Entrepreneur Experience and 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 0.7 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 $200,000, 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 success 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, measured as the number of years between the graduation of one's highest degree and the startup's founding.

The founder's initial experience is of particular importance from a policy standpoint, as it can be influenced by the design of entrepreneurship programs, such as incubators and fellowships. The increasing interest in fostering innovation and new ventures has led to a rise in the prevalence of entrepreneurship promotion programs. In the United States alone, there were approximately 1400 incubators as of 2016[1]. These programs play a pivotal role in shaping the experiences of founders through various eligibility criteria and training opportunities. However, program designs vary widely. For example, the Thiel Fellowships[2] require founders to drop out of college to qualify, while Venture for America[3] trains and staffs budding entrepreneurs in existing startups to gain experience. Quantifying the impact of prior job experience on startups is essential for designing effective policies to promote entrepreneurship.

[1]Source: https://inbia.org/wp-content/uploads/2018/08/NumberofECsimage.jpg?x62369
[2]https://thielfellowship.org/
[3]https://ventureforamerica.org/

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 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.

Prior empirical research has identified a positive correlation between the age and experience of entrepreneurs and favorable startup outcomes (Chatterji, 2009; Klepper and Sleeper, 2005; Gompers et al., 2005; Agarwal et al., 2004). However, these findings cannot be interpreted causally as entrepreneurs endogenously choose the number of years of experience before their first startup. Existing literature is unclear regarding the characteristics of entrepreneurs who choose to accumulate more experience. For instance, Hacamo and Kleiner (2022) observed an enhancement in entrepreneur quality when college students are compelled to initiate businesses directly due to a weakened job market. These findings suggest that higher-quality candidates may opt to accumulate more experience before founding a new firm. In contrast, Wadhwa et al. (2008) found that entrepreneurs from prestigious educational backgrounds tend to have lower levels of experience. Consequently, the direction of bias remains uncertain, complicating the interpretation of the true impact of experience on entrepreneurial outcomes using simple correlations. An ideal experimental setup to answer this question would involve the random assignment of years of experience to startup founders, followed by an examination of the differential outcomes across the firms they establish. While achieving such an ideal scenario may pose challenges, 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, Mexico, and the Philippines, where demand for GCs far surpasses the country-based limit. 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, and across cohorts, is exceedingly challenging. Wait times can fluctuate due to several unpredictable factors such as overall GC demand in other categories and countries[6], policy implementation[7], and errors within the United States Citizenship and Immigration Services (USCIS)[8]. For example, Chinese EB-2 immigrants[9] experienced a wait time increase of over 2 years between those who applied for the GC in the first quarter versus the last quarter of 2013. The within-country variation in these GC wait times serves as our instrumental variable for founder experience prior to their first startup.

Data availability has posed a significant obstacle in examining the impact of immigration

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

[5]For instance, the average wait time for India is 8.5 years, 3.4 years for China, 0.6 years for Mexico, and 1.5 years for the Philippines in our sample including EB-2 and EB-3 immigrant visas.

[6]Unused GCs from family-based category can be used in employment-based categories

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

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

[9]Immigrants with master's degrees

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, 2020a; 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 2,317 startup founders, 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 18% as female. The information technology and service industry and California account for 25% and 42% 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[10]. Immigrant entrepreneurs found about a quarter of these high-growth startups in the US (Kerr and Kerr, 2020a; 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,

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

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 50, significantly exceeding conventional thresholds for weak instruments. The balance of panel tests demonstrates that our instrument effectively captures as-if-random variation in founder experience, remaining uncorrelated with any observable employee characteristics. While persistent cross-country differences in GC wait times may lead to employee selection across origin countries, we find no significant impact of out-migration or startup formation due to the relatively smaller and unpredictable changes in GC wait times within the same country, which serves as our primary instrument for experience.

Our analysis reveals that greater founder experience benefits startups across various metrics. Specifically, each additional year of experience corresponds to a 13% 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 total funding exceeding $100 million. Additionally, startups led by founders with an extra year of experience issue 4% more patents and garner 5% more citations than the mean, while also experiencing a 12% higher growth rate in their workforce. These benefits significantly elevate the likelihood 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, a 1.5-p.p. lower probability of exit (employment dropping permanently to zero), and a 0.7-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 200,000 dollars. 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.

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

Green Card Categories

Any immigrant seeking to work full-time in their own business permanently in the US needs to obtain legal permanent residency, colloquially known as a Green Card (GC). Immigrants entering the US for education or employment typically pursue one of three routes to obtain legal permanent status[11]: investor-based GC (EB-5 category), extra-ordinary ability-based GC (EB-1A category)[12], or employment-based GC (EB-1B/1C/2/3 category) (Kerr and Kerr, 2020b).

Investor-based green cards (EB-5) require immigrants to invest at least a million dollars and create ten new jobs in the US. However, these visas have been criticized

[11] 32.7% of immigrant business owners enter the US as legal permanent residents using family-based GCs (Hunt, 2011). However, founders entering on family-based GCs are only half as likely as others to pursue high-growth startups as those who enter for work or education (Hunt, 2011). Hence, we focus on employees entering as temporary workers, as they better represent high-growth startups.

[12] EB-1 GCs can further be divided into EB-1A for extra-ordinary talent, EB-1B for professors, and EB-1C for high level managers.

for primarily financing real estate investments rather than actual startups[13]. Immigrants with extra-ordinary abilities, demonstrated through sustained national and international acclaim[14], can self-apply for a GC in the EB-1A category. Self-petitioning immigrants who first come to the US for a degree could in principle launch a business using the optional training (OPT) period and transition to EB-1A GC in the next three years[15]. However, the high legal fees, uncertainty (immigrants would lose legal status if unable to qualify for a GC during the OPT period), and the rigorous adjudication standards involved in obtaining these GCs often discourage most immigrants from pursuing this route (Kerr and Kerr, 2020b).

The most common path for immigrants is to first obtain a temporary employment visa (H1-B for high-skilled workers, L-1 for managers) and then have their employer file for their employment-based GC (under the EB-1, EB-2, or EB-3 category) on their behalf. Employees sponsored under these visas are restricted from making managerial decisions or exerting significant operational influence within the sponsoring firms. Therefore, immigrants entering the US through this route must obtain a GC to establish and work full-time in their own startups. Given the large relative size of the employment-based GC category compared to others, we focus on employer-sponsored GCs in this paper. We further focus on EB-2 and EB-3 GCs in the employment-based categories as we do not observe any wait-line for the EB-1 category during our sample period.[16]

[13]During FY2014 and 2015, more than 80% of total invested EB-5 money went into real estate - https://iiusa.org/wp-content/uploads/2019/03/Joint-Report-Asessment-of-EB-5-economic-impact.pdf

[14]USCIS requires fulfilling 3 of 10 criteria as listed in the link - https://www.uscis.gov/working-in-the-united-states/permanent-workers/employment-based-immigration-first-preference-eb-1

[15]OPT period consists of 12 months for those who completed a US degree and an extension of 24 months for STEM majors. The OPT extension was 17 months before May 10, 2016.

[16]In FY2015, the numbers of visas issued and adjustments of status for the EB1, EB2, and EB3 categories were 41,990, 44,479, and 35,421, respectively, as detailed in the U.S. State Department's report available at https://travel.state.gov/content/dam/visas/Statistics/AnnualReports/FY2015AnnualReport/FY15AnnualReport-TableV-Part2.pdf.

Green Card Process

A typical Green Card (GC) application involves three sequential steps, each adjudicated independently (Figure D1). 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 140,000 on the annual number of Adjustment of Status applications for employment-based GCs[17]. A maximum of 28.6% of these 140,000 GCs can be allocated to each GC category.[18] Further, a maximum of 7% of the combined employee and family-based GCs can be filed annually by any single country. Employees from countries and categories where the demand for GCs exceeds the cap are not allowed 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[19] released by the Department of State. This system has resulted in significant wait times for high-demand countries, with an average wait of 8.6 years for India, 3.4 years for China, 0.6 years for Mexico, and 1.5 years for the Philippines, in our sample of EB-2 and EB-3 GCs.

Green Card Wait Times

Green Card (GC) wait times demonstrate two distinct types of variation - across and within combinations of country of origin and GC category, i.e., country-category. There exist significant differences of five to eight years observed across countries and categories. However, within-country-category variation exhibits smaller fluctuations of up to four years across

[17] An annual limit of 226,000 applies to family-based GCs

[18] There are three GC categories (EB-1, EB-2, EB-3), categorized based on worker education and experience. To qualify for an EB-1B GC, applicants must show three years of experience teaching or conducting research in their field. This requires an advanced degree like a Ph.D. EB-2 requires a master's degree or a bachelor's degree and five years of relevant post-degree experience. EB-3 requires a US bachelor's degree or less than two years of work experience.

[19] https://travel.state.gov/content/travel/en/legal/visa-law0/visa-bulletin.html

different cohorts. While across-country-category variation is persistent, it is exceedingly difficult to forecast across-cohort variations within the same country-category, as various unpredictable factors often influence them. These include overall demand for family-based GCs (as unused family-based GCs are captured into employment-based and distributed to any employment-based category), policy nuances (different administrations may apply GC recapture differently, with some even recapturing unused surplus from previous years), demand in other employment-based categories (unused EB-4, and EB-5 GCs can be used for EB-1, 2, and 3 categories), other countries' demand within own category (excess GCs within each category are recaptured without regard of country limit), 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). We explain these various factors in detail in Appendix B. Figure 1 shows this within country-category variation. This figure illustrates how wait times can vary significantly across cohorts separated by just a few quarters, sometimes fluctuating by more than two years. These fluctuations do not appear to be correlated across country-categories within the same cohort. For instance, Chinese EB-2 immigrants experienced a wait time increase of over two years between those who applied for the GC in the first and last quarters of 2013. However, the same cohorts of other country-categories did not exhibit a correlated increase; in fact, the wait times for Chinese EB-3 visas and Indian EB-2 and EB-3 visas decreased. This within-country-category variation in GC wait times 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[20] 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[21] and salary for each position is imputed based on the position title, firm, and location by Revelio Labs. The

[20]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.

[21]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.

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.

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[22]. 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.

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 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

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

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.[23] 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.

3.2 Data cleaning & matching process

We construct our final database of immigrant founders through a three-step process. First, we identify all founders on LinkedIn using two criteria: individuals who joined startups (as identified by Crunchbase) within two years of founding, and individuals who self-identify as founders in their LinkedIn job titles. Second, we match these LinkedIn profiles with the PERM database to determine immigrant status and ascertain the green card wait time for each individual. While PERM filings do not include individual names, we are able to uniquely identify and match individuals based on other detailed characteristics present in both datasets, including education institution, degree, graduation date, employer firm name, location, and job title at the time of PERM filing. We manually verify all matches for accuracy. This process yields a sample of 2,317 immigrant founders. Finally, we match these startups to their corresponding profiles on Crunchbase and the patent filing database. We also extract the work history of all employees at these startups using LinkedIn. For further details on the matching process, please refer to Appendix A.

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

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 2,317 observations, while startup outcomes in Panel C are at the firm-year level with 19,365 observations. We also present summary statistics for the sample of all founders in Table C2 for comparison. On average, immigrant founders have 10.7 years of experience from the time they graduate with their highest degrees until they establish their first startups, compared to a lower average of 7.8 years among all founders. Table C5 provides a detailed breakdown of this timeline for immigrant founders, showing mean duration of 4.4 years from graduation to priority date, 3.5 years on avaerage spent in the GC wait line, 0.7 years for GC application processing, and 2.1 years from obtaining a green card to the launch of the startup. 48% of immigrant founders are white compared to 71% in the overall founder population. A higher percentage of immigrant founders have advanced degrees (72%) 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 C3. They are also more likely to concentrate in certain states like California as presented in Table C4 and Figure D2. These patterns are generally consistent with the focus on immigrants biasing our sample toward high-growth startups.

4 Empirical Design

Our primary objective in this paper is to ascertain the impact of founders' experience on the success of the first startup they establish. We initially establish basic correlations between these variables using a naive OLS regression model:

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

The coefficient β denotes the 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. We control for founder citizenship fixed effects, founder degree-level fixed effects, firm founding-year fixed effects, calendar year fixed effects, firm industry fixed effects, and firm state fixed effects in the baseline, encapsulated by the vector $\boldsymbol{X}_{i,t}$. We cluster the standard errors at the firm level, the level at which founder-experience varies. However, despite the granular controls, deriving a causal claim regarding the impact of experience on startup success from this analysis poses challenges. Different quality founders may endogenously select work experience, potentially introducing bias into the results. To address this issue, we employ experience-instrumented GC wait time as our primary explanatory variable. Specifically, we estimate the IV regression in two steps:

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

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

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, such as funding and patents. The controls and clustering are similar to equation 1.

We also implement the same two-stage least squares design in the cross-section for some time-invariant dependent variables including initial startup characteristics and founder 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-invariant 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 regressions above.

First Stage Results

Our instrument demonstrates strong predictive power for the length of founder experience. The results of the first stage estimation using Equations (2) and (5) are reported in Table 2. In particular, Column 5 in Panel (a) presents the estimates from our baseline specification, revealing that each additional year of GC wait time corresponds to an increase of approximately 9 to 10 months in founder experience. The F-statistic exceeds 60, significantly surpassing conventional thresholds for weak instruments. Importantly, this relationship remains robust across different fixed effect specifications, as depicted in the columns.

Additionally, Figure 2 presents the corresponding binned scatter plot. We observe a strong linear relation between GC wait time and the length of founder experience for both the panel and cross-sectional specifications. The strong linear effect, with a slope close to one, underscores the stringency of these laws, indicating that an extra year in the GC wait line on average delays entrepreneurship by almost the same amount of time.

Identifying Assumption and Validity Checks

The main exclusion restriction for our instrument is that the GC wait time faced by founders only affects startup outcomes through its influence on the founder's experience prior to founding the firm. In other words, we need to ensure that the GC wait time faced by the founder is orthogonal to any omitted founder characteristics that could be correlated with startup outcomes, in order to ensure the validity of our instrumental variable.

Figure 3 presents the results of balancing regressions, demonstrating that our instrumental variable (GC wait time) does not exhibit correlations with various founder characteristics, including whether the founder graduated from a top 500 university, the seniority of their first job, the salary of their first job, gender, or race, conditional on the fixed effects included in our baseline specification. These results help verify that our instrument is uncorrelated with any observable founder characteristic.

Our analysis also reveals that the majority of founders in our sample established their startups within three years of receiving their green cards, as indicated in Table C5. This suggests that GC wait lines merely delayed the founders by a few years rather than altering the decision of immigrants to start new firms. It also alleviates concerns that immigrant founders had an advantage in "timing" the market, as their timing seems primarily constrained by immigration policy.

Another concern may be that changes in GC wait times could affect the quality of immigrants who choose to remain in the US or become founders, leading to selection bias. Hence, our exclusion restriction requires that our instrument is uncorrelated with any such selection. It is important to clarify that our assumption is not that GC wait times do not cause any out-migration or changes in the propensity to start new firms. Indeed, previous literature has documented differential out-migration trends for Indian and Chinese immigrant founders in long GC wait lines of ten plus years (Lee and Glennon, 2023). Our exclusion restriction requires a much smaller claim: that small changes in GC wait times within the same country and category across different cohorts (typically of the magnitude of one to three years) do not cause a change in the propensity of immigrants to out-migrate or found startups.

We explicitly test this claim in Table C7, utilizing the full sample of PERM filings. We regress the dependent variable on GC wait times while controlling for individual citizenship and degree level, similar to our baseline specification. Column 1 uses an indicator for the immigrant leaving the US as the dependent variable. Columns 2, 3, and 4 use an indicator for the immigrant eventually starting their own startup at any location, in the US, and outside the US, respectively, as the dependent variable. We find no statistically or economically significant results for any outcome. These findings assuage concerns that our instrument could be associated with selection on founder quality, indicating that our results are unlikely to be driven by differences in ex-ante founder characteristics.

Direction of Bias in OLS

We also try to understand the direction of bias in naive OLS results by regressing employee experience on various employee characteristics. As shown in Figure 3 and Table C6, our results reveal that founders with less experience are more likely to have graduated from highly-ranked universities, even after controlling for fixed effects. These findings are similar to Wadhwa et al. (2008) and suggest a positive selection, wherein high-quality entrepreneurs (from top schools) tend to initiate their ventures earlier, possibly driven by the anticipation of higher returns from their endeavors. Conversely, we find that employees with higher initial salaries and job titles tend to accumulate more experience before founding a new firm. These results point towards a negative selection effect consistent with Hacamo and Kleiner (2022), where high-quality entrepreneurs might delay launching their ventures due to the elevated opportunity cost associated with starting their own business. While these findings underscore the presence of selection biases in the naive OLS regression, accurately quantifying the direction of bias remains challenging. Therefore, employing an instrument becomes crucial to understand the causal impact of experience.

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. Table 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,[24] one additional year of experience increases the total funding amount received from VCs by 13%. In Columns (1) & (3), we further investigate what is driving the higher funding received. We find one additional year of experience leads to 0.19 additional rounds of funding received (9.0% increase relative to the mean), and a 1.65 percentage points (p.p.) higher chance of securing a total funding amount exceeding $100 million (28% 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, our second 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 4.2%. 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 5.4%. 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 4.5% higher adjusted citations.

Our third dimension of startup performance is the firms' growth in employment (Azoulay

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

et al., 2020; Kerr and Kerr, 2020a). 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 0.7 p.p. per one additional year of experience. In addition to examining favorable outcomes, we present evidence in Table C9 that greater founder experience can mitigate business failures, as measured by permanent declines in employment size. Specifically, each additional year of experience a founder possesses reduces the likelihood of employment dropping to 100% of its peak size by 1.4 p.p.

We report additional startup outcomes, with different employment cutoffs and other measures for patent quality in C10. We find results consistent with our main results for all outcomes. 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.

We present our OLS estimates derived from Equation 1 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 point towards an overall positive selection, where high-quality entrepreneurs tend to initiate their ventures earlier. These results are also consistent with university results in Figure 3, where founders from esteemed universities, are considerably more inclined to establish firms without prior experience.

Identification Concerns & Robustness Checks

Figure 1 depicts the variation in GC wait time depending on the founder's country of origin and their cohort applying for a green card. It's possible that unobserved factors correlated with these variables could directly impact startups, violating the exogeneity restriction of our instrument. To address this concern, in Table 4, Panel A, we introduce controls for both the founder's origin country fixed effects and the founder's cohort or graduation year fixed effects.[25] This approach enables us to compare startups founded by immigrants from the same country and cohort of applications. Results remain robust across various performance measures.

Another potential concern is that changes in GC wait times may be influenced by industry- and location-specific time trends, which could independently affect startup outcomes. Table 4, Panel B, demonstrates that our results are robust to using more flexible dynamic fixed effects, such as firm-industry-by-year fixed effects and firm-state-by-year fixed effects. These controls help alleviate concerns that our results are driven by dynamic industry or geography-specific time trends.

Longer wait times for a green card could potentially change the composition and quality of immigrants coming to the US over time. Talented immigrants might be discouraged from coming to the US if they observe increasing wait times for green cards. This could lead to systematic compositional shifts across immigrant cohorts, impacting the quality of immigrant-founded startups. To address this concern, in Table 4, Panel C, we replace the instrument with the unanticipated green card wait time. We define the unanticipated wait time as the difference between the actual GC wait time of the founder and the expected wait time of the cohort suggested by the Visa Bulletin when the founder starts his first US job. For example, consider an immigrant from China with a master's degree who started his first U.S. job in July 2013. The July 2013 Visa Bulletin indicated that Chinese EB-2 applicants with a priority date (GC filing date) earlier than May 15th, 2008 could apply for Adjustment of Status, suggesting an expected wait time of around 5.1 years. However, in reality, he waited only 3.6 years, based on a GC filing date of September 2nd, 2014. We would take -1.5 years as his unanticipated wait time in this case. This measure captures the random component of the realized wait time, which the immigrant could not predict accurately. Our 2SLS estimates are generally robust to using the alternative instrument, though the statistical powers are reduced for some outcomes. The unpredictable nature

[25] We can only include one of the firm founding and founder cohort fixed effects, as both together are collinear with founder experience.

of actual GC wait times helps mitigate potential biases arising from shifts in immigrants' quality due to longer GC wait times.

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 C8 that our results for logarithmic outcomes are robust to using Poisson regression. We use the control function approach with a bootstrap for standard errors for the Poisson regression with IV, following Wooldridge (1997) and Cameron and Trivedi (2013).

Heterogeneous Effects

Table 5 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 for females on the number of VC funding rounds (46% vs. 10% for males), and employment level (51% vs. 11%) that is statistically significant at the 5% and 10% level, respectively. 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, with many that are statistically significant at least at the 10% level. For example, one year of experience increases the total VC funding by 24.6% (vs. 2.9% for White), 23.1% higher employment growth (vs. -1.2% 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 0.29 additional rounds of VC funding with one additional year of experience (vs. 0.11 additional rounds for founders with below median social connections), and generate both more and better patents, with differences significant at the 5% level.

All three results are broadly consistent with prior experiences 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 C13, 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 D4 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 the literature has explored: 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 6 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 5.1% and the number of co-founders by 5.5%. 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 3.1 p.p. higher chance of having any of the founder's previous colleagues as initial employees, increasing the number by 3.8%. 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 3.4%. 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.

Column (4) and (5) 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. Column 4 tests if the LinkedIn-classified industry of the startup is the same as that of the previous employer. In column (5), we check the average cosine similarity between textual descriptions of the startup and companies where the founder worked before. However, we observe no statistically significant impact in either column.

Column (6) tests for the novelty of the startup relative to other startups. We measure novelty as 1 minus the average cosine similarity between the text descriptions of the startup and the other startups in CrunchBase in the same category and founded in the same year[26]. We find no statistically significant evidence indicating that more experienced founders start firms that differ significantly from others within the same industry and cohort.

Table 7 and Figure D3 check if these intermediate variables drive our results. We should observe larger results for firms with more initial employees and co-founders 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 14%

[26]We used OpenAI's text-embedding-ada-002 model to generate text embeddings.

increase in total VC funding (vs. -1.7% for founders with below median initial employees), 2.2 p.p. higher chance of exceeding $100 million in VC funding (vs. -0.5 p.p.), 1.8 p.p. higher chance of reaching 1000 employees (vs. -0.05 p.p.). These effects are statistically significant at the 10% level. Further, one additional year of experience also enhances the number of patents granted by 9.4% and the patent citations received by 10.0% to 12.0%. 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 co-founders instead. We again see outsized effects of experience on startup performance for firms with more co-founders, 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 C11, consistent with improved financing ability, or industry-specific knowledge, not driving our results.

Another potential explanation is that some founders may delay launching their businesses to better align with market conditions. However, Table C5 reveals that 64.4% of the founders in our sample established their startups within three years of receiving their green cards. Additionally, Table C12 indicates that the impact of prior experience on startup outcomes is significant only for those founders who started their businesses within this three-year period. This suggests that the timing of startup launches is largely influenced by immigration policy, rather than market timing strategies.

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 C14 reports the assumptions. We find that each additional year of experience can be valued at approximately 200,000 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 that aim to foster new firm formation directly out of college. Thiel Fellowship offers students \$100,000 a year to drop out of college and start their own firms. Our estimates imply that the expected value of experience for these students might be higher on average compared with the money offered.

	Mean	S.D.	P10	P50	P90
Panel A: Founder Characteristics					
Experience (years)	10.7	5.56	4.00	11.0	18.0
Green Card Wait Time (years)	3.48	3.71	0.17	2.16	9.51
1{Female}	0.18	0.39	0.00	0.00	1.00
1{White}	0.48	0.50	0.00	0.00	1.00
1{Advanced Degree}	0.72	0.45	0.00	1.00	1.00
1{Top 500 Universities}	0.74	0.44	0.00	1.00	1.00
Num. of Social Connections	452	110	276	500	500
Seniority of the First Job	2.10	1.22	1.00	2.00	4.00
Salary of the First Job	72,601	22,760	45,428	69,767	107,594
Observations			2,317		
Panel B: Initial Startup Characteristics					
Initial Emp. Size	4.97	9.10	1.00	2.00	11.00
Num. of Cofounders	2.82	2.17	1.00	2.00	6.00
Num. of Previous Colleagues	2.59	4.54	0.00	1.00	8.00
Num. of Previous Colleagues in Initial Employees	0.78	2.00	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	1.22	1.84	0.00	1.00	3.00
$\mathbb{1}${Experience in the Same Industry}	0.34	0.48	0.00	0.00	1.00
$\mathbb{1}${Experience in Firms with Emp. $\geq$ 1000 }	0.70	0.46	0.00	1.00	1.00
$\mathbb{1}${Experience in Firms with Age $\geq$10ys}	0.37	0.48	0.00	0.00	1.00
Observations			2,317		
Panel C: Startup Outcomes					
Employment Size	177	227	0.00	5.00	134
IPO	0.01	0.10	0.00	0.00	0.00
Num. of Funding Rounds	2.14	2.26	0.00	1.00	5.00
Amount of Funding (2015 M$)	15.3	40.8	0.00	0.92	41.7
Num. of Patents	0.19	1.58	0.00	0.00	0.00
Num. of Citations	1.30	23.4	0.00	0.00	0.00
Adjusted Num. of Citations	0.26	3.43	0.00	0.00	0.00
Num. of Top Patents	0.03	0.45	0.00	0.00	0.00
KPSS Value (2015 M$)	9.87	453	0.00	0.00	0.00
Observations			19,365		

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. The KPSS value refers to the economic value of patents calculated by Kogan et al. (2017), deflated to be in 2015 dollars. 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.

Panel A: Panel Regression					
	(1) Experience	(2) Experience	(3) Experience	(4) Experience	(5) Experience
Wait Time	0.853***	0.825***	0.840***	0.804***	0.804***
	(0.140)	(0.106)	(0.110)	(0.109)	(0.109)
Founder Citizenship FE	Y	Y	Y	Y	Y
Founder Degree Level FE	Y	Y	Y	Y	Y
Firm Cohort FE		Y	Y	Y	Y
Firm Industry FE			Y	Y	Y
Firm State FE				Y	Y
Year FE					Y
Obs.	19,158	18,708	18,708	18,505	18,505
R-squared	0.0806	0.566	0.606	0.620	0.620
F stat	37.06	60.20	58.75	54.10	54.05

Panel B: Cross-sectional Regression				
	(1) Experience	(2) Experience	(3) Experience	(4) Experience
Wait Time	0.920***	0.969***	0.963***	0.933***
	(0.126)	(0.107)	(0.110)	(0.111)
Founder Citizenship FE	Y	Y	Y	Y
Founder Degree Level FE	Y	Y	Y	Y
Firm Cohort FE		Y	Y	Y
Firm Industry FE			Y	Y
Firm State FE				Y
Obs.	2291	2265	2222	2185
R-squared	0.0875	0.540	0.568	0.578
F stat	53.23	82.23	76.37	71.13

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 in Panel (a) present the coefficients α obtained by estimating Equation (2) from the panel. The cells in Panel (b) present the coefficients α obtained by estimating Equation (5) from 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 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 firm cohort or founding year FEs. Column 3 adds controls for firm industry FEs. Column 4 adds controls for firm-state FEs. Column 5 adds controls for year 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 $\geq$100M	Log(Patents)	Log(Citations)	Log(Adjusted Citations)	Log(Emp.)	Emp.$\geq$1000	IPO
Panel A: 2SLS									
Experience	0.192**	0.130**	0.0165**	0.0420**	0.0539**	0.0451**	0.119*	0.0111**	0.00696**
	(0.0838)	(0.0540)	(0.00718)	(0.0201)	(0.0257)	(0.0219)	(0.0641)	(0.00535)	(0.00336)
Panel B: OLS									
Experience	0.0373**	0.0427***	0.00460**	0.00486*	0.00672*	0.00589*	0.0571***	0.00171**	0.000742
	(0.0171)	(0.0151)	(0.00195)	(0.00276)	(0.00381)	(0.00319)	(0.0113)	(0.000788)	(0.000513)
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.	7,380	7,380	7,380	18,505	18,505	18,505	16,755	16,755	13,683
First-stage F	26.77	26.77	26.77	54.05	54.05	54.05	51.05	51.05	31.09
Mean Outcome	2.14	15.3	0.06	0.19	1.30	0.26	177	0.04	0.01
Magnitude (%)	8.97	13.0	28.3	4.20	5.39	4.51	11.9	25.8	74.3

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 $\geq$100M	Log(Patents)	Log(Citations)	Log(Adjusted Citations)	Log(Emp.)	Emp.$\geq$1000	IPO
Panel A: Founder Cohort FEs									
Experience	0.302*	0.218**	0.0332**	0.0810**	0.104**	0.0901**	0.228*	0.0233**	0.0101*
	(0.166)	(0.110)	(0.0147)	(0.0380)	(0.0497)	(0.0417)	(0.118)	(0.0105)	(0.00519)
First-stage F	13.55	13.55	13.55	32.74	32.74	32.74	27.60	27.60	19.84
Panel B: Firm State $\times$ Year FEs + Firm Industry $\times$ Year FEs									
Experience	0.205**	0.145**	0.0177**	0.0410**	0.0511*	0.0435*	0.120*	0.0102*	0.00685*
	(0.0917)	(0.0588)	(0.00784)	(0.0209)	(0.0264)	(0.0227)	(0.0666)	(0.00561)	(0.00352)
First-stage F	24.67	24.67	24.67	49.91	49.91	49.91	46.37	46.37	29.25
Panel C: Unanticipated Wait Time									
Experience	0.203*	0.167*	0.0264**	0.0576*	0.0770**	0.0657**	0.159*	0.0168**	0.00578
	(0.122)	(0.0908)	(0.0126)	(0.0295)	(0.0386)	(0.0325)	(0.0882)	(0.00768)	(0.00376)
First-stage F	18.39	18.39	18.39	43.39	43.39	43.39	43.14	43.14	30.71
Obs.	7,380	7,380	7,380	18,505	18,505	18,505	16,755	16,755	13,683
Mean Outcome	2.14	15.3	0.06	0.19	1.30	0.26	177	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 $\times$ year FEs, and firm state $\times$ 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. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

	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	0.0966	0.101*	0.0127*	0.0417*	0.0543*	0.0443*	0.114	0.0144**	0.00569
	(0.0668)	(0.0560)	(0.00710)	(0.0226)	(0.0289)	(0.0248)	(0.0723)	(0.00628)	(0.00357)
Female									
Experience	0.460***	0.273***	0.0160	0.0936	0.110	0.0988	0.506**	0.0210	0.0135
	(0.173)	(0.104)	(0.0148)	(0.0810)	(0.0991)	(0.0852)	(0.209)	(0.0158)	(0.0111)
Diff.									
	0.363**	0.171	0.00328	0.0519	0.0553	0.0545	0.392*	0.00663	0.00777
	(0.185)	(0.118)	(0.0164)	(0.0841)	(0.103)	(0.0887)	(0.222)	(0.0170)	(0.0116)
Panel B: by Race									
Non-white									
Experience	0.306**	0.246**	0.0149	0.0550	0.0624	0.0519	0.231***	0.0230***	0.0101*
	(0.154)	(0.101)	(0.0126)	(0.0345)	(0.0425)	(0.0371)	(0.0855)	(0.00791)	(0.00528)
White									
Experience	0.115	0.0292	0.0103	-0.0105**	-0.00943	-0.00545	-0.0123	-0.00990	0.00951
	(0.0881)	(0.0857)	(0.0103)	(0.00486)	(0.00614)	(0.00458)	(0.0991)	(0.00661)	(0.00685)
Diff.									
	-0.191	-0.217	-0.00460	-0.0656*	-0.0719*	-0.0573	-0.243*	-0.0329***	-0.000595
	(0.177)	(0.132)	(0.0163)	(0.0348)	(0.0429)	(0.0374)	(0.131)	(0.0103)	(0.00865)
Panel C: by Number of Social Connections									
Number of Social Connections < Median									
Experience	0.113	0.0830	0.00857	-0.00509	-0.00870	-0.00229	0.183	0.0247**	0.0182
	(0.0719)	(0.0759)	(0.0106)	(0.00616)	(0.00818)	(0.00568)	(0.136)	(0.0117)	(0.0117)
Number of Social Connections > Median									
Experience	0.292**	0.183**	0.0128	0.0540*	0.0664*	0.0561*	0.140**	0.0113**	0.00601
	(0.114)	(0.0747)	(0.00925)	(0.0283)	(0.0354)	(0.0306)	(0.0675)	(0.00548)	(0.00448)
Diff.									
	0.179	0.100	0.00427	0.0591**	0.0752**	0.0584*	-0.0432	-0.0134	-0.0122
	(0.134)	(0.106)	(0.0141)	(0.0289)	(0.0363)	(0.0311)	(0.151)	(0.0129)	(0.0125)

Table 5: 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.

Panel A: Effects on Intermediate Variables						
	(1) Log(Initial Emp.)	(2) Log(Cofounders)	(3) Years to First Funding	(4) $\mathbb{1}\{\text{Same Industry}\}$	(5) Continuity	(6) Novelty
Experience	0.0507**	0.0554**	0.0143	0.0103	0.00433	-0.000427
	(0.0237)	(0.0270)	(0.0472)	(0.0105)	(0.00295)	(0.000575)
Founder Citizenship FE	Y	Y	Y	Y	Y	Y
Founder Degree Level 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.	2,019	1,987	885	2,134	1,136	1,244
First-stage F	74.68	73.25	34.00	74.28	38.80	39.95
Mean Outcome	4.97	2.82	1.22	0.34	0.20	0.24

Panel B: Effects on Previous Colleagues				
	Previous Colleagues in Initial Emp.		Previous Colleagues in Cofounders	
	(1) $\mathbb{1}\{\text{Num.}>0\}$	(2) Log(Num.)	(3) $\mathbb{1}\{\text{Num.}>0\}$	(4) Log(Num.)
Experience	0.0314***	0.0380***	0.0269**	0.0340***
	(0.0118)	(0.0141)	(0.0114)	(0.0126)
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.	2,019	2,019	2,019	2,019
First-stage F	74.68	74.68	74.68	74.68
Mean Outcome	0.35	0.78	0.32	0.45

Table 6: 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. In Panel (a), we present effects for the log of initial employment size, the log of the number of cofounders, years to the first funding round, whether the founder worked in the same industry before, continuity of the startup relative to companies where the founder worked before, and novelty of the startup relative to other startups. 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. We measure continuity using the average cosine similarity between textual descriptions of the startup and companies where the founder worked before. We measure novelty using 1 minus the average cosine similarity between text embedding vectors of descriptions of the startup and the other startups in CrunchBase in the same category and founded in the same year. In Panel (b), we present effects for 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, and the log of the number of previous colleagues in 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 $\geq$100M	Log(Patents)	Log(Citations)	Log(Adjusted Citations)	Log(Emp.)	Emp.$\geq$1000	IPO
Panel A: by Initial Employment Size									
Initial Employment Size < Median									
Experience	0.00808	-0.0165	-0.00473	-0.0133	-0.0177	-0.0148	0.0700	-0.000508	0.000904
	(0.115)	(0.0724)	(0.00881)	(0.0107)	(0.0156)	(0.0142)	(0.0602)	(0.000425)	(0.00554)
Initial Employment Size > Median									
Experience	0.246*	0.141*	0.0220**	0.0940**	0.120**	0.0998**	0.123	0.0177**	0.00974**
	(0.126)	(0.0811)	(0.0112)	(0.0418)	(0.0523)	(0.0447)	(0.0869)	(0.00895)	(0.00463)
Diff.									
	0.238	0.157	0.0268*	0.107**	0.138**	0.115**	0.0533	0.0182**	0.00883
	(0.170)	(0.109)	(0.0143)	(0.0431)	(0.0546)	(0.0469)	(0.106)	(0.00896)	(0.00722)
Panel B: by Number of Cofounders									
Number of Cofounders < Median									
Experience	0.0371	0.0240	-0.00499	-0.0141	-0.0179	-0.0148	0.0579	-0.000475	0.00154
	(0.114)	(0.0780)	(0.00940)	(0.0103)	(0.0149)	(0.0136)	(0.0576)	(0.000398)	(0.00545)
Number of Cofounders > Median									
Experience	0.269*	0.141	0.0242*	0.107**	0.134**	0.112**	0.123	0.0183*	0.0101**
	(0.137)	(0.0894)	(0.0123)	(0.0471)	(0.0588)	(0.0502)	(0.0941)	(0.00965)	(0.00475)
Diff.									
	0.231	0.117	0.0292*	0.121**	0.152**	0.127**	0.0646	0.0187*	0.00853
	(0.178)	(0.119)	(0.0155)	(0.0482)	(0.0606)	(0.0520)	(0.110)	(0.00966)	(0.00722)

Table 7: 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.

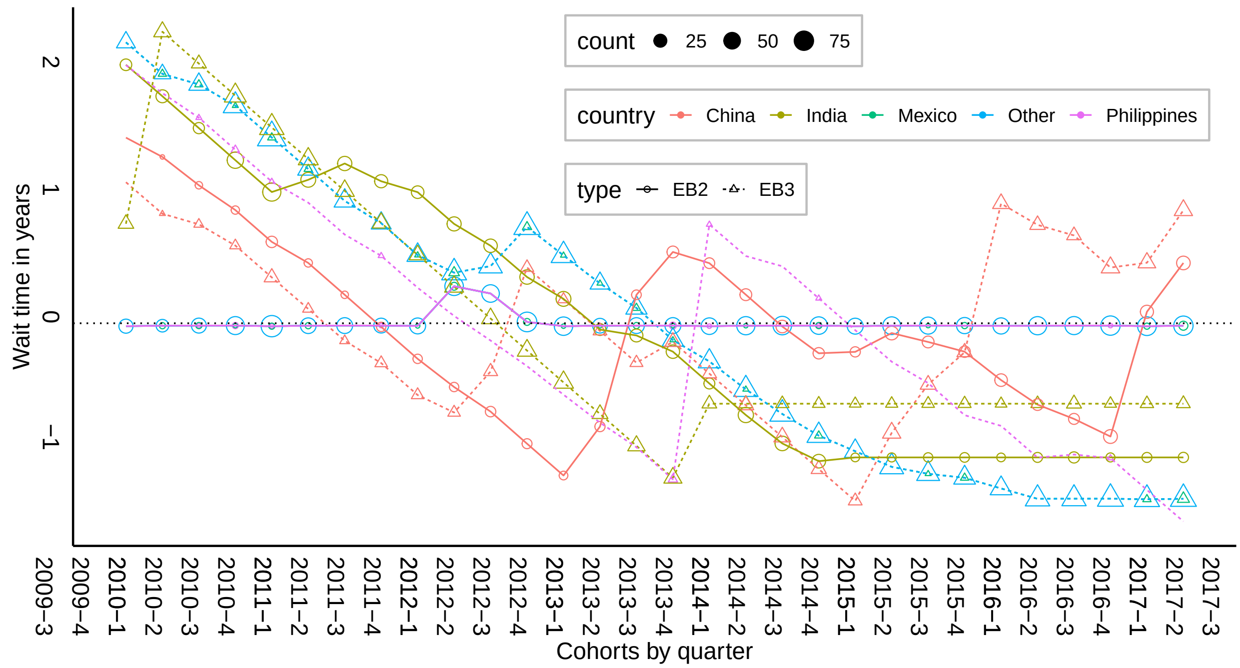
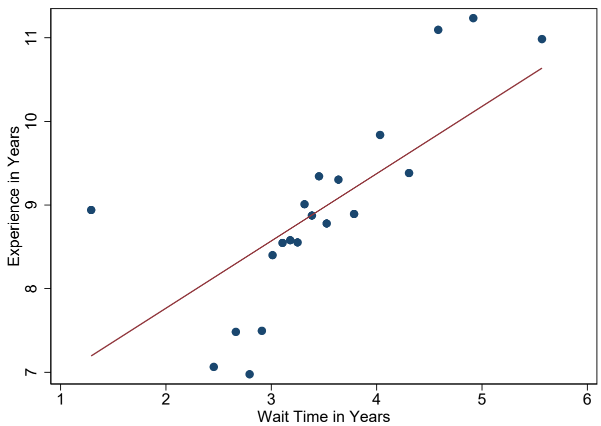
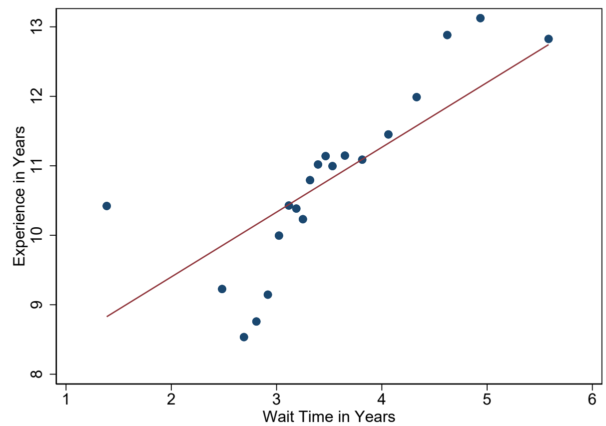


Figure 1: Green Card Wait Time across Cohorts

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.



(a) Panel (Slope = 0.804 ± 0.109, F=54.1)



(b) Cross-section (Slope = 0.933 ± 0.111, F=71.1)

Figure 2: Binned Scatterplot of First Stage Regression

Notes: This figure presents the binned scatterplot that visualizes the relationship between green card wait time and experience of immigrant entrepreneurs. 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. Panel (a) presents the panel version by estimating Equation (2), controlling for founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. Panel (b) presents the cross-sectional version by estimating Equation (5), controlling for founder citizenship FEs, founder degree-level FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs.

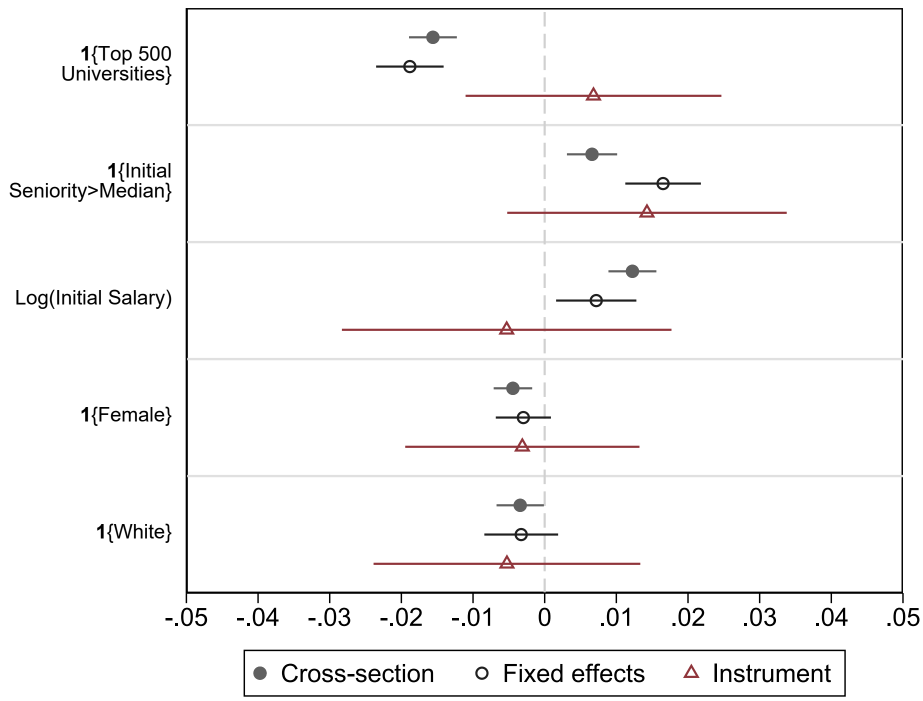


Figure 3: Balancing Regressions

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 Details of Matching Process

A.1 Identifying founders

We identify founders using two sources of information: CrunchBase and LinkedIn. Initially, we filter all firms identified as startups on Crunchbase. Individuals in the U.S. who joined these startups within two years of the companies' founding are classified as founders (Babina (2020) takes a similar assumption). CrunchBase provides unique LinkedIn URLs for each firm and individual, facilitating matching. Additionally, we screen LinkedIn job titles for individuals working for U.S. companies, specifically identifying those with job titles containing "founder", "cofounder" or "founding". This process results in a database of 837,289 founders, with 13.5% identified from CrunchBase, and the remainder from LinkedIn.

A.2 PERM Data

We exclude cases involving multiple PERM applications, as the priority date for individuals is unclear in such instances. Multiple PERM applications constitute 0.1% of our sample. Each PERM identifier uniquely identifies an individual. While individual names are not provided in PERM filings, the rich granular data allow us to uniquely identify and match each person. PERM filings include details such as employer firm name, job title, worksite state, employee home state, citizenship, major, education completion year, education institution, and education level for each person. These characteristics uniquely identify individuals in 98% of cases.

A.3 LinkedIn PERM Match

We match LinkedIn data to PERM filings using granular characteristics present in both datasets: education (degree, institution, and year), job at time of filing (firm name, position, location), and country of origin. Initially, we employ *rapidfuzz* to fuzzy match school names in PERM filings and LinkedIn profiles, requiring a match score (token sort ratio) above

95% and manual verification. We keep only matches with the same degree level and with a maximum difference of one year in graduation dates between the two datasets. For profiles matched on education, we use *rapidfuzz* to fuzzy match the company names of each job position, requiring a match score (weighted ratio) above 95% and manual verification. We also validate that the start date of matched positions is no later than one year after the priority date for GC application, and the end date is no earlier than the priority date. Additionally, we ensure consistency in worksite states between LinkedIn and PERM. Utilizing PERM applicant citizenship, we predict country of origin using the *gpt-3.5-turbo* API from OpenAI based on LinkedIn names. Inconsistencies in countries between two datasets are permitted if the citizenship is from immigrant-heavy countries such as Canada or Australia. In cases with multiple PERM matches to a LinkedIn profile, we conduct further fuzzy matching based on fields of study and job titles using *rapidfuzz* and weighted ratios, selecting the best match. Finally, all potential matches are manually reviewed based on (predicted) countries of origin, school names, majors, graduation dates, company names, job titles, and locations, with the best matches retained.

We obtain matches between 2,976 LinkedIn users and 2,857 PERM cases, with these users establishing 3,164 startups. The multiple-match issue (one PERM case matched with multiple LinkedIn users) is primarily attributed to multiple LinkedIn profiles for the same individual. For instance, out of 74 PERM cases matched with multiple LinkedIn profiles, 57 share identical full names across profiles. Additionally, individuals commonly establish multiple startups. Hence, we assume all LinkedIn users and startups associated with the same PERM case belong to the same individual, selecting the earliest established startup and corresponding LinkedIn user for each PERM case. After selecting a single startup for each PERM case, if additionally a startup is linked to multiple founders (PERM cases), we select the one with the most experience. Ultimately, we identify 2,317 unique founders and startups.

A.4 Match to CrunchBase & PatentView

Founders identified from CrunchBase are already linked to companies within the platform. For those identified solely from LinkedIn, we match their startups on LinkedIn with CrunchBase companies based on company LinkedIn page URLs. If LinkedIn URLs are unavailable, we conduct fuzzy matching on company names using *rapidfuzz* and weighted ratios, requiring a match score above 95% and manual verification. This process associates them with 927 startups in CrunchBase. For all startups available in CrunchBase, we utilize firm identifiers from the platform. For those only available on LinkedIn, we utilize firm identifiers from LinkedIn.

We match founders and their startups with patent assignees in PatentsView using fuzzy matching on company names, time match, and location match, employing the *rapidfuzz* package in Python and weighted ratios. A match score above 95% is required, followed by manual verification. We then sort possible matches from PatentsView by whether the first patent is filed after the company is founded, consistency in the state of location, and the match score on names, and select the best match from PatentsView assignees for each startup. We then obtain the patent information of each firm from the PatentsView database.

A.5 Identify other startup employees

We extract the work history for all employees of these matched startups from LinkedIn. We track the number of active employees in each firm for each year since the establishment using LinkedIn position-level data. 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 its founding are considered initial employees. Additionally, employees with job titles containing "founder", "cofounder" or "founding" are identified as cofounders.

B GC Wait time process

In this section, we describe the main factors that govern fluctuations in GC wait times. Our explanations are based on declarations made by Andrew Parker, chief of the Residence and Admissibility Branch (RAB) within the Office of Policy & Strategy (OP&S) of U.S. Citizenship and Immigration Services (USCIS), in a case filed at the US district court in Seattle[27].

The USCIS must adhere to three main limits when allocating employment-based GCs: a 140,000 limit on overall GCs, a 28.6% limit for EB-1, EB-2, and EB-3 categories within the overall GC issuance, and a 7% cap for each origin country which applies to the total GCs in both family- and employment-based categories. However, these limits are often breached, leading to unpredictable wait times.

The overall 140,000 limit on employment-based GCs can be breached due to low usage of family-based GCs or the recapture of previously unused employment-based GCs. The USCIS attempts to capture any unused family-based GCs and add them to increase the subsequent limit on employment-based GCs in the next year. For example, in FY 2021, 141,507 family-based GCs were unused. As a result, the FY 2022 EB annual limit for employment-based GCs was 140,000 plus 141,507, totaling 281,507. Similarly, Congress can recapture employment-based GCs that remained unused in previous years. For instance, 130,107 GCs not used in FY 1999 and 2000 were recaptured and used in FY 2005[28]. Many proposals for the recapture of unused GCs have been presented to Congress in recent years.

The 28.6% per category limit can be breached as GCs not used in a particular category can be made available to another category. These are colloquially called the "fall up/fall down" provisions. Specifically, GCs not required in the EB-4 and EB-5 categories are made available to the EB-1 category, GCs not used in the EB-1 category are made available to EB-2, and visas not required by the EB-2 are made available to the EB-3 category. For

[27] https://www.aila.org/files/o-files/view-file/FED8DA72-8312-42BC-B06D-654E7D7D8C1A

[28] https://travel.state.gov/content/travel/en/legal/visa-law0/visa-bulletin/2005/visa-bulletin-for-january-2005.html

example, during FY 2022, the "fall up/fall down" provisions resulted in additional GCs being made available in the EB-2 category.

The 7% country cap can be breached if any excess GCs are available in a category or if not all of the 7% country cap is used by the family-based GCs. Suppose the number of available GCs exceeds demand within a particular category. In that case, the remaining GCs can be used for the most retrogressed country, regardless of the per-country limit. For example, in FY 2021, Indian nationals used over 50% of all EB-1 GCs, 47% of the EB-2 GCs, and 27% of the EB-3 GCs, well above the 7% limit, as there were excess GCs left in each category after applying the country limits. The 7% country limit applies to the total GCs in both employment- and family-based categories. Hence, any unused family-based GCs can be used to breach the country limit for employment-based GCs. For example, as previously mentioned, the sum of the employment-based and family-sponsored limit for FY 2022 was 507,507 (281,507 employment-based GCs plus the 226,000 family-sponsored cap). Hence, any single country could receive a maximum of 35,525 GCs (7% of the total). However, if India used only 5,000 family-sponsored visas, they could use 30,525 EB visas, which could be divided in any possible way among the various EB categories.

Apart from the complexity in legislation, further complexity is introduced into the GC process as USCIS is often unable to predict the correct number of immigrants in each wait line. This is because many people can have multiple applications or change their family size while awaiting the final GC. As a result, USCIS is often forced to retrogress the wait line if it invites applications from more candidates than it can issue the GC to. This unpredictability makes predicting GC wait times near impossible.

C Additional Tables

	Mean (Exp. $<$ Med.)	Mean (Exp. $>$ Med.)
Panel A: Founder Characteristics		
Experience (years)	6.41	15.2
Green Card Wait Time (years)	2.92	4.05
$1\{\text{Female}\}$	0.19	0.17
$1\{\text{White}\}$	0.49	0.47
$1\{\text{Advanced Degree}\}$	0.76	0.68
$1\{\text{Top 500 Universities}\}$	0.81	0.67
Num. of Social Connections	443	461
Seniority of the First Job	2.06	2.14
Salary of the First Job	69,646	76,392
Panel B: Initial Startup Characteristics		
Initial Emp. Size	4.78	5.16
Num. of Cofounders	2.91	2.73
Num. of Previous Colleagues	2.37	2.80
Num. of Previous Colleagues in Initial Employees	0.63	0.92
Num. of Previous Colleagues in Cofounders	0.37	0.52
Years to the First Funding Round	1.42	1.01
$\mathbb{1}\{\text{Experience in the Same Industry}\}$	0.27	0.42
$\mathbb{1}\{\text{Experience in the Startups with Emp.} \geq 1000\}$	0.64	0.75
$\mathbb{1}\{\text{Experience in Firms with Age} \geq \text{10ys}\}$	0.32	0.42

Table C1: 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 for 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
$\mathbb{1}\{$Female$\}$	0.18	0.23
$\mathbb{1}\{$White$\}$	0.48	0.71
$\mathbb{1}\{$Advanced Degree$\}$	0.72	0.49
$\mathbb{1}\{$Top 500 Universities$\}$	0.74	0.56
Obs.	2,317	19,365
Panel B: Startup Outcomes		
IPO	0.01	0.01
Num. of Funding Rounds	2.14	1.96
Amount of Funding (2015M$)	15.3	10.2
Obs.	19,365	725,576

Table C2: 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	24.7	19.7
Computer software	14.1	8.4
Internet	7.7	9.1
Marketing and advertising	4.0	6.8
Financial services	3.0	5.0
Hospital and health care	3.0	5.2

Table C3: 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	42.3	28.6
New York	12.5	14.4
Washington	7.8	2.9
Massachusetts	4.5	5.9
Texas	4.2	6.5
Illinois	4.2	3.9
Florida	2.3	4.2

Table C4: 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.

Time Period (in Years)	Mean	Median
From Graduation to Priority Date	4.38	4.69
GC Wait Time	3.48	2.16
Processing Time	0.75	0.75
From Obtaining GC to Founding the Startup	2.14	2.23
Experience (from Graduation to Founding the Startup)	10.7	11.0

Table C5: Decomposition of Experience

Notes: This table presents the mean and median of four components of the founder's experience at the time of founding the startup, which is time in years from the highest degree graduation to the startup's founding. GC wait time is from the priority date until the priority date is earlier than the application date in the visa bulletin for 3 consecutive months. Processing time is from when the priority date is earlier than the application date in the visa bulletin for 3 consecutive months to obtaining the green card. We assume that the processing time is 9 months. The median processing time disclosed by USCIS is 8.7 months on average from FY2016 to 2024 (`https://www.uscis.gov/sites/default/files/document/fact-sheets/historical_pt_factsheet_fy16_to_fy24.pdf`). 43.3% of the founders in our sample established their startups within one year of receiving their green cards, 53.1% within two years, and 64.4% within three years.

	(1) 1{Top 500 Universities}	(2) 1{Seniority>Median}	(3) Log(Salary)	(4) 1{Female}	(5) 1{White}
Panel A: Cross-section					
Experience	-0.0156***	0.00661***	0.0122***	-0.00443***	-0.00342**
	(0.00170)	(0.00179)	(0.00171)	(0.00137)	(0.00169)
Panel B: Fixed effects					
Experience	-0.0188***	0.0165***	0.00720**	-0.00298	-0.00327
	(0.00240)	(0.00269)	(0.00286)	(0.00196)	(0.00263)
Panel C: Instrument					
Wait Time	0.00681	0.0143	-0.00530	-0.00312	-0.00527
	(0.00911)	(0.00995)	(0.0117)	(0.00834)	(0.00950)
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.	2,317	2,317	1,411	2,317	1,806

Table C6: 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 refer 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) $\mathbb{1}$\{Leaving US\}	(2) $\mathbb{1}$\{Founder\}	(3) $\mathbb{1}$\{US Founder\}	(4) $\mathbb{1}$\{Non-US Founder\}
Wait Time	0.000473	0.000275	0.000147	0.000128
	(0.000914)	(0.000752)	(0.000725)	(0.000209)
Individual Citizenship FE	Y	Y	Y	Y
Individual Degree Level FE	Y	Y	Y	Y
Obs.	55891	55961	55961	55961
Mean Outcome	0.0654	0.0439	0.0407	0.0032
Magnitude (%)	0.72	0.63	0.20	4.00

Table C7: Effect of GC Wait Time on Probability of Leaving the US and Becoming a Founder

Notes: This table presents estimates of the relationship between green card wait time and the probability of leaving the US and being a founder. The cells present the coefficients obtained by regressing the indicator of whether an immigrant left the US or whether an immigrant became a (US or non-US) 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. Immigrants are considered US founders if they enter our main sample of immigrant founders. Immigrants are considered to leave the US if they didn't become US founders, and the current country on the LinkedIn profile is not the US or the location of the latest position is outside the US when the current country is missing. Immigrants are considered non-US founders if they left the US and have positions with explicit founder titles outside of the US after the priority date. Immigrants are considered founders if they are US or non-US founders. 6.5% of PERM applicants left the US without ever being a US founder, among which 4.9% became founders outside the US. Overall 0.3% of PERM applicants left the US and became founders outside the US. All the regressions include individual citizenship and individual degree-level FEs. Magnitude refers to the effect of an additional year of wait time relative to the mean of the outcome in percent terms. Standard errors are clustered by individual. ***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	0.0395**	0.0619***	0.107***	0.0948***	0.0544***
	(0.0161)	(0.0225)	(0.0339)	(0.0279)	(0.0146)
Panel B: IV Poisson					
Experience	0.112**	0.282**	0.496**	0.382**	0.0585
	(.0558)	(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.	7,440	14,227	12,932	12,932	16,940

Table C8: 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.

	(1) $\mathbb{1}\{<25\%$ Max Emp.$\}$	(2) $\mathbb{1}\{<50\%$ Max Emp.$\}$	(3) $\mathbb{1}\{<75\%$ Max Emp.$\}$	(4) $\mathbb{1}\{<100\%$ Max Emp.$\}$
Experience	-0.00873	-0.0132	-0.0143	-0.0152*
	(0.00803)	(0.00832)	(0.00874)	(0.00872)
Founder Citizenship FE	Y	Y	Y	Y
Founder Degree Level FE	Y	Y	Y	Y
Year 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.	16,755	16,755	16,755	16,755
First-stage F	51.05	51.05	51.05	51.05
Mean Outcome	0.15	0.20	0.26	0.33

Table C9: Effects on the Permanent Drop in Employment Size

Notes: This table presents estimates of the relationship between the experience of immigrant entrepreneurs and the permanent drop in employment size of the startups, 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 on whether the startup's employment size drops below 25%, 50%, 75%, or 100% of its maximum size in the year of observation with no return later above that level. 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	0.119*	0.00811	0.0141*	0.0127*	0.0107	0.0111**
	(0.0641)	(0.0106)	(0.00832)	(0.00725)	(0.00655)	(0.00535)
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.	16,755	16,755	16,755	16,755	16,755	16,755
First-stage F	51.05	51.05	51.05	51.05	51.05	51.05

Panel B: Patents					
	(1) Log(Patents)	(2) Log(Citations)	(3) Log(Adjusted Citations)	(4) Log(Top Patents)	(5) Log(KPSS Value)
Experience	0.0420**	0.0539**	0.0451**	0.0305**	0.0429**
	(0.0201)	(0.0257)	(0.0219)	(0.0146)	(0.0215)
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.	18,505	18,505	18,505	18,505	18,505
First-stage F	54.05	54.05	54.05	54.05	54.05

Table C10: 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. The KPSS value refers to the economic value of patents calculated by Kogan et al. (2017), deflated to be in 2015 dollars. 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	0.203**	0.151***	0.0217**	0.0369	0.0431	0.0367	0.155**	0.0156**	0.00557
	(0.0886)	(0.0568)	(0.00843)	(0.0287)	(0.0359)	(0.0319)	(0.0781)	(0.00721)	(0.00391)
Years to the First Funding Round > Median									
Experience	0.0912	0.0869	0.00192	0.0146	0.0260	0.0179	-0.0220	0.00585	0.0100
	(0.0686)	(0.0974)	(0.00686)	(0.0240)	(0.0325)	(0.0257)	(0.136)	(0.00824)	(0.00894)
Diff.									
	-0.112	-0.0640	-0.0198*	-0.0222	-0.0171	-0.0188	-0.177	-0.00975	0.00446
	(0.112)	(0.113)	(0.0109)	(0.0374)	(0.0484)	(0.0410)	(0.157)	(0.0110)	(0.00975)
Panel B: by Experience in the Same Industry									
Without Experience in the Same Industry									
Experience	0.121	0.0506	0.0146	0.0373	0.0454	0.0397	0.169**	0.0193***	0.00379
	(0.0817)	(0.0701)	(0.00961)	(0.0236)	(0.0300)	(0.0259)	(0.0799)	(0.00731)	(0.00343)
With Experience in the Same Industry									
Experience	0.277*	0.198*	0.0190	0.0610	0.0778	0.0635	0.109	0.00495	0.0122*
	(0.154)	(0.105)	(0.0128)	(0.0419)	(0.0523)	(0.0446)	(0.123)	(0.00932)	(0.00712)
Diff.									
	0.156	0.147	0.00442	0.0238	0.0324	0.0238	-0.0593	-0.0143	0.00841
	(0.174)	(0.126)	(0.0160)	(0.0481)	(0.0603)	(0.0516)	(0.147)	(0.0118)	(0.00790)
Panel C: by Number of Previous Colleagues									
Number of Previous Colleagues < Median									
Experience	-0.0663	-0.0995**	-0.00301	0.0429	0.0551	0.0470	0.0378	0.00877*	0.00435
	(0.0465)	(0.0486)	(0.00236)	(0.0288)	(0.0347)	(0.0299)	(0.0752)	(0.00494)	(0.00426)
Number of Previous Colleagues > Median									
Experience	0.314**	0.209**	0.0204*	0.0279	0.0319	0.0278	0.0932	0.00698	0.00623
	(0.135)	(0.0901)	(0.0112)	(0.0289)	(0.0371)	(0.0323)	(0.0951)	(0.00832)	(0.00451)
Diff.									
	0.380***	0.309***	0.0234**	-0.0150	-0.0232	-0.0192	0.0554	-0.00179	0.00189
	(0.142)	(0.102)	(0.0115)	(0.0408)	(0.0508)	(0.0440)	(0.121)	(0.00967)	(0.00621)
Panel D: by Number of Colleagues in Initial Employees									
Number of Colleagues in Initial Employees < Median									
Experience	0.139	0.0350	0.00729	0.0262	0.0317	0.0224	0.132	0.0103*	0.00980
	(0.118)	(0.0976)	(0.0115)	(0.0278)	(0.0352)	(0.0302)	(0.0843)	(0.00600)	(0.00741)
Number of Colleagues in Initial Employees > Median									
Experience	0.213*	0.150**	0.0179**	0.0358*	0.0482**	0.0434**	0.0618	0.00423	0.00607*
	(0.120)	(0.0648)	(0.00909)	(0.0186)	(0.0245)	(0.0212)	(0.0860)	(0.00730)	(0.00350)
Diff.									
	0.0743	0.115	0.0107	0.00961	0.0165	0.0210	-0.0697	-0.00608	-0.00372
	(0.168)	(0.117)	(0.0147)	(0.0335)	(0.0428)	(0.0369)	(0.120)	(0.00945)	(0.00819)
Panel E: by Number of Colleagues in Cofounders									
Number of Colleagues in Cofounders < Median									
Experience	0.204*	0.0939	0.0159	0.0232	0.0278	0.0195	0.169*	0.0167**	0.00992
	(0.122)	(0.102)	(0.0127)	(0.0268)	(0.0340)	(0.0291)	(0.0878)	(0.00730)	(0.00752)
Number of Colleagues in Cofounders < Median									
Experience	0.183*	0.110*	0.0125	0.0375**	0.0512**	0.0436**	0.0889	0.00562	0.00561*
	(0.111)	(0.0585)	(0.00824)	(0.0179)	(0.0236)	(0.0204)	(0.0732)	(0.00594)	(0.00316)
Diff.									
	-0.0207	0.0161	-0.00348	0.0142	0.0234	0.0241	-0.0800	-0.0110	-0.00431
	(0.165)	(0.117)	(0.0151)	(0.0323)	(0.0414)	(0.0356)	(0.114)	(0.00941)	(0.00816)

Table C11: Heterogeneity Tests on Additional Intermediate Variables

Notes: This table presents how the relationship between the 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
Gap<*1y*									
Experience	0.352*	0.152	0.0291*	0.110**	0.136**	0.122**	0.188	0.0279**	0.0200**
	(0.210)	(0.115)	(0.0160)	(0.0537)	(0.0668)	(0.0573)	(0.160)	(0.0140)	(0.00929)
Gap<2y									
Experience	0.247*	0.124*	0.0176*	0.0780**	0.0972**	0.0856**	0.170	0.0186**	0.0132**
	(0.129)	(0.0721)	(0.00991)	(0.0369)	(0.0461)	(0.0394)	(0.107)	(0.00906)	(0.00573)
Gap<3y									
Experience	0.210**	0.0909	0.0158*	0.0573**	0.0729**	0.0635**	0.180**	0.0184**	0.0106**
	(0.103)	(0.0592)	(0.00818)	(0.0277)	(0.0347)	(0.0296)	(0.0884)	(0.00781)	(0.00452)
Gap≥3y									
Experience	0.663	0.918	0.0322	-0.0152	-0.0194	-0.0286	0.0361	0.0000384	-0.00915
	(1.210)	(1.316)	(0.0681)	(0.0392)	(0.0527)	(0.0503)	(0.111)	(0.00527)	(0.0105)

Table C12: Sub-sample Analysis by Time Gap from Obtaining GC to Founding the Startup

Notes: This table presents how the relationship between the experience of immigrant entrepreneurs and startup performance depends on the time gap from obtaining the green card to founding the startup, 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. We assume that the date of obtaining the green card is 9 months after the priority date is earlier than the application date in the visa bulletin for 3 consecutive months. 43.3% of the founders in our sample established their startups within one year of receiving their green cards, 53.1% within two years, and 64.4% within three years. 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 $\geq$100M	Log(Patents)	Log(Citations)	Log(Adjusted Citations)	Log(Emp.)	Emp.$\geq$1000	IPO
Panel A: by Degree from Top 500 Universities in the World									
Without Degree from Top 500 Universities in the World									
Experience	0.264	0.307**	0.0336*	0.0467*	0.0615*	0.0493*	0.305**	0.00878	0.0146*
	(0.166)	(0.136)	(0.0184)	(0.0259)	(0.0329)	(0.0283)	(0.120)	(0.00762)	(0.00824)
With Degree from Top 500 Universities in the World									
Experience	0.187*	0.131**	0.0150*	0.0412	0.0500	0.0443	0.0282	0.0103	0.00294
	(0.105)	(0.0667)	(0.00866)	(0.0275)	(0.0348)	(0.0299)	(0.0810)	(0.00682)	(0.00326)
Diff.									
	-0.0769	-0.175	-0.0185	-0.00550	-0.0115	-0.00499	-0.276*	0.00150	-0.0117
	(0.196)	(0.151)	(0.0203)	(0.0378)	(0.0479)	(0.0412)	(0.145)	(0.0102)	(0.00887)
Panel B: by Experience in Startups (Emp. $\leq$1000)									
Without Experience in Startups									
Experience	0.142	0.317	0.0272	0.0695	0.0787	0.0651	-0.115	0.00215	0.0104
	(0.358)	(0.399)	(0.0363)	(0.0721)	(0.0924)	(0.0800)	(0.217)	(0.0148)	(0.0133)
With Experience in Startups									
Experience	0.244**	0.140**	0.0162**	0.0117	0.0161	0.0133	0.0990	0.00524	0.00956**
	(0.0971)	(0.0563)	(0.00817)	(0.0108)	(0.0136)	(0.0115)	(0.0695)	(0.00545)	(0.00422)
Diff.									
	0.102	-0.177	-0.0110	-0.0579	-0.0625	-0.0518	0.214	0.00309	-0.000810
	(0.370)	(0.403)	(0.0372)	(0.0729)	(0.0934)	(0.0809)	(0.227)	(0.0158)	(0.0140)
Panel C: by Experience in Startups (Age $\leq$10yrs)									
Without Experience in Startups									
Experience	0.235*	0.217**	0.0228*	0.0252	0.0251	0.0220	0.0247	0.00568	0.00867
	(0.123)	(0.0980)	(0.0126)	(0.0275)	(0.0353)	(0.0308)	(0.0844)	(0.00670)	(0.00595)
With Experience in Startups									
Experience	0.270**	0.131**	0.0217**	0.0185*	0.0304**	0.0209*	0.207**	0.00907	0.0109**
	(0.113)	(0.0625)	(0.00904)	(0.00955)	(0.0122)	(0.0108)	(0.105)	(0.00720)	(0.00468)
Diff.									
	0.0345	-0.0856	-0.00109	-0.00675	0.00534	-0.00108	0.183	0.00339	0.00227
	(0.167)	(0.116)	(0.0155)	(0.0291)	(0.0374)	(0.0326)	(0.135)	(0.00984)	(0.00757)

Table C13: Heterogeneity Tests on Additional Founder characteristics

Notes: This table presents how the relationship between the 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	0.70 %
× Average Proceeds at IPO	$186 Million
× Average Pre-IPO Founder Ownership Share	15 %
= Dollar Value of 1 Year of Experience	**$0.20 Million**

Table C14: 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 are 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.).

D Additional Figures

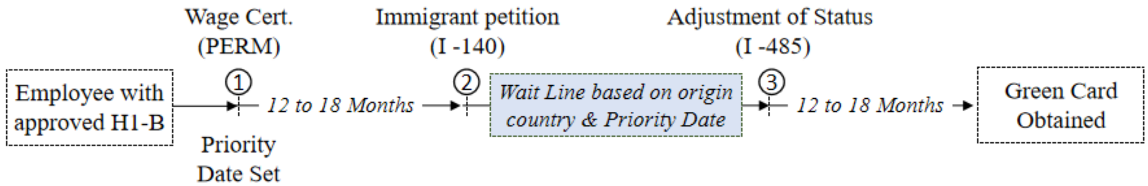


Figure D1: Green Card Timeline

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).

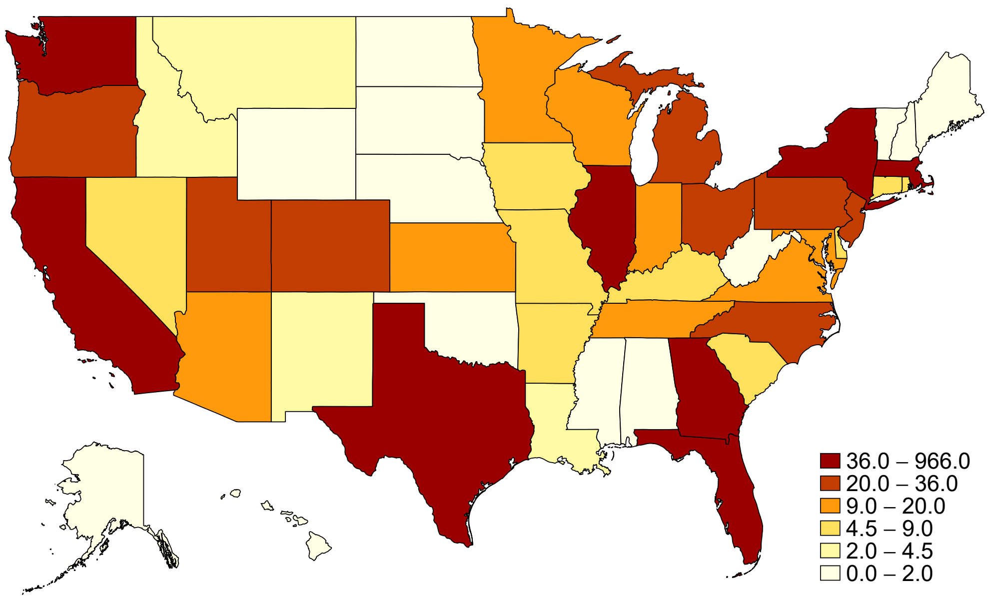
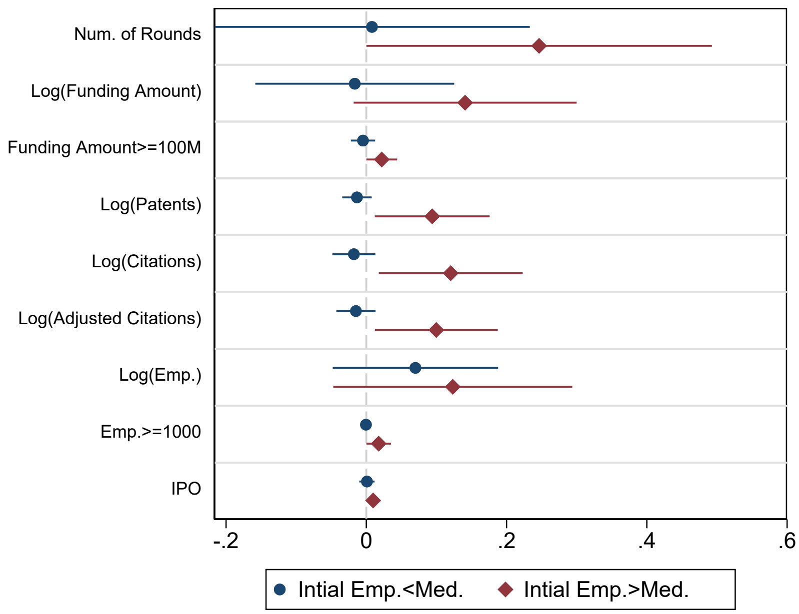
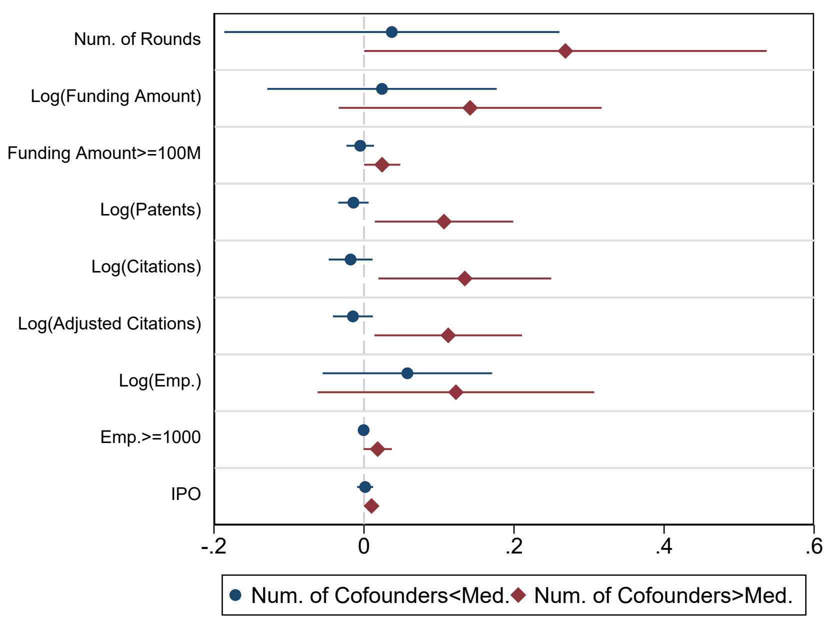


Figure D2: Geographical Distribution of Startups

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.



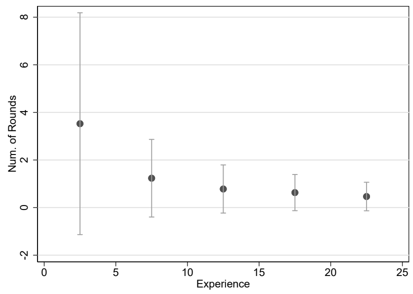
(a) by Initial Employment Size



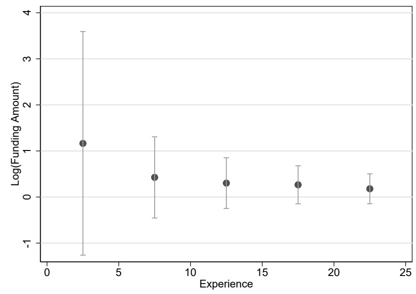
(b) by Num. of Cofounders

Figure D3: Heterogeneity Test on Intermediate Variables

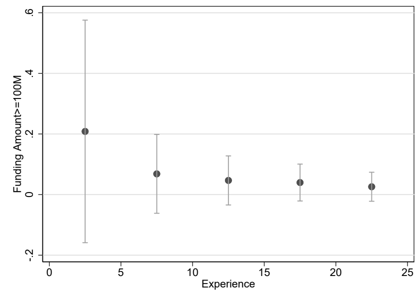
Notes: This figure presents how the relationship between the experience of immigrant entrepreneurs and startup performance depends on some intermediate variables using subsample analysis. The independent variable is the founder's experience at the time of founding the startup, calculated based on time 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.



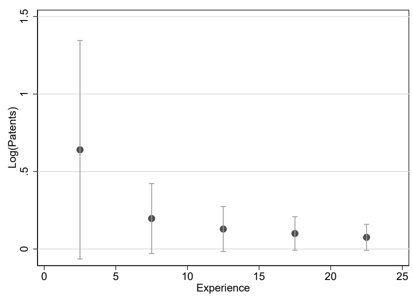
(a) Num. of Rounds



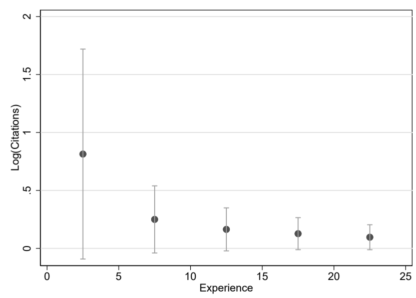
(b) Log(Funding Amount)



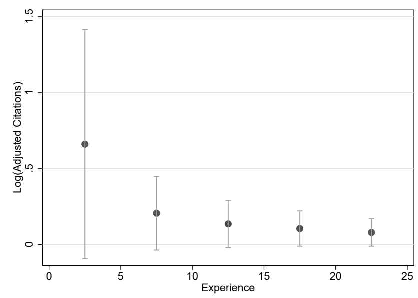
(c) Funding Amount $\geq$ 100M



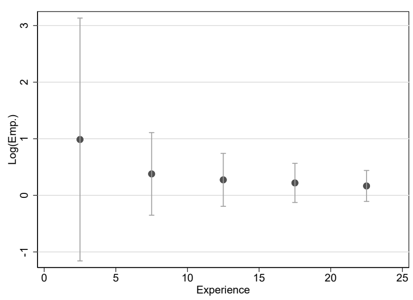
(d) Log(Num. of Patents)



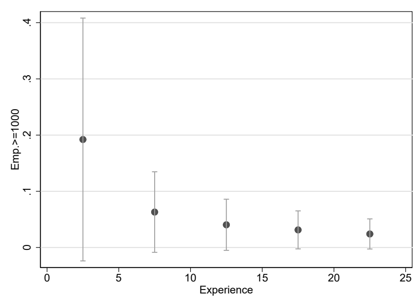
(e) Log(Num. of Citations)



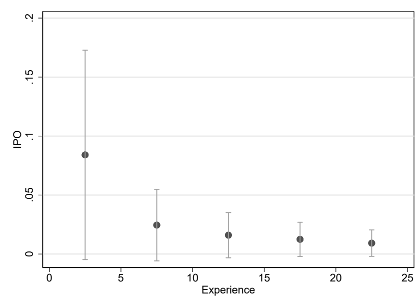
(f) Log(Adjusted Num. of Citations)



(g) Log(Emp.)



(h) Emp.$\geq$1000



(i) IPO

Figure D4: 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 3 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.