ENTREPRENEUR EXPERIENCE AND SUCCESS: CAUSAL EVIDENCE FROM IMMIGRATION WAIT LINES*

Abhinav Gupta†, Franklin Qian‡, & Yifan Sun§

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Abstract: This study investigates how prior work experience influences startup success. Using variations in Green Card waiting periods as an instrument for the experience of immigrant first-time entrepreneurs, we find that startups led by more experienced founders are more successful in securing funding, generating patents, and expanding their workforce. The primary driver of this success is a larger initial team, enabled by founders' ability to recruit former colleagues. Our findings suggest that each additional year of experience adds approximately $200,000 in value, offering key insights for policymakers and investors.

Keywords: Entrepreneurship; Immigration; Innovation; IPO

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†UNC Kenan-Flagler Business School, Department of Finance. Email: abhinav_gupta@kenan-flagler.unc.edu.

‡UNC Kenan-Flagler Business School, Department of Finance. Email: franklin_qian@kenan-flagler.unc.edu.

§University of Pennsylvania, Department of Economics. Email: sunyifan@sas.upenn.edu.

I INTRODUCTION

Startups drive economic growth by fostering innovation and reallocating talent to more productive endeavors (Schumpeter, 1942; Lucas, 1978; Baumol, 1990; Murphy et al., 1991; Gennaioli et al., 2013). Yet, despite their importance, startups face significant uncertainty—approximately 75% of venture-backed ventures fail (Pollman, 2023). Understanding what improves the odds of success is, therefore, essential. Yet, the optimal path for aspiring entrepreneurs remains unclear. Should they drop out of college and launch a company immediately, or would gaining experience at an established firm first improve their odds of success?

This question has direct implications for policy and program design. As of 2016, the US hosted roughly 1,400 startup incubators[1], yet these programs take divergent approaches due to a lack of empirical evidence on the role of prior work experience. The Thiel Fellowship[2] incentivizes founders to forgo traditional career paths and start companies immediately, while Venture for America[3] embeds aspiring entrepreneurs in established firms before they launch their own ventures. Understanding which approach yields better outcomes is crucial for policymakers, investors, and founders alike.

In this paper, we provide the first causal evidence on how prior job experience influences *first-time* startup success, leveraging exogenous variation in US immigration wait times that delay entrepreneurial entry for high-skilled immigrants. Our findings quantify whether delaying startup formation to gain additional experience leads to tangible benefits—and if so, by how much.

The impact of prior experience on entrepreneurship is theoretically ambiguous. Some argue that experience entrenches entrepreneurs in existing paradigms, limiting their ability to introduce groundbreaking ideas (Azoulay et al., 2020; Bernstein et al., 2022). This view is reinforced by anecdotal evidence: figures like Bill Gates and Mark Zuckerberg—both college

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

dropouts—went on to build multi-billion-dollar enterprises. In contrast, other research highlights the benefits of experience, showing that greater market knowledge (Gruber et al., 2008; Chatterji, 2009; Agarwal et al., 2004), technical expertise (Klepper and Sleeper, 2005; Agarwal et al., 2004), and broader social networks (Singh et al., 1999; Honig and Davidsson, 2000; Kerr and Kerr, 2019; Kerr and Mandorff, 2023) are strongly associated with entrepreneurial success. If experience strengthens these factors, it should, in theory, enhance startup performance. Given these conflicting perspectives, the true impact of prior experience remains an empirical question.

Identifying this impact empirically presents a significant challenge. Entrepreneurs endogenously choose how many years of experience to acquire before launching a startup, making it difficult to separate the causal effect of experience from unobserved founder quality. An ideal experiment would randomly assign aspiring entrepreneurs different levels of pre-startup experience and compare their outcomes. While such a design is infeasible, we approximate this setup by leveraging natural variation in the US immigration system, where high-skilled immigrants face exogenous delays in entrepreneurial entry due to visa wait times.

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 (GC), 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

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

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 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 connecting the exact date of the 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

[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 with PERM applications between 2010 and 2017.

[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

average GC wait time of 3.5 years and an average experience of 10.7 years before their first startups. Of these founders, 48% 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, we investigate whether founders who endure longer 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.

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.

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

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 permanent employment drops, and a 0.7-p.p. higher probability of participating in an IPO. In addition to increasing the likelihood of success in the first startup, additional initial job experience also improves the probability of long-term entrepreneurial success in any venture five years after the initial entry into entrepreneurship.

The validity of our instrumental variable depends on the assumption that GC wait times affect startup outcomes exclusively by delaying startup formation. Two key identification challenges warrant consideration. First, GC wait times differ by the founder's country of origin, which could independently affect startup outcomes. We incorporate citizenship fixed effects into our baseline model and verify the robustness of our findings to including founder citizenship-year of the first US job fixed effects. Second, longer wait times could impact the quality of immigrants entering the US or their likelihood of remaining to establish firms, thereby affecting the quality of immigrant-led startups. We mitigate this concern by focusing on unanticipated wait times—defined as the gap between actual and expected wait times at the time of the first US job—and demonstrate that our findings remain consistent, reducing the likelihood of selection bias. We also test whether our instrument correlates with the rate of out-migration or the likelihood of becoming an entrepreneur. Our analysis finds no economically or statistically significant relationship. It is important to clarify that we do not claim that overall differences (of up to ten years) in GC wait times across countries have no impact on startup formation or out-migration. Rather, our argument is more specific: modest variations of one to three years in GC wait times within the same country and category (as captured by our instrument) do not appear to influence individuals' decisions to migrate or start new businesses.

We next test if our results reflect the impact of job experience rather than age or market timing effects. Our analysis shows that the results remain robust even when controlling for employee age, indicating that US job experience, rather than age alone, drives the observed

outcomes. Furthermore, we find that a majority of employees form startups within three years of receiving their GCs. This subset of employees predominantly drives our results, suggesting that the timing of startup formation was primarily influenced by immigration policy constraints, rather than deliberate market timing strategies.

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, starting more novel firms, or in securing funding earlier due to increased experience. However, founders with more extensive experience establish larger firms with more diverse founding teams. These experienced entrepreneurs recruit a greater number of co-founders and early employees representing a broader range of professional roles. Notably, a significant proportion of these early joiners come from the founder's network of 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 suggest that each additional year of experience is valued at approximately $200,000. While this figure comes with several caveats—primarily that it is derived from immigrants, for whom such social capital may hold greater value, and that our identification strategy limits us to evaluating small changes in experience (up to three years), thereby not accounting for potential nonlinearity – it nonetheless represents the

first causal estimate of the impact of experience on startup success. More importantly, the primary mechanism appears to center around professional social networks, suggesting that incubators should prioritize fostering connections between founders and potential co-founders or employees to increase the likelihood of startup success.

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), personal wealth (Bellon et al., 2021), work flexibility (Kwan et al., 2024; Denes et al., 2025), founding experience or serial entrepreneurship (Lafontaine and Shaw, 2016; Gompers et al., 2010; Wright et al., 1997; Hsu, 2007; Zhang, 2011). Most closely related to our work is Azoulay et al. (2020), who document a positive correlation between founder age and startup success, and research by Agarwal et al. (2004); Gompers et al. (2005); Klepper and Sleeper (2005); Chatterji (2009) , who provide evidence on how incumbent firm characteristics shape spinout performance. Our contribution differs in two significant ways. First, we investigate a distinct question: How does prior experience (over and above age) in an incumbent firm influence the success of a first-time entrepreneur launching an *unrelated* new venture? Second, we address a major methodological concern in this literature—selection bias. Older entrepreneurs, or those creating spin-outs maybe inherently different, and these difference can drive the startup results. To our knowledge, this is the first study to provide causal evidence on how pre-startup experience influences the success of an entrepreneur's first startup.

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.

II 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 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 GCs (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 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

[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.

[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.

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.

Green Card Process

A typical 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 US system sets a fixed cap of 140,000 on the annual number of Adjustment of Status applications for employment-based GCs[16]. A maximum of 28.6% of these 140,000 GCs can be allocated to each GC category.[17] 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 queues and may only apply for Adjustment of Status when the Department of State's monthly visa bulletin[18] indicates that their priority date has become current (i.e. when the application date listed in the bulletin is later than their own). 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 with PERM applications between 2010 and 2017.

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

[17] 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.

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

Green Card Wait Times

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 ten years observed across countries and categories. However, within-country-category variation exhibits smaller fluctuations of up to three years across 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 A.

Figure I 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.

III 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.

III.A 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[19] of all universities in the education history of the founders. The granular nature of this data allows

[19]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.

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[20] and salary for each position is imputed based on the position title, firm, and location by Revelio Labs. The number of social connections is also available in one's LinkedIn profile. We also get the industry classification and locations of the startups from their LinkedIn pages.

PERM Data: Obtaining a labor certification (PERM) from the Department of Labor (DOL) is the first step in the GC filing process. These filings include detailed information about the employee, such as their country of origin, current employment details, job location, work history, and education. The filings can be accessed through the DOL website[21]. Each PERM filing is assigned a case number, which reveals the filing date[22]—this date serves as the priority date, determining the applicant's place in the GC processing queue, to apply for Adjustment of Status[23]. Applicants become eligible to file for Adjustment of Status upon reaching the front of the GC queue, as determined by the Department of State's monthly visa bulletin[24]. The visa bulletin specifies the cut-off priority date, and individuals with an earlier priority date become eligible to file for Adjustment of Status. Once the Adjustment of Status application is processed, typically within a year, the applicant achieves GC status.

The primary source of variation in wait times lies in the delay between the applicant's priority date and their ability to file for Adjustment of Status. While the priority date is directly observable from PERM filings, the filing date for Adjustment of Status must be inferred from visa bulletin data. Imputing wait times based on the application date ensures that our analysis does not capture changes resulting from individuals strategically switching

[20]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.

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

[22]For example, the case number "A-16210-XXXXX" implies that the filing date is the 210th day of the year 2016, so the priority date in this case would be July 28th, 2016.

[23]The US system sets a fixed country and category based cap on the annual number of Adjustment of Status applications in a yea

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

between wait lines.[25] To account for variability in visa bulletin movements, eligibility for Adjustment of Status is defined as the point when an applicant's priority date is earlier than the cut-off date in three consecutive bulletins. Finally, we calculate the GC wait time as the difference between the date when the applicant's priority date appears as current in the visa bulletin for at least three consecutive months, and the priority date listed in the PERM filings. For example, consider an immigrant from China with a master's degree who began their first US job in July 2013 and filed for PERM certification on September 1, 2014. The September 2017 visa bulletin was the first to mark this September 2014 priority date as current. It remained current in the October and November 2017 bulletins. Based on this, we calculate a wait time of 36 months, spanning from September 2014 to September 2017.

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 US patent data. It covers over 4 million US patents tracking patent specifics, inventors, assignees, technology classifications, and citation networks. We use PatentsView to

[25]Individuals may strategically switch between EB-2 and EB-3 categories to optimize wait times.

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.[26] 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.

III.B 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[27]: 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 GC 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, accounting for 23% of all immigrant founders in the sample. Finally, we match these startups to their corresponding profiles on Crunchbase and the patent filing database. We also extract the work history of

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

[27]95.3% of the companies in CrunchBase have founders with associated LinkedIn profiles.

all employees at these startups using LinkedIn. For further details on the matching process, please refer to Appendix B.

III.C Summary Statistics

We present summary statistics of key variables for the sample of immigrant founders and their startups in Table I, 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 C1 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 C2 provides a detailed breakdown of this timeline for immigrant founders, showing a mean duration of 4.4 years from graduation to priority date, 3.5 years on average spent in the GC wait line, 0.7 years for GC application processing, and 2.1 years from obtaining a GC 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.

IV 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, which is defined as the difference between the year an individual founded their first startup i and the year they completed their highest educational degree, 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 instrument experience using GC wait times. 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, calculated as the difference between the date an employee becomes eligible to apply for Adjustment of Status and the GC application date (i.e., the priority date), as outlined

in Section III.A,[28] and the length of experience of the founder, Exp_i, which is defined as the difference between the year an individual founded their first startup i and the year they completed their highest educational degree. It is important to note that wait times are assigned based on the application date, and we do not account for variations caused by individuals changing their GC category.[29] By fixing the instrument at the time of application, we ensure that our analysis does not capture any strategic manipulation. 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

We begin by examining whether changes in GC wait times can predict delays in startup formation. If employees are eager to establish startups but are constrained solely by GC wait

[28] 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.

[29] Individuals may strategically switch between EB-2 and EB-3 categories to optimize wait times.

times, we would expect an estimate close to 1, indicating a direct one-to-one relationship between GC wait time and delays in startup formation. Conversely, if employees prefer to gain significantly more experience than the GC wait period before founding a startup, we would observe little to no impact of GC wait time on their experience, yielding an estimate near zero.

The results of the first-stage estimation, based on Equations (2) and (5), are presented in Table II. Specifically, Column 5 in Panel (a) provides estimates from our baseline specification. These findings reveal that each additional year of GC wait time corresponds to an increase of approximately 9 to 10 months in founder experience. This supports the notion that GC wait times meaningfully delay startup formation. The F-statistic exceeds 50, well above the conventional thresholds for weak instruments, affirming the strength of the relationship. Moreover, this result remains robust across various fixed-effect specifications, as shown in the table's columns.

Additionally, Figure II 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.

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 III 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.

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 III and Table C5, 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.

V 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 III, 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,[30] 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 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 C6 that greater founder experience can mitigate business failures, as measured by permanent declines in employment size. Specifically, each additional year of

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

experience a founder possesses reduces the likelihood of employment dropping to 100% of its peak size by 1.5 p.p. We also show in Table C7 that greater founder experience results in a general rightward shift in the distribution of final employment size. This pattern suggests improved overall performance across the spectrum, rather than changes in risk dynamics driving better outcomes.

We report additional startup outcomes, with different employment cutoffs and other measures for patent quality in Table C8. 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.

The results indicate that employees with longer professional experience prior to launching their first firm tend to achieve better outcomes in their initial ventures. Additionally, we also track employees across multiple startups and study the probability eventual startup success, to compare the value of professional experience to the experience gained from founding an unsuccessful startup. As shown in Table C9, our analysis reveals a significant positive effect of professional experience on the likelihood of success in any venture, five years after the first startup. These findings align with existing research on persistence in serial entrepreneurship (Gompers et al., 2010), demonstrating that early success driven by greater professional experience also fosters long-term entrepreneurial success.

We present our OLS estimates derived from Equation 1 in Table III, 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.

Identification Concerns

Our empirical strategy leverages variation in GC wait times to identify the causal effect of founder experience on startup outcomes. To ensure the validity of this identification, it

is critical to verify the exclusion restriction: that changes in GC wait times affect startup outcomes solely through their impact on the timing of startup formation. However, GC wait times may correlate with compositional shifts in immigrant quality, time-varying industry or location trends, and selective migration or employment decisions—factors that could independently influence startup outcomes and violate the exclusion restriction. This section outlines the strategies we employ to address these potential threats to validity.

A key concern is that founders entering the US in different years may differ systematically in unobservable quality. For example, changes in economic conditions in the home countries could influence the composition of immigrant cohorts, confounding the relationship between GC wait times and startup outcomes. To address this, we include fixed effects for the founder's citizenship interacted with the year of their first US job. This approach ensures comparisons among startups founded by immigrants from the same country and cohort, mitigating biases due to compositional changes. As shown in Table IV, Panel A, our results are consistent across multiple performance metrics under this specification.

Another concern is that industry- or location-specific time trends could influence GC wait times and startup outcomes. For instance, technological advancements or regional economic shocks might change GC wait times and independently affect startups. To account for such dynamic trends, we introduce firm-industry-by-year and firm-state-by-year fixed effects. Table IV, Panel B, demonstrates that the inclusion of these flexible controls does not alter our main findings, alleviating concerns that industry or geography-specific trends drive the observed relationships.

Longer GC wait times may also deter high-skilled immigrants from coming to the U.S., leading to systematic shifts in the quality of immigrant cohorts and potentially confounding our estimates. To address this concern, we construct an alternative instrument using unanticipated GC wait times. The unanticipated wait time is defined as the difference between the actual GC wait time experienced by an applicant and the expected wait time for their cohort, as inferred from the Visa Bulletin at the start of their first US job.

Expected wait times are calculated based on the observed wait times for the cohort most recently eligible for GCs. Specifically, we calculate the expected wait time as the difference between an applicant's first US job start date and the priority date most recently current in the Visa Bulletin at that time. The unanticipated wait time, which captures the random component of realized wait durations, is then derived by subtracting the expected wait time from our actual wait time instrument. For instance, consider a Chinese immigrant with a master's degree who began their first US job in July 2013. Based on the July 2013 Visa Bulletin, their anticipated wait time was approximately 5.1 years, but their actual wait time was 3.6 years, resulting in an unanticipated wait time of -1.5 years. This instrument ensures that our estimates are not driven by decisions based on expected wait durations. Table IV, Panel C, shows that our results are robust to this alternative specification, despite some loss of statistical power for outcomes such as IPOs.

A related concern is that GC wait times might influence the propensity of immigrants to remain in the US or to found startups, leading to selection bias. 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 assumption in Table C10, using the full sample of PERM filings. We regress GC wait times on indicators for (1) whether the immigrant left the U.S., (2) whether the immigrant founded a startup at any location, (3) whether they founded a startup in the U.S., and (4) whether they founded a startup outside the US Controlling for individual characteristics such as citizenship and degree level, we find no statistically or economically significant relationships. These results suggest that within-country and category variations

in GC wait times do not systematically influence immigrant retention or startup propensities, supporting the validity of our exclusion restriction.

Finally, one might worry that more talented individuals apply for GCs earlier in their careers, leading to shorter wait times for higher-quality employees. However, this concern is mitigated by the six-year maximum period within which immigrants must apply for a GC. As shown in Figure D3, 89% of applicants file for GCs within the first three years of starting their jobs, leaving little room for systematic differences in application timing to bias our results.

Alternative Interpretations

Our main independent variable is the number of years of experience between an entrepreneur's highest degree and the formation of their first startup. A critical concern is whether this variable captures accumulated experience or merely the passage of time, such as the effects of age or market timing. If the passage of time independently enhances employee performance or enables better market timing, we cannot interpret our results as the causal impact of experience. We address these concerns as follows.

One potential confounding factor is that our results may reflect the influence of age rather than US experience. To separate these effects, we control for the entrepreneur's age at the time of startup formation, as detailed in Table C11. The age is proxied by the difference between the year an individual founded their first startup and the year they completed their bachelor's degree. This adjustment reduces statistical power and lowers F-statistics, as our instrument impacts both age and US job experience. Nevertheless, we exploit variation in the US experience among entrepreneurs of the same age who immigrated at different points in their careers. Our findings reveal that the coefficients become larger and remain statistically significant for key outcomes, including patents, employment, and IPOs. For funding-related outcomes, statistical power diminishes substantially (with F-statistics dropping to 3.6), but the point estimates are larger than in the baseline specification. Taken together, these results

strongly suggest that US job experience, rather than age alone, drives the observed outcomes.

Another possible explanation is that founders delay launching their startups to align with favorable market conditions. However, 64.4% of founders in our sample established their startups within three years of receiving their GCs. This suggests that GC wait lines caused short delays in startup formation rather than influencing strategic market timing. Furthermore, Table C12 demonstrates that the impact of prior experience on startup outcomes is significant only for founders who launched their businesses within these three years. These findings underscore that the timing of startup formation was primarily driven by immigration policy constraints rather than deliberate market timing strategies. Additionally, Table C13 demonstrates that our results are robust to using the subsample of startups in the information technology sector, where early entrants tend to have superior performance (Yao et al., 2020). This exercise confirms that our findings are not driven by a set of industries insensitive to the timing of launch.

Robustness Tests

Finally, we demonstrate the robustness of our results to various modeling choices, as summarized in Table C14. In Panel A, we redefine total experience by measuring the number of years since an individual's bachelor's degree, rather than their highest degree. In Panel B, we introduce additional controls for the state of residence at the time of the GC application, alongside the state of the startup. Our findings remain consistent across both specifications, reinforcing the reliability and validity of our results.

Additionally, as noted by Chen and Roth (2023), log-like transformations can pose challenges when the outcome variable contains zero values. To address this concern, we follow their recommendations and re-estimate our models using Poisson regression, as shown in Table C15. For the Poisson regression with instrumental variables, we employ the control function approach and use bootstrap methods to compute standard errors, following the methodologies outlined in Wooldridge (1997) and Cameron and Trivedi (2013). These results

confirm that our findings for logarithmic outcomes remain robust under this alternative specification.

Heterogeneous Effects

Table V 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%) with differences 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 additional year of experience leads to 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 shows that experience appears to be more valuable for founders who had a higher number of social connections on LinkedIn as of 2017. It is important to note that these connections are measured after the fact, making this regression on LinkedIn connections endogenous. However, we believe it is still useful in highlighting the heterogeneity in our results. We find that founders with more social connections generate 5.4% more patents and 6.6% more citations with one additional year of experience (vs. -0.5% and -0.8% for founders with below median social connections), 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 C16, 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.

Mechanisms

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; D'Acunto et al., 2020), financing availability (Lerner, 2000; Hsu, 2007; Cohen and Wirtz, 2018; Kerr et al., 2014; Krishnan et al., 2015), and industry-specific knowledge accumulation (Agarwal et al., 2004; Klepper and Sleeper, 2005; Chatterji, 2009).

Table VI 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%. Column (3) additionally shows that an additional year of experience increases the number of unique previous job categories[31] of cofounders by 4.2%, which suggests cross-departmental expertise within the founding team. Panel B further demonstrates that these increases result from the founder's former professional connections with previous colleagues. An additional year of experience leads

[31]We use 7 job categories (Admin, Engineer, Finance, Marketing, Operations, Sales, Scientist) from Revelio.

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.

Columns (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 any of the previous employers. 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[32]. 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 VII and Figure D5 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

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

to a 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.). 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%. 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 C17, consistent with improved financing ability, or industry-specific knowledge, not driving our results.

VI VALUE OF EXPERIENCE

Finally, we perform 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 C18 reports the assumptions. We find that each additional year of experience can be valued at approximately 200,000 dollars.

Given the large dollar value of each year of experience, it is surprising that entrepreneurs often forgo these rewards by starting their ventures too early. While we do not take a position on the specific frictions that may drive this behavior, the literature suggests two potential explanations: over-optimism and the non-pecuniary benefits of entrepreneurship. Cassar (2009) find that entrepreneurs tend to significantly overestimate their expected future sales, with 62% overestimating first-year sales. Similarly, Cooper et al. (1988) report that 68% of entrepreneurs believe their business has better odds of success than similar ventures, while only 5% think their odds are worse. Beyond financial motivations, non-pecuniary benefits also play a crucial role in the decision to start a business. In the 1992 Economic Census Characteristics of Business Owners, over 21% of survey respondents cited "being their own boss" as the primary reason for founding their firm, rather than pursuing a

primary or secondary income source. Additionally, Williams et al. (2025) find that while the monetary return to micro-entrepreneurship averages just 4.2%, the full return—including non-pecuniary benefits—averages 68%, highlighting the substantial intrinsic rewards of entrepreneurship.

It is important to acknowledge several caveats when using this estimate to impute the dollar value of additional experience. First, this estimate is derived from a sample of immigrant entrepreneurs. Although this group represents a significant segment of the population—accounting for approximately a quarter of all high-growth startups in the US (Kerr and Kerr, 2020a; Azoulay et al., 2022)—the impact of additional experience may differ for native-born entrepreneurs, even though the underlying economics of experience might be similar. Second, our instrument captures variations in experience ranging from one to three years due to changes in wait times within the same country and immigration category. Previous research has identified an inverse U-shaped relationship between age and high-growth entrepreneurship (Azoulay et al., 2020). Our estimates only address the early portion of this curve, limiting our ability to examine the nonlinear effects of experience on entrepreneurial success. Finally, while our findings highlight an unexpected positive aspect of GC wait times, this paper does not attempt to quantify the overall impact of this policy on entrepreneurship. Indeed, Gupta (2023) finds that extended GC wait times discourage immigrant employees from joining startups, while (Lee and Glennon, 2023) documents significant out-migration of Indian and Chinese entrepreneurs from the US following the introduction of startup visas in Canada. Developing an immigration-related policy recommendation would require a comprehensive model that considers all such benefits and costs, which is beyond the scope of this paper.

VII CONCLUSION

This paper seeks to understand the causal impact of prior work experience on entrepreneurial outcomes. Entrepreneurs typically select their optimal level of experience, making it

challenging to isolate this effect using standard OLS regressions. To address this endogeneity, we instrument for experience by leveraging unexpected variations in GC wait times within specific country-categories. Our findings reveal that prior work experience significantly enhances startup outcomes for first-time founders across various metrics, including funding, innovation, growth, and eventual IPO success. Moreover, we attribute this improvement to the enhanced ability of founders to attract larger and more skilled initial teams, drawing on their previous work experience. Consistent with this reasoning, we observe even stronger effects among groups with fewer pre-existing social connections, such as women and minorities.

Our findings have significant policy implications for the design of incubators aimed at promoting startups. First, incubators should prioritize fostering social connections between founders and potential co-founders or employees. This is particularly crucial for fellowships and incubators where participants, such as college dropouts, may have limited opportunities to develop social networks organically. Second, these connections are especially valuable for minorities and women. Given the increasing focus on encouraging entrepreneurship among these groups, policymakers should consider strategies to enhance their social capital.

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TABLES AND FIGURES

Table I
Summary Statistics

	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$10ys}	0.37	0.48	0.00	0.00	1.00
Observations			2,317		
Panel C: Startup Outcomes					
Employment Size	142	530	0.00	5.00	134
IPO	0.01	0.10	0.00	0.00	0.00
Num. of Funding Rounds	2.14	2.26	0.00	1.00	5.00
Amount of Funding (2015 M$)	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		

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 the founder characteristics from LinkedIn and PERM. We obtain employment information for startups from LinkedIn. Industries are from LinkedIn firm pages. Table C3 shows the top frequent industries. We obtain the IPO and funding information of startups from CrunchBase. We obtain the patent information of startups from PatentsView.

Table II
First Stage

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

Notes: This table presents estimates of the relationship between GC 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 GC 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.

Table III
Baseline Results

	Funding			Patents			Employment		IPO
	(1) Num. of Rounds	(2) Log(Funding Amount)	(3) Funding Amount ≥100M	(4) Log(Patents)	(5) Log(Citations)	(6) Log(Adjusted Citations)	(7) Log(Emp.)	(8) Emp.≥1000	(9) 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

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, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree. The instrumental variable is the GC 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.

Table IV
Robustness Tests

	Funding			Patents			Employment		IPO
	(1) Num. of Rounds	(2) Log(Funding Amount)	(3) Funding Amount ≥100M	(4) Log(Patents)	(5) Log(Citations)	(6) Log(Adjusted Citations)	(7) Log(Emp.)	(8) Emp.≥1000	(9) IPO
Panel A: Citizenship × Year of First U.S. Job FEs									
Experience	0.241	0.192*	0.0310**	0.0878**	0.111**	0.0972**	0.196*	0.0226**	0.00967*
	(0.156)	(0.106)	(0.0140)	(0.0397)	(0.0517)	(0.0435)	(0.118)	(0.0107)	(0.00500)
First-stage F	13.18	13.18	13.18	30.14	30.14	30.14	26.16	26.16	19.90
Panel B: Firm State × Year FEs + Firm Industry × 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

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 III. The independent variable is the founder's experience, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree. 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-by-first-US-job-year FEs, founder degree-level FEs, firm age FEs, firm industry FEs, and firm state FEs. In Panel B, we control for founder citizenship FEs, founder degree-level FEs, firm cohort or founding year FEs, firm industry × year FEs, and firm state × year FEs. In Panel C, we replace the instrumental variable with the unanticipated GC 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.

Table V
Heterogeneity Tests on Founder characteristics

	Funding			Patents			Employment		IPO
	(1) Num. of Rounds	(2) Log(Funding Amount)	(3) Funding Amount ≥100M	(4) Log(Patents)	(5) Log(Citations)	(6) Log(Adjusted Citations)	(7) Log(Emp.)	(8) Emp.≥1000	(9) 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)

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 III. The independent variable is the founder's experience, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree, instrumented by the GC 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.

Table VI
Effects on Intermediate Variables

Panel A: Effects on Intermediate Variables							
	(1) Log(Initial Emp.)	(2) Log(Cofounders)	(3) Num. of Cofounders' Previous Job Categories	(4) Years to First Funding	(5) 𝟙{Same Industry}	(6) Continuity	(7) Novelty
Experience	0.0507**	0.0554**	0.0744**	0.0143	0.0103	0.00433	-0.000427
	(0.0237)	(0.0270)	(0.0305)	(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	1,949	885	2,134	1,136	1,244
First-stage F	74.68	73.25	74.97	34.00	74.28	38.80	39.95
Mean Outcome	4.97	2.82	1.77	1.22	0.34	0.20	0.24

Panel B: Effects on Previous Colleagues				
	Previous Colleagues in Initial Emp.		Previous Colleagues in Cofounders	
	(1) 𝟙{Num.>0}	(2) Log(Num.)	(3) 𝟙{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

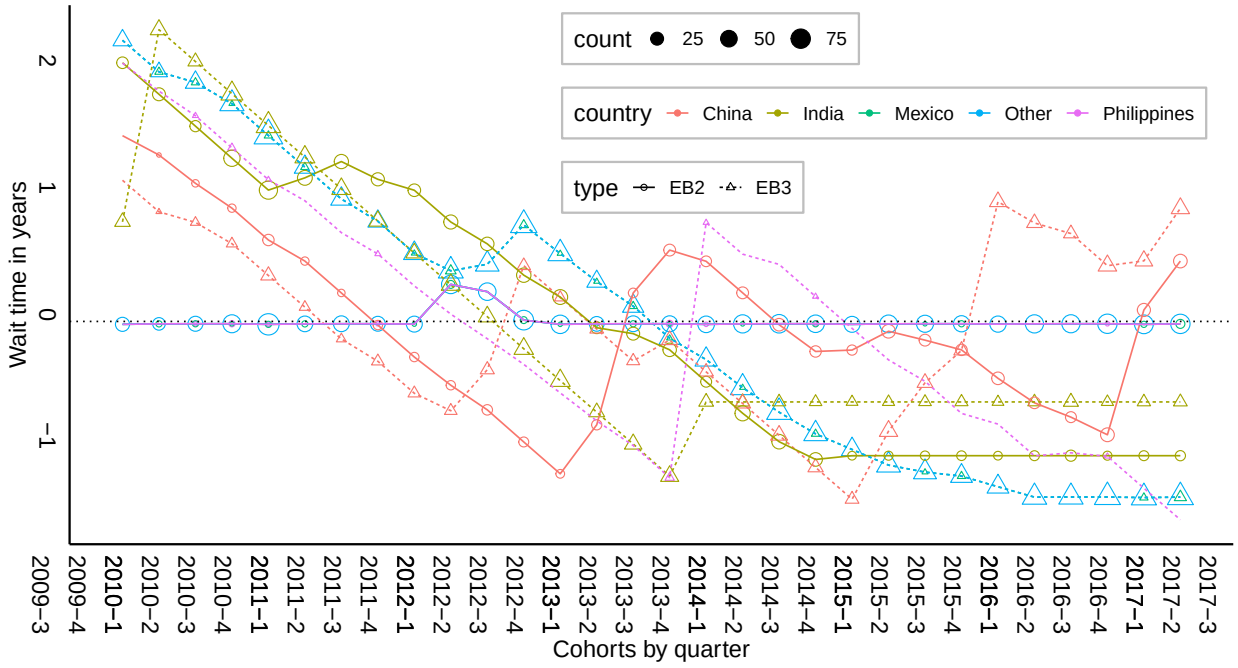
Notes: This table presents estimates of the relationship between the experience of immigrant entrepreneurs and several intermediate variables of startups. Each cell presents the coefficient $\tilde{\beta}$ obtained by estimating Equation (6) from the cross-section. The independent variable is the founder's experience, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree, instrumented by the GC 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, the number of unique previous job categories 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 use the 7 job categories from Revelio to classify previous positions of cofounders before joining the startup. Industries are from LinkedIn firm pages. The top frequent industries are shown in Table C3. 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.

Table VII
Heterogeneity Tests on Intermediate Variables

	Funding			Patents			Employment		IPO
	(1) Num. of Rounds	(2) Log(Funding Amount)	(3) Funding Amount ≥100M	(4) Log(Patents)	(5) Log(Citations)	(6) Log(Adjusted Citations)	(7) Log(Emp.)	(8) Emp.≥1000	(9) 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)

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 III. The independent variable is the founder's experience, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree, instrumented by the GC 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.

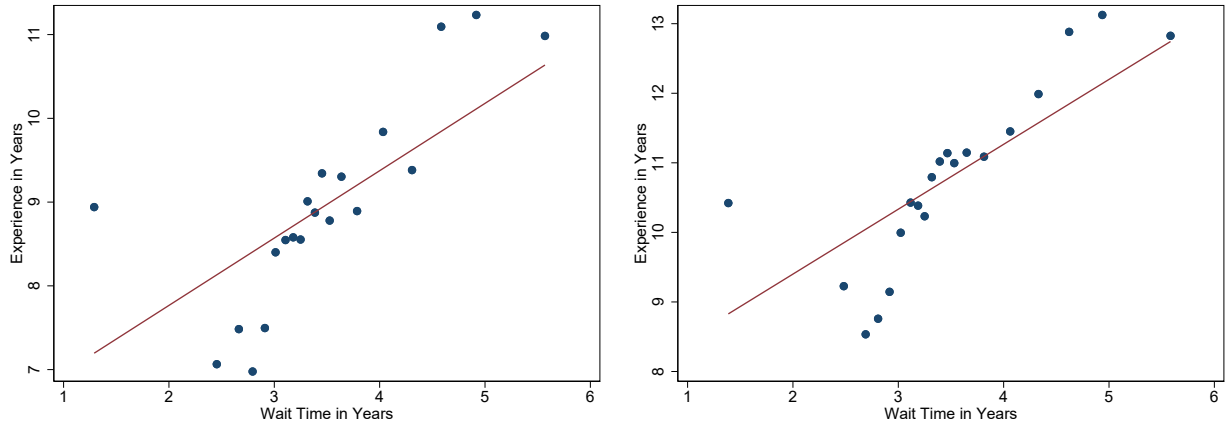
Figure I
Green Card Wait Time across Cohorts



Notes: This figure presents the average GC 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 GC wait time is the time in years from the priority date until the priority date is earlier than the application date in the visa bulletin for 3 consecutive months. The wait time is de-meaned within each line.

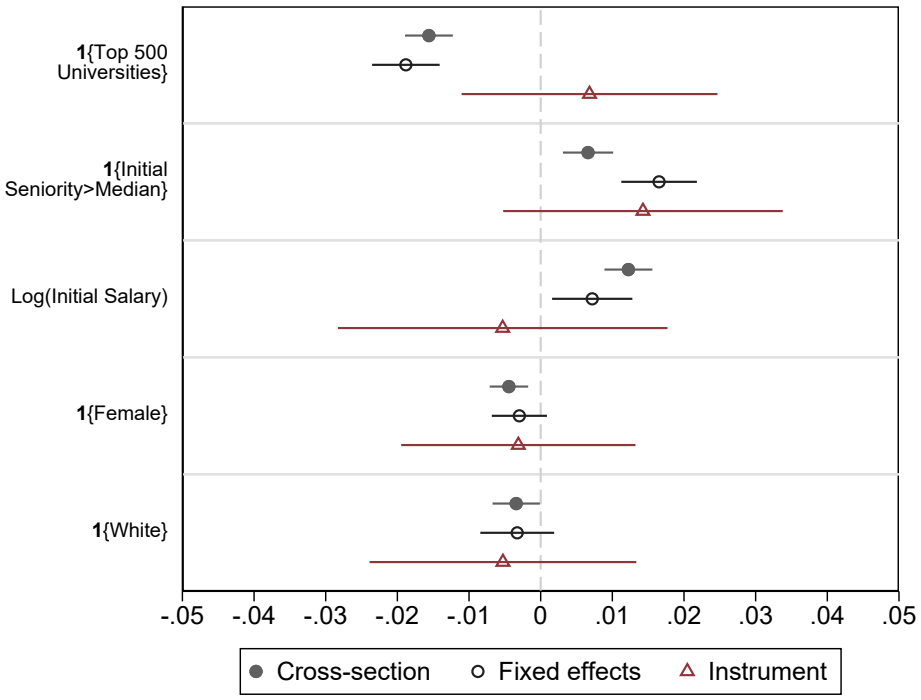
Figure II
Binned Scatterplot of First Stage Regression

(a) Panel (Slope = 0.804 ± 0.109, F=54.1) (b) Cross-section (Slope = 0.933 ± 0.111, F=71.1)



Notes: This figure presents the binned scatterplot that visualizes the relationship between GC wait time and experience of immigrant entrepreneurs. The independent variable is the GC 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 III
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.

APPENDIX FOR ONLINE PUBLICATION

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A 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 US Citizenship and Immigration Services (USCIS), in a case filed at the US district court in Seattle[33].

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[34]. 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

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

[34] 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 GCs, they could use 30,525 EB GCs, 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.

B DETAILS OF MATCHING PROCESS

II.A 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 US who joined these startups within two years of the companies' founding are classified as founders. CrunchBase provides unique LinkedIn URLs for each firm and individual, facilitating matching. Additionally, we screen LinkedIn job titles for individuals working for US companies, specifically identifying those with job titles containing "founder", "cofounder" or "founding".

II.B 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.

II.C 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 begin with a founder sample of 135,910 unique LinkedIn users who had their first US jobs between 2007 and 2017. These individuals had prior US job experience before becoming founders and did not hold Ph.D. degrees. Following Gupta (2023) and Amanzadeh et al. (2024), we identify 13,326 of these users as immigrants, based on their LinkedIn profiles showing a non-U.S. origin in either their education or job history.[35] Ultimately, we obtain 3,076 matches between LinkedIn users and 2,957 PERM cases, representing 3,164 startups. Based on our estimate of immigrant entrepreneurs, the match rate is 23%. For founders of startups listed in CrunchBase, the match rate rises to 47%, supporting the notion that higher-growth startups are more likely to have immigrant founders on employment-based visas.

The issue of multiple matches (where a single PERM case matches with multiple LinkedIn

[35]Some immigrant profiles may not include experiences prior to their arrival in the US As a loose upper bound of the number of immigrants, 44,273 of the 135,910 founders have non-U.S. names, as predicted by the *gpt-3.5-turbo* API from OpenAI. This yields a 7% match rate for the overall sample and 15% for the CrunchBase sample.

users) is mainly due to individuals having multiple LinkedIn profiles.[36] Additionally, some individuals establish multiple startups. To address this, we assume that all LinkedIn users and startups linked to the same PERM case belong to the same person. For each PERM case, we select the earliest established startup and its associated LinkedIn user. If a startup is linked to multiple founders (PERM cases), we prioritize the founder with the most experience. After this process, we identify 2,531 unique founders and startups. Finally, after excluding individuals who are not primary founders (e.g., founding engineers), the final sample consists of 2,317 founders and startups.

II.D 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. 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.

[36] Of the 74 PERM cases with multiple LinkedIn matches, 57 share identical full names across profiles.

II.E Identify Other Startup Employees

We extracted the work history of 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.

C ADDITIONAL TABLES

Table C1
Summary Statistics of Immigrant Startups and All Startups

	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	77,366
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

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.

Table C2
Decomposition of Experience

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

Notes: This table presents the mean and median of four components of the founder's experience, which is the difference between the year an individual founded their first startup and the year they completed their highest educational degree. 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 GC. 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 GCs, 53.1% within two years, and 64.4% within three years. We also found in Figure D3 that 6.1% of employers apply for a GC for their employees on average within one year of starting their jobs, 58.4% within 2 years, 88.9% within 3 years.

Table C3
Top 5 Industries

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

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.

Table C4
Top 5 States

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

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.

Table C5
Balancing Regressions

	(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

Notes: This table presents the 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.

Table C6
Effects on the Permanent Drop in Employment Size

	(1) 𝟙{<25% Max Emp.}	(2) 𝟙{<50% Max Emp.}	(3) 𝟙{<75% Max Emp.}	(4) 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

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 III. The independent variable is the founder's experience, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree. 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.

Table C7
Effects on the Distribution of Final Employment Size

	(1) 𝟙{0-25%}	(2) 𝟙{25-50%}	(3) 𝟙{50-75%}	(4) 𝟙{75-100%}
Experience	-0.0243**	-0.00318	0.0182**	0.0154
	(0.0106)	(0.00846)	(0.00927)	(0.0108)
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.	2,185	2,185	2,185	2,185
First-stage F	71.13	71.13	71.13	71.13

Notes: This table presents estimates of the relationship between the experience of immigrant entrepreneurs and the distribution of final employment size of the 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, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree. We present effects on whether the startup's final employment size is in the 0-25%, 25-50%, 50-75%, and 75-100% quartiles. 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.

Table C8
Additional Outcomes

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

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 III. The independent variable is the founder's experience, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree. 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.

Table C9
Long-term Effects on the Startup Outcomes after 5 Years

	Funding		Patents			Employment
	(1) Num. of Rounds	(2) Log(Funding Amount)	(3) Log(Patents)	(4) Log(Citations)	(5) Log(Adjusted Citations)	(6) Log(Emp.)
Experience	0.212**	0.139*	0.0136	0.0420**	0.0264**	0.0947*
	(0.0841)	(0.0714)	(0.00914)	(0.0195)	(0.0116)	(0.0534)
Obs.	669	669	1,570	1,570	1,570	1,436
First-stage F	19.47	19.47	41.18	41.18	41.18	39.60

Notes: This table presents estimates of the relationship between the experience of immigrant entrepreneurs and the long-term startup outcomes after 5 years from their first entrepreneurship. We select the best startup if the founder is associated with multiple startups at that time. Each cell presents the coefficient $\tilde{\beta}$ obtained by estimating Equation (6) from the cross-section. The independent variable is the founder's experience, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree. We present effects for the cumulative number of funding rounds, the log of the cumulative funding amount, 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, and the log of employment size. We don't include as outcomes whether the cumulative funding amount is over 100M$, whether the employment size is over 1000, or whether the firm went public, because these events are too rare given the limited sample size with long-term outcomes. 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.

Table C10
Effect of GC Wait Time on Probability of Leaving the US and Becoming a Founder

	(1) 𝟙{Leaving US}	(2) 𝟙{Founder}	(3) 𝟙{US Founder}	(4) 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

Notes: This table presents estimates of the relationship between GC 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 GC 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.

Table C11
Effects of Experience with Age Controlled for

	Funding			Patents			Employment		IPO
	(1) Num. of Rounds	(2) Log(Funding Amount)	(3) Funding Amount ≥100M	(4) Log(Patents)	(5) Log(Citations)	(6) Log(Adjusted Citations)	(7) Log(Emp.)	(8) Emp.≥1000	(9) IPO
Experience	1.246	0.677	0.0926	0.111**	0.142**	0.119**	0.273	0.0317*	0.0218*
	(0.842)	(0.502)	(0.0683)	(0.0528)	(0.0669)	(0.0570)	(0.187)	(0.0165)	(0.0119)
First-stage F	3.592	3.592	3.592	20.65	20.65	20.65	19.01	19.01	9.531
Obs.	6,708	6,708	6,708	16,320	16,320	16,320	14,814	14,814	12,089

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 III. The independent variable is the founder's experience, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree, instrumented by the GC wait time of the founder. 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. We additionally control for the founder's age, or the difference between the year an individual founded their first startup and the year they completed their bachelor's degree, in addition to 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.

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

	Funding			Patents			Employment		IPO
	(1) Num. of Rounds	(2) Log(Funding Amount)	(3) Funding Amount ≥100M	(4) Log(Patents)	(5) Log(Citations)	(6) Log(Adjusted Citations)	(7) Log(Emp.)	(8) Emp.≥1000	(9) 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)

Notes: This table presents how the relationship between the experience of immigrant entrepreneurs and startup performance depends on the time gap from obtaining the GC 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 GC wait time of the founder. We assume that the date of obtaining the GC 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 GCs, 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.

Table C13
Effects of Experience within the Information Technology Sector

	Funding			Patents			Employment		IPO
	(1) Num. of Rounds	(2) Log(Funding Amount)	(3) Funding Amount ≥100M	(4) Log(Patents)	(5) Log(Citations)	(6) Log(Adjusted Citations)	(7) Log(Emp.)	(8) Emp.≥1000	(9) IPO
Experience	0.180*	0.153**	0.0130	0.0577*	0.0735*	0.0575*	0.163*	0.0125*	0.00834*
	(0.0943)	(0.0645)	(0.00810)	(0.0322)	(0.0400)	(0.0346)	(0.0887)	(0.00715)	(0.00452)
First-stage F	19.84	19.84	19.84	26.04	26.04	26.04	23.08	23.08	20.63
Obs.	4,242	4,242	4,242	9,255	9,255	9,255	8,428	8,428	7,632

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 III. We restrict the analysis to the subsample of startups within industries of the information technology sector, such as "information technology and services", "computer software", and "internet". The independent variable is the founder's experience, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree. 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. 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.

Table C14
Additional Robustness Tests

	Funding			Patents			Employment		IPO
	(1) Num. of Rounds	(2) Log(Funding Amount)	(3) Funding Amount ≥100M	(4) Log(Patents)	(5) Log(Citations)	(6) Log(Adjusted Citations)	(7) Log(Emp.)	(8) Emp.≥1000	(9) IPO
Panel A: Experience From Bachelor's Degree									
Experience	0.177**	0.110**	0.0144**	0.0447**	0.0576**	0.0480**	0.125*	0.0126**	0.00683**
	(0.0786)	(0.0508)	(0.00681)	(0.0194)	(0.0245)	(0.0211)	(0.0662)	(0.00547)	(0.00331)
First-stage F	28.20	28.20	28.20	51.79	51.79	51.79	46.70	46.70	31.27
Panel B: Application Location FEs									
Experience	0.195***	0.125**	0.0150**	0.0440**	0.0564**	0.0473**	0.143**	0.0138**	0.00759**
	(0.0755)	(0.0511)	(0.00667)	(0.0207)	(0.0261)	(0.0223)	(0.0632)	(0.00540)	(0.00330)
First-stage F	30.23	30.23	30.23	55.75	55.75	55.75	52.19	52.19	32.38
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

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 III. The independent variable is the founder's experience, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree. 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 replace the independent variable with the founder's experience in years from the bachelor's degree graduation to the startup's founding. 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. In Panel B, we additionally control for the primary worksite state in the founder's PERM application, in addition to founder citizenship FEs, founder degree-level FEs, year FEs, firm cohort or founding year FEs, firm industry FEs, and firm state FEs. In Panel C, we additionally control for the founder's age or experience from the bachelor's degree graduation to the startup's founding, in addition to 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.

Table C15
Poisson Regressions

	(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

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 III. Panel A presents the coefficients estimated from Poisson regressions. The independent variable is the founder's experience, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree. 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 GC 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.

Table C16
Heterogeneity Tests on Additional Founder characteristics

	Funding			Patents			Employment		IPO
	(1) Num. of Rounds	(2) Log(Funding Amount)	(3) Funding Amount ≥100M	(4) Log(Patents)	(5) Log(Citations)	(6) Log(Adjusted Citations)	(7) Log(Emp.)	(8) Emp.≥1000	(9) 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. ≤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 ≤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)

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, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree, instrumented by the GC 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.

Table C17
Heterogeneity Tests on Additional Intermediate Variables

	Funding			Patents			Employment		IPO
	(1) Num. of Rounds	(2) Log(Funding Amount)	(3) Funding Amount ≥100M	(4) Log(Patents)	(5) Log(Citations)	(6) Log(Adjusted Citations)	(7) Log(Emp.)	(8) Emp.≥1000	(9) 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)

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, calculated based on the difference between the year an individual founded their first startup and the year they completed their highest educational degree, instrumented by the GC 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.

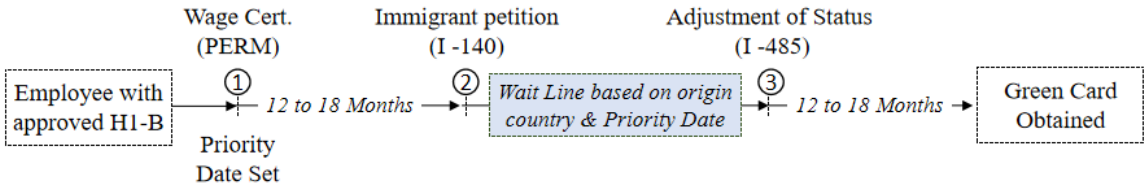
Table C18
The Dollar Value of One Additional Year of Founder's Experience

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**

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 III. 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 (Lemkin).

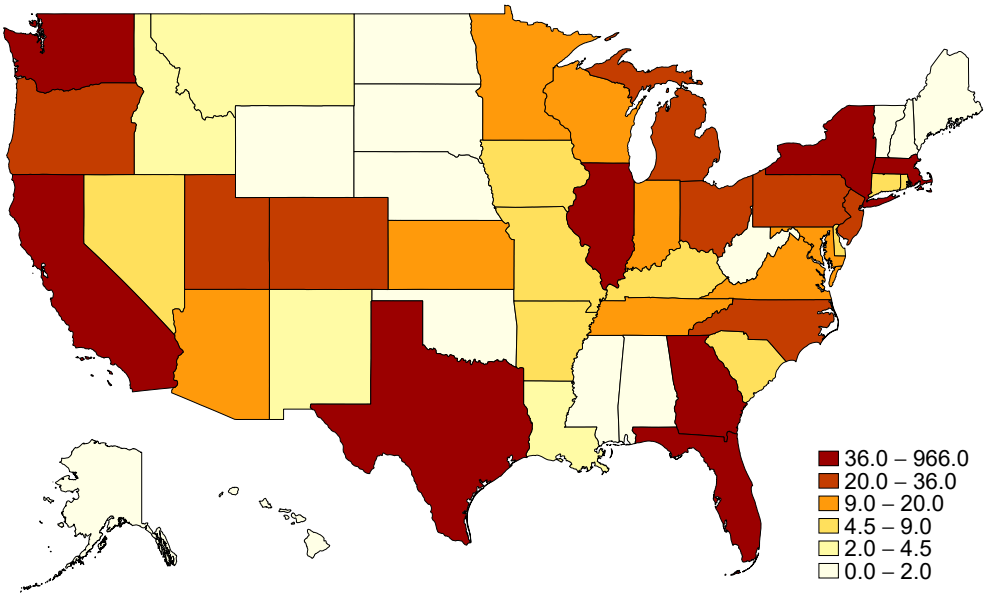
D ADDITIONAL FIGURES

Figure D1
Green Card Timeline



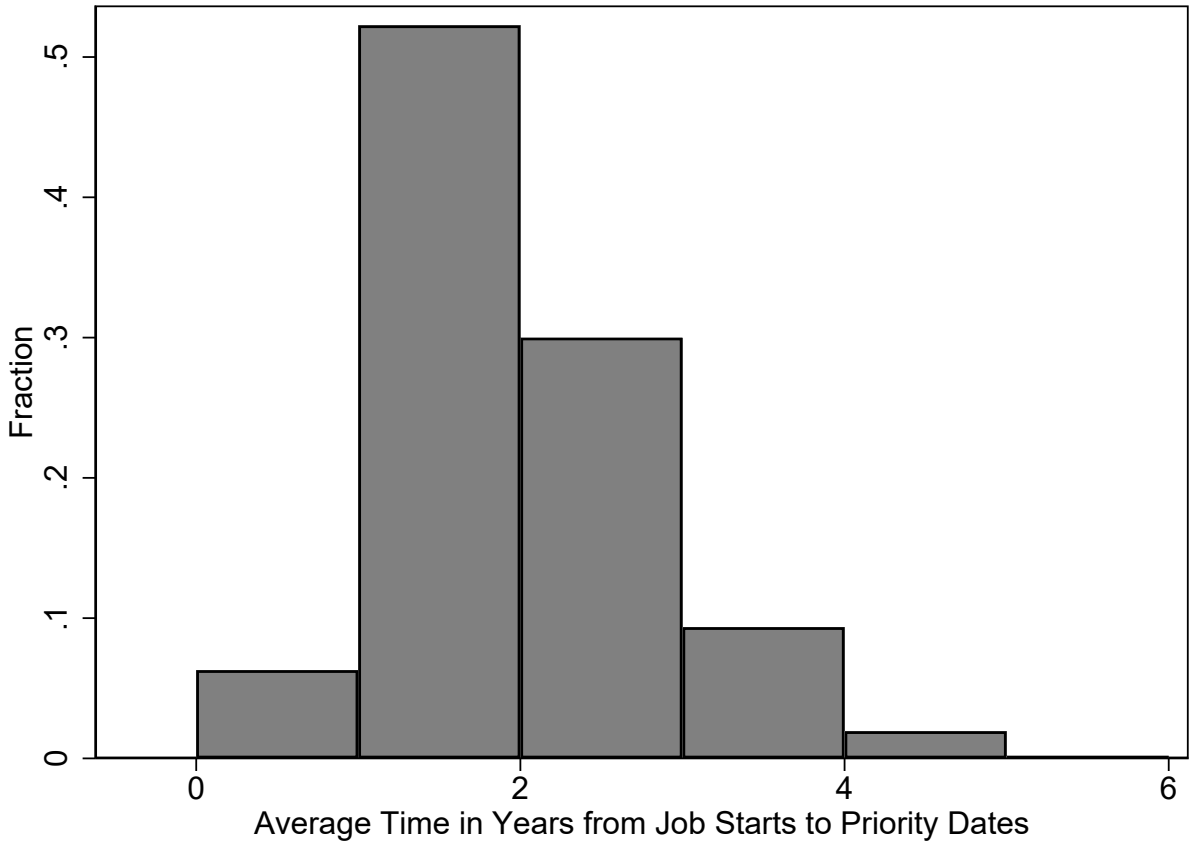
Notes: This figure illustrates the typical process and timeline for an employee with an approved H-1B visa to obtain a GC in the United States through employment-based sponsorship, including Wage Certification (PERM), Immigrant Petition (I-140), and Adjustment of Status (I-485).

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.

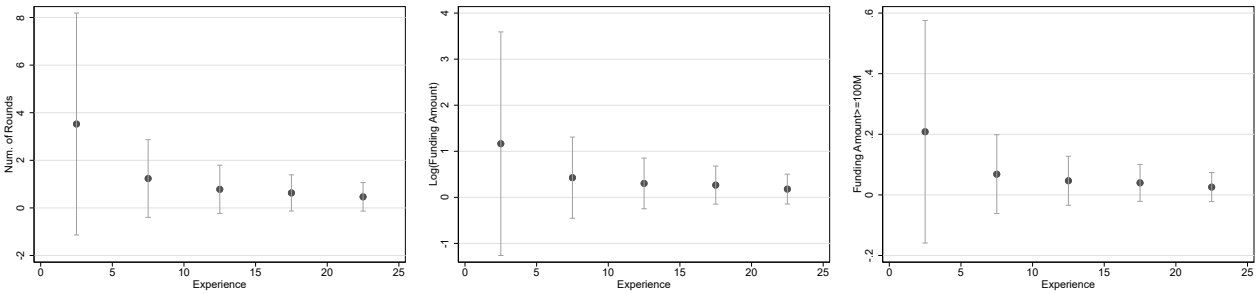
Figure D3
Average Time in Years from Job Starts to Priority Dates



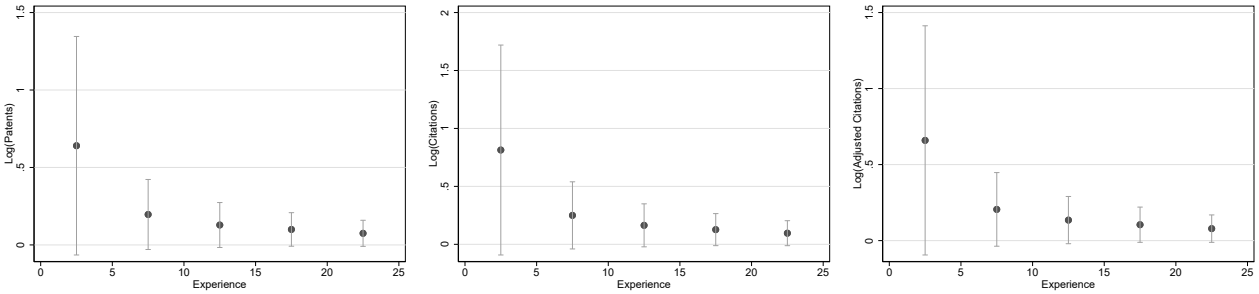
Notes: This figure illustrates the distribution across firms of average time in years from job start dates to priority dates in PERM applications for their immigrant employees in our LinkedIn-PERM merged sample. We obtain job start dates from employee's LinkedIn profiles. 6.1% of employers apply for a GC for their employees on average within one year of starting their jobs, 58.4% within 2 years, 88.9% within 3 years.

Figure D4
Results by Experience Bins

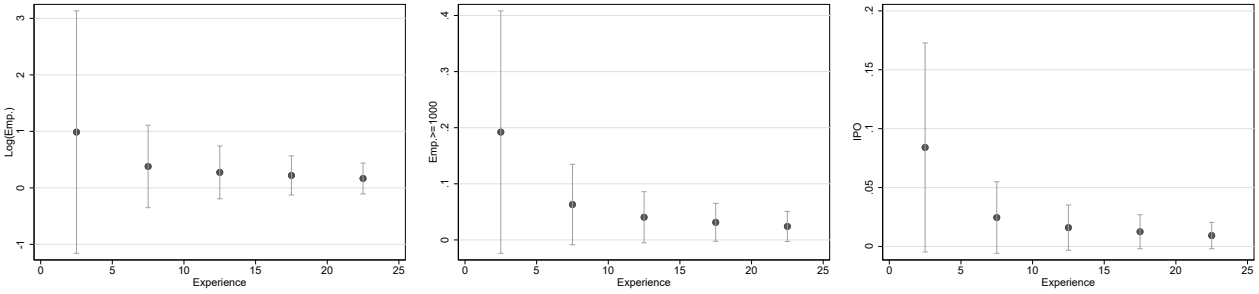
(a) Num. of Rounds (b) Log(Funding Amount) (c) Funding Amount ≥ 100M



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



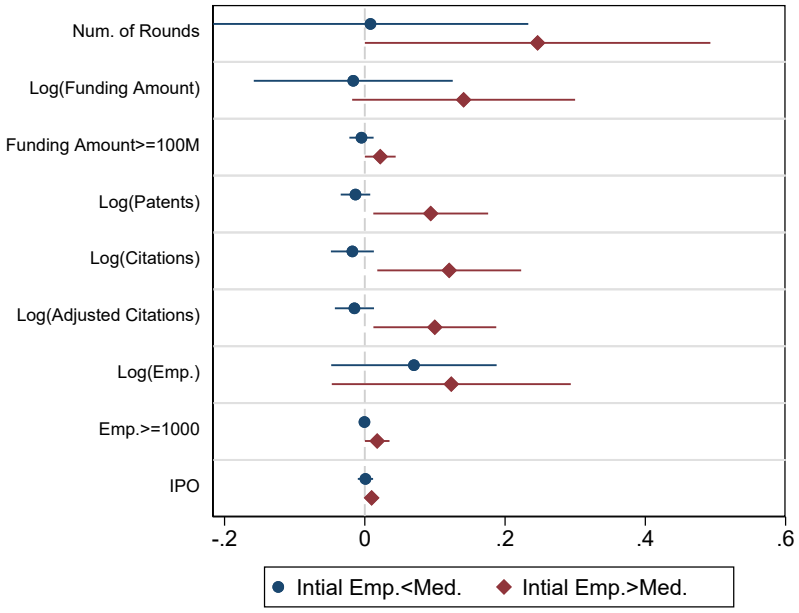
(g) Log(Emp.) (h) Emp.≥1000 (i) IPO



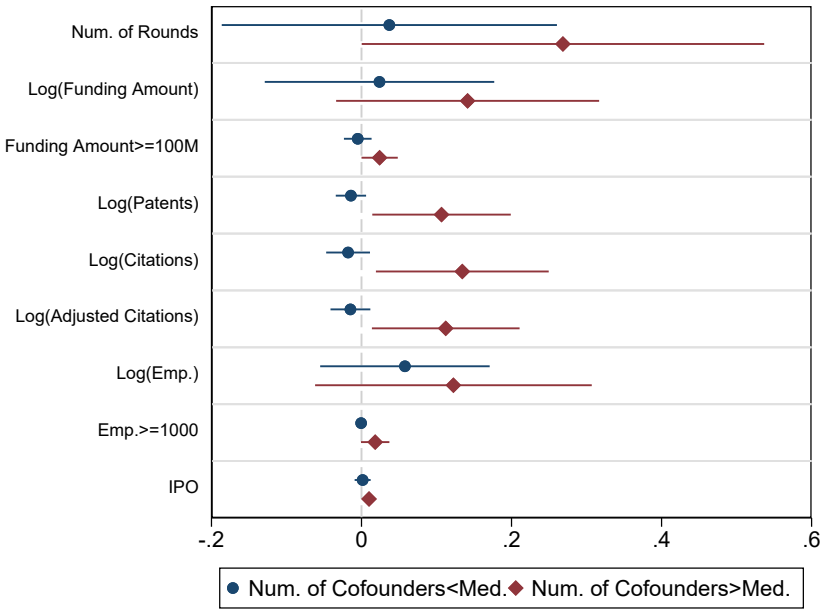
Notes: This figure estimates the heterogeneity of the relationship between founder experience and startup performance by experience bins. The founder's experience is calculated based on time in years from the highest degree graduation to the startup's founding. We group founders by experience at five-year intervals. We allow the coefficient on experience to vary across different groups when estimating Equation 3 instrumented by GC 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.

Figure D5
Heterogeneity Test on Intermediate Variables

(a) by Initial Employment Size



(b) by Num. of Cofounders



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 GC 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.