Citizenship FE	Y	Y	Y	Y	Y
Founder Degree Level FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Firm Cohort FE	Y	Y	Y	Y	Y
Firm Industry FE	Y	Y	Y	Y	Y
Firm State FE	Y	Y	Y	Y	Y
Obs.	7,826	15,094	14,113	14,113	18,341

Table A7: Poisson Regressions

Notes: This table presents results from specification checks on the relationship between the experience of immigrant entrepreneurs and startup performance, corresponding to results in Table 3. Panel A presents the coefficients estimated from Poisson regressions. The independent variable is the founder's experience at the time of founding the startup, calculated based on time in years from the highest degree graduation to the startup's founding. We present effects for the funding amount, the number of patents, the number of citations, the adjusted number of citations normalized by the average in the same year and CPC class, and the employment size. Panel B presents the coefficients for the same outcomes obtained by estimating IV Poisson regressions, instrumented by the green card wait time of the founder. All the regressions include founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. Standard errors are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.1.

Panel A: Employment						
	(1) Log(Emp.)	(2) Emp.≥50	(3) Emp.≥100	(4) Emp.≥200	(5) Emp.≥500	(6) Emp.≥1000
Experience	0.118**	0.00846	0.0130*	0.0123*	0.0101*	0.0102**
	(0.0588)	(0.00964)	(0.00765)	(0.00665)	(0.00597)	(0.00486)
Founder Degree Level FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm Cohort FE	Y	Y	Y	Y	Y	Y
Firm Industry FE	Y	Y	Y	Y	Y	Y
Firm State FE	Y	Y	Y	Y	Y	Y
Obs.	18,143	18,143	18,143	18,143	18,143	18,143
First-stage F	59.43	59.43	59.43	59.43	59.43	59.43

Panel B: Patents					
	(1) Log(Patents)	(2) Log(Citations)	(3) Log(Adjusted Citations)	(4) Log(Top Patents)	(5) Log(KPSS Value)
Experience	0.0387**	0.0491**	0.0415**	0.0281**	0.0399**
	(0.0188)	(0.0240)	(0.0205)	(0.0137)	(0.0203)
Founder Degree Level FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Firm Cohort FE	Y	Y	Y	Y	Y
Firm Industry FE	Y	Y	Y	Y	Y
Firm State FE	Y	Y	Y	Y	Y
Obs.	19,893	19,893	19,893	19,893	19,893
First-stage F	62.21	62.21	62.21	62.21	62.21

Table A8: Additional Outcomes

Notes: This table presents estimates of the relationship between the experience of immigrant entrepreneurs and more startup performance measures, corresponding to results in Panel A in Table 3. The independent variable is the founder's experience at the time of founding the startup, calculated based on time in years from the highest degree graduation to the startup's founding. In Panel A, we present effects for the log of employment size, whether the employment size is over 50, 100, 200, 500, and 1000. In Panel B, we present effects for the log of the number of patents, the log of the number of citations, the log of the adjusted number of citations normalized by the average in the same year and CPC class, the log of the number of top 10% patents in citations, and the log of the total KPSS value of patents. All the regressions include founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. Standard errors are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.1.

	Funding			Patents			Employment		IPO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Num. of Rounds	Log(Funding Amount)	Funding Amount ≥100M	Log(Patents)	Log(Citations)	Log(Adjusted Citations)	Log(Emp.)	Emp.≥1000	IPO
Panel A: by Years to the First Funding Round									
Years to the First Funding Round < Median									
Experience	0.175**	0.123**	0.0192**	0.0334	0.0379	0.0326	0.136*	0.0140**	0.00519
	(0.0806)	(0.0527)	(0.00772)	(0.0262)	(0.0330)	(0.0294)	(0.0718)	(0.00657)	(0.00362)
Years to the First Funding Round > Median									
Experience	0.0642	0.121	-0.00157	0.0169	0.0260	0.0183	0.0384	0.00585	0.00807
	(0.0681)	(0.0969)	(0.00645)	(0.0220)	(0.0293)	(0.0230)	(0.126)	(0.00786)	(0.00744)
Diff.									
	-0.111	-0.00167	-0.0208**	-0.0165	-0.0120	-0.0144	-0.0972	-0.00819	0.00288
	(0.105)	(0.109)	(0.0100)	(0.0342)	(0.0440)	(0.0372)	(0.144)	(0.0102)	(0.00820)
Panel B: by Experience in the Same Industry									
Without Experience in the Same Industry									
Experience	0.105	0.0730	0.0132	0.0355	0.0433	0.0380	0.170**	0.0175***	0.00335
	(0.0815)	(0.0689)	(0.00934)	(0.0230)	(0.0293)	(0.0251)	(0.0738)	(0.00669)	(0.00315)
With Experience in the Same Industry									
Experience	0.223	0.142	0.0163	0.0640	0.0802	0.0660	0.110	0.00562	0.0104*
	(0.137)	(0.0921)	(0.0115)	(0.0449)	(0.0554)	(0.0475)	(0.121)	(0.00931)	(0.00607)
Diff.									
	0.119	0.0686	0.00310	0.0285	0.0368	0.0280	-0.0598	-0.0119	0.00709
	(0.159)	(0.115)	(0.0148)	(0.0503)	(0.0625)	(0.0536)	(0.142)	(0.0114)	(0.00682)
Panel C: by Number of Previous Colleagues									
Number of Previous Colleagues < Median									
Experience	-0.0675	-0.107**	-0.00292	0.0480	0.0614*	0.0526*	0.0495	0.00936*	0.00420
	(0.0490)	(0.0510)	(0.00242)	(0.0301)	(0.0369)	(0.0315)	(0.0748)	(0.00510)	(0.00411)
Number of Previous Colleagues > Median									
Experience	0.238**	0.173**	0.0173*	0.0282	0.0313	0.0273	0.0790	0.00540	0.00506
	(0.113)	(0.0782)	(0.00965)	(0.0280)	(0.0356)	(0.0309)	(0.0874)	(0.00765)	(0.00388)
Diff.									
	0.305**	0.280***	0.0202**	-0.0197	-0.0302	-0.0253	0.0295	-0.00396	0.000864
	(0.123)	(0.0934)	(0.00997)	(0.0411)	(0.0512)	(0.0441)	(0.115)	(0.00919)	(0.00565)
Panel D: by Number of Colleagues in Initial Employees									
Number of Colleagues in Initial Employees < Median									
Experience	0.118	0.0226	0.00831	0.0271	0.0321	0.0237	0.121	0.00945*	0.00855
	(0.107)	(0.0907)	(0.0110)	(0.0269)	(0.0343)	(0.0292)	(0.0783)	(0.00559)	(0.00653)
Number of Colleagues in Initial Employees > Median									
Experience	0.181	0.143**	0.0166*	0.0469*	0.0612*	0.0542*	0.0548	0.00368	0.00631*
	(0.113)	(0.0648)	(0.00866)	(0.0266)	(0.0334)	(0.0288)	(0.0881)	(0.00770)	(0.00353)
Diff.									
	0.0622	0.120	0.00828	0.0197	0.0291	0.0305	-0.0665	-0.00577	-0.00223
	(0.156)	(0.111)	(0.0140)	(0.0378)	(0.0478)	(0.0410)	(0.118)	(0.00950)	(0.00743)
Panel E: by Number of Colleagues in Cofounders									
Number of Colleagues in Cofounders < Median									
Experience	0.179	0.0758	0.0161	0.0242	0.0283	0.0210	0.152*	0.0150**	0.00878
	(0.111)	(0.0945)	(0.0121)	(0.0258)	(0.0330)	(0.0281)	(0.0806)	(0.00663)	(0.00665)
Number of Colleagues in Cofounders < Median									
Experience	0.159	0.111*	0.0121	0.0527*	0.0691*	0.0591*	0.0762	0.00438	0.00609*
	(0.110)	(0.0611)	(0.00819)	(0.0289)	(0.0361)	(0.0312)	(0.0840)	(0.00721)	(0.00329)
Diff.									
	-0.0195	0.0353	-0.00392	0.0286	0.0408	0.0380	-0.0757	-0.0106	-0.00269
	(0.156)	(0.113)	(0.0146)	(0.0387)	(0.0489)	(0.0419)	(0.116)	(0.00978)	(0.00742)

Table A9: Heterogeneity Tests on Additional Intermediate Variables

Notes: This table presents how the relationship between experience of immigrant entrepreneurs and startup performance depends on some intermediate variables using subsample analysis. The independent variable is the founder's experience at the time of founding the startup, calculated based on time in years from the highest degree graduation to the startup's founding, instrumented by the green card wait time of the founder. The intermediate variables include years to the first funding round, whether the founder has experience in the same industry, the number of previous colleagues in all employees, in initial employees, and in cofounders. All the regressions include founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. Standard errors are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.1.

	Funding			Patents			Employment		IPO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Num. of Rounds	Log(Funding Amount)	Funding Amount ≥100M	Log(Patents)	Log(Citations)	Log(Adjusted Citations)	Log(Emp.)	Emp.≥1000	IPO
Panel A: by Degree from Top 500 Universities in the World									
Without Degree from Top 500 Universities in the World									
Experience	0.168	0.173	0.0235	0.0371*	0.0482*	0.0389*	0.249***	0.00644	0.0124*
	(0.134)	(0.113)	(0.0148)	(0.0213)	(0.0271)	(0.0233)	(0.0926)	(0.00591)	(0.00695)
With Degree from Top 500 Universities in the World									
Experience	0.162*	0.126**	0.0137*	0.0405	0.0491	0.0435	0.0411	0.00961	0.00261
	(0.0965)	(0.0638)	(0.00815)	(0.0266)	(0.0338)	(0.0290)	(0.0776)	(0.00649)	(0.00304)
Diff.									
	-0.00568	-0.0476	-0.00976	0.00340	0.000847	0.00470	-0.208*	0.00317	-0.00981
	(0.164)	(0.129)	(0.0167)	(0.0341)	(0.0432)	(0.0371)	(0.120)	(0.00875)	(0.00753)
Panel B: by Experience in Startups (Emp. ≤1000)									
Without Experience in Startups									
Experience	0.222	0.315	0.0304	0.0554	0.0614	0.0511	-0.110	0.000377	0.00798
	(0.273)	(0.275)	(0.0264)	(0.0590)	(0.0762)	(0.0662)	(0.185)	(0.0127)	(0.0102)
With Experience in Startups									
Experience	0.192**	0.127**	0.0141*	0.0112	0.0152	0.0124	0.0945	0.00505	0.00868**
	(0.0865)	(0.0534)	(0.00737)	(0.0102)	(0.0128)	(0.0108)	(0.0648)	(0.00505)	(0.00379)
Diff.									
	-0.0295	-0.189	-0.0163	-0.0442	-0.0463	-0.0387	0.204	0.00467	0.000697
	(0.287)	(0.281)	(0.0274)	(0.0598)	(0.0773)	(0.0671)	(0.196)	(0.0137)	(0.0109)
Panel C: by Experience in Startups (Age ≤10yrs)									
Without Experience in Startups									
Experience	0.226**	0.219**	0.0224*	0.0243	0.0238	0.0215	0.0475	0.00504	0.00652
	(0.114)	(0.0935)	(0.0117)	(0.0266)	(0.0341)	(0.0297)	(0.0811)	(0.00626)	(0.00511)
With Experience in Startups									
Experience	0.226**	0.0939	0.0185**	0.0163*	0.0267**	0.0183*	0.180*	0.00824	0.0102**
	(0.102)	(0.0594)	(0.00843)	(0.00847)	(0.0108)	(0.00964)	(0.0920)	(0.00635)	(0.00435)
Diff.									
	0.000367	-0.125	-0.00391	-0.00805	0.00289	-0.00319	0.133	0.00320	0.00371
	(0.153)	(0.111)	(0.0144)	(0.0280)	(0.0358)	(0.0312)	(0.123)	(0.00892)	(0.00671)

Table A10: Heterogeneity Tests on Additional Founder characteristics

Notes: This table presents how the relationship between experience of immigrant entrepreneurs and startup performance depends on founder characteristics using subsample analysis. The independent variable is the founder's experience at the time of founding the startup, calculated based on time in years from the highest degree graduation to the startup's founding, instrumented by the green card wait time of the founder. The founder characteristics include whether the founder has degrees from the top 500 universities in the world and whether the founder previously worked in startups, either defined by companies with fewer than 1000 employees or companies less than 10 years old. All the regressions include founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. Standard errors are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.1.

Item	Value
Effect of 1 Year of Experience on the Probability of IPO	0.62 %
× Average Proceeds at IPO	$186 Million
× Average Pre-IPO Founder Ownership Share	15 %
= Dollar Value of 1 Year of Experience	**$0.17 Million**

Table A11: The Dollar Value of One Additional Year of Founder's Experience

Notes: This table illustrates how we calculate the dollar value of one additional year of the founder's experience. The effect of 1 year of experience on the probability of IPO is from our baseline IV estimate in Table 3. The average proceeds at IPO is from the IPO statistics in 2015 on Jay R. Ritter's website. The average pre-IPO founder ownership share is from Kaplan et al. (2009). The estimate of 15% is also consistent with Levtov (2016) and Lemkin (n.d.).

B Additional Figures

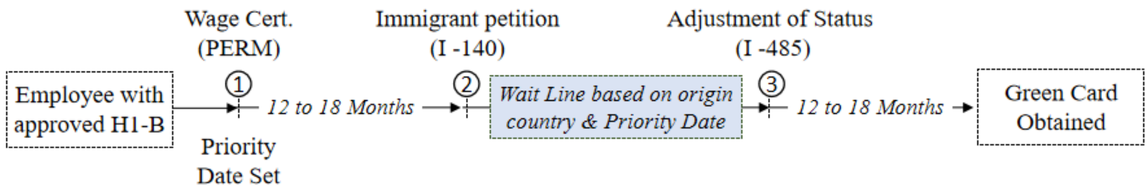


Figure B1: Green Card Wait Time across Cohorts

Notes: This figure illustrates the typical process and timeline for an employee with an approved H-1B visa to obtain a Green Card in the United States through employment-based sponsorship, including Wage Certification (PERM), Immigrant Petition (I-140), and Adjustment of Status (I-485).

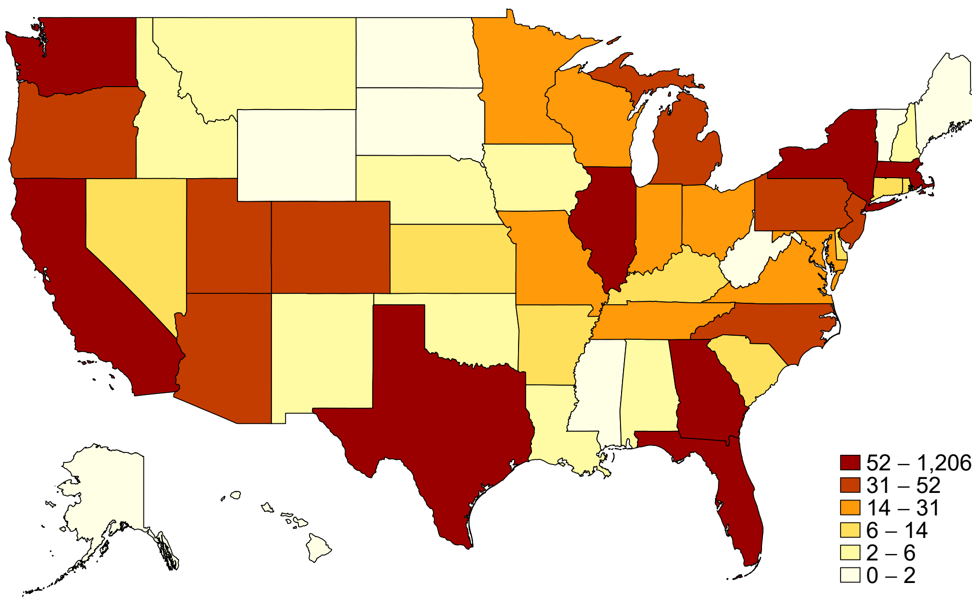
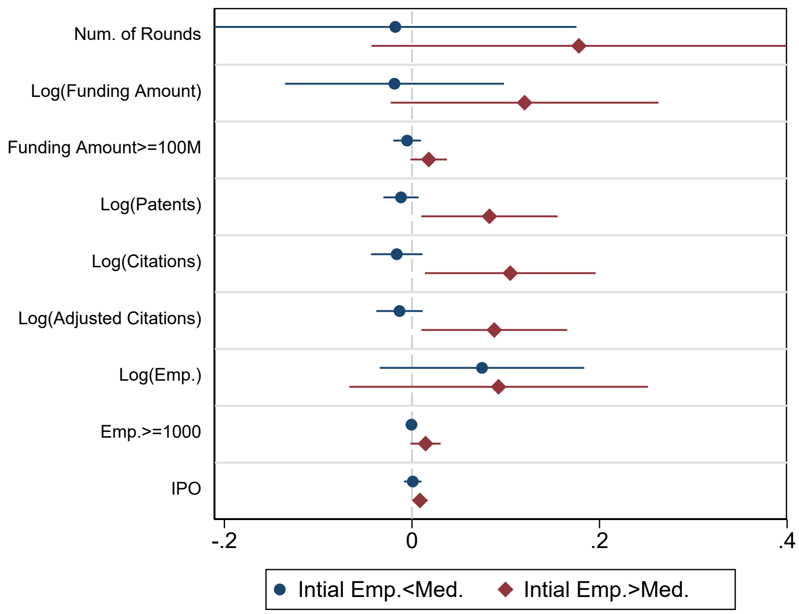
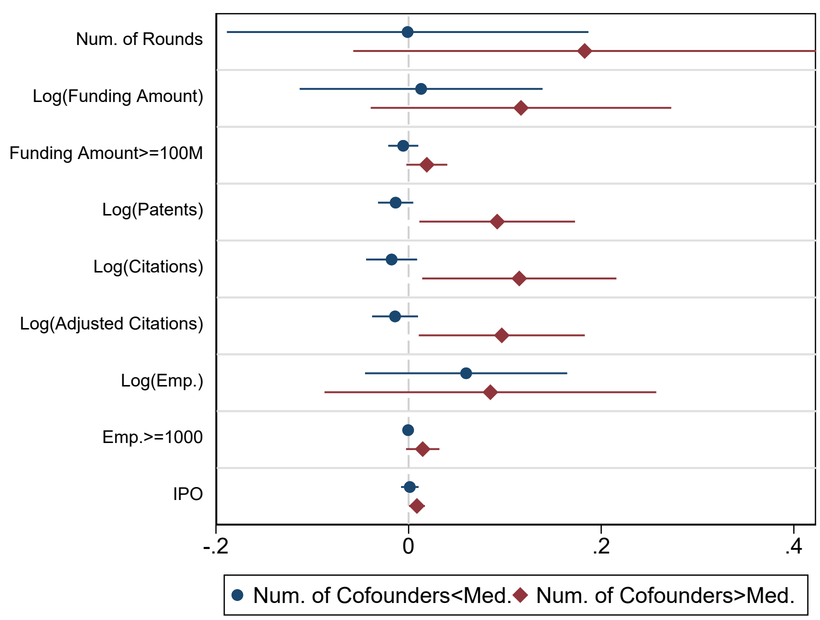


Figure B2: Geographical Distribution of Startups

Notes: This figure presents the geographic distribution of startups in our sample across states. Darker colors represent a higher number of startups located in a state. The data source for the location of the company is LinkedIn or CrunchBase.



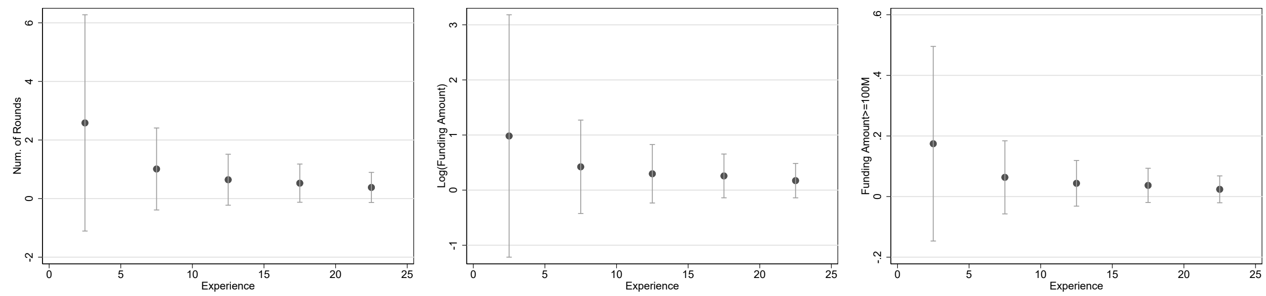
(a) by Initial Employment Size



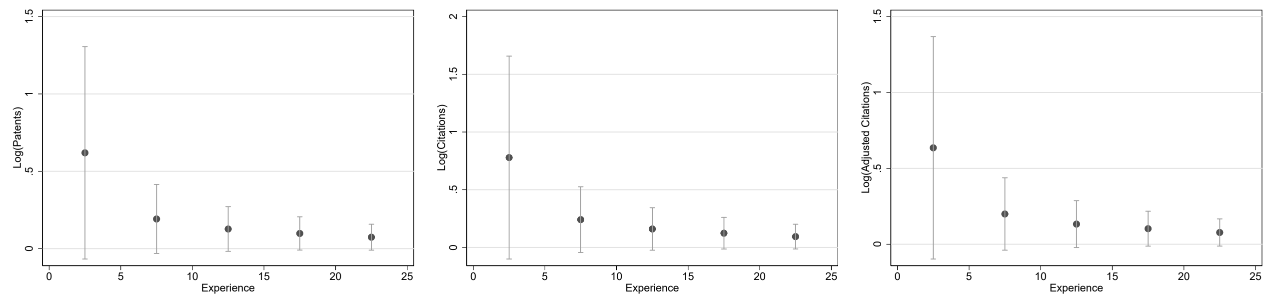
(b) by Num. of Cofounders

Figure B3: Heterogeneity Test on Intermediate Variables

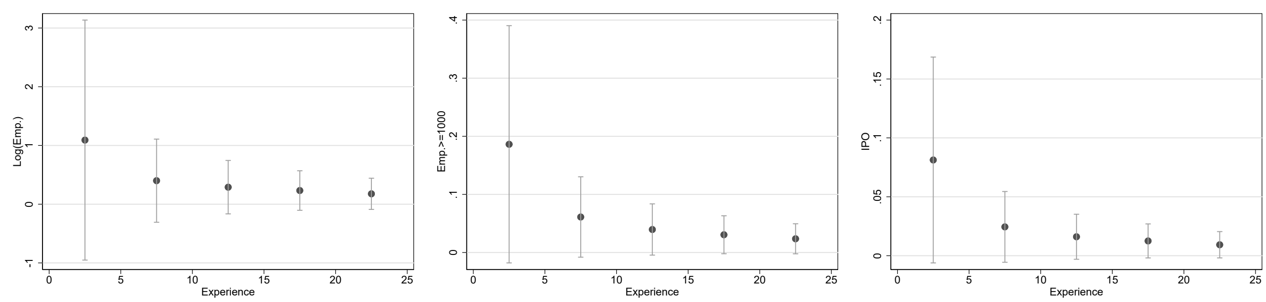
Notes: This figure presents how the relationship between experience of immigrant entrepreneurs and startup performance depends on some intermediate variables using subsample analysis. The independent variable is the founder's experience at the time of founding the startup, calculated based on time in years from the highest degree graduation to the startup's founding, instrumented by the green card wait time of the founder. The intermediate variables include initial employment size and the number of cofounders. All the regressions include founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. 95% confidence intervals are shown along with point estimates. Standard errors are clustered by firm.



(a) Num. of Rounds (b) Log(Funding Amount) (c) Funding Amount $\geq$ 100M



(d) Log(Num. of Patents) (e) Log(Num. of Citations) (f) Log(Adjusted Num. of Citations)



(g) Log(Emp.) (h) Emp.$\geq$1000 (i) IPO

Figure B4: Results by Experience Bins

Notes: This figure estimates the heterogeneity of the relationship between founder experience and startup performance by experience bins. The founder's experience is calculated based on time in years from the highest degree graduation to the startup's founding. We group founders by experience at five-year intervals. We allow the coefficient on experience to vary across different groups when estimating Equation ? instrumented by green card wait time. Panels (a)-(i) present the results of different performance measures, which are the number of funding rounds, the log of the funding amount, whether the funding amount is over 100M$, the log of the number of patents, the log of the number of citations, the log of the adjusted number of citations normalized by the average in the same year and CPC class, the log of employment size, whether the employment size is over 1000, and whether the firm went public, as dependent variables. We control for founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. 95% confidence intervals are shown along with point estimates. Standard errors are clustered by firm.