Exposure to Advanced Host Countries and Returnee Entrepreneurship: Evidence from the U.S.

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Abstract

This paper examines how professional exposure in advanced host countries affects returning migrants' likelihood of founding startups in their home countries. Using career histories of migrants returning from the United States, I estimate the effects of prior U.S. professional experience on startup founding, controlling for individual characteristics. To address endogeneity, I instrument for U.S. experience using (i) variation from the 2004 H-1B cap reduction and the introduction of home-country-specific U.S. visa categories, and (ii) green card waiting time at graduation. A one-year increase in prior U.S. professional experience raises returning migrants' propensity to found startups by 3.11 percentage points, a 63.5% increase relative to the mean. Returnees who worked in large U.S. firms gain additional benefits, and the effects are concentrated among those in hard science & engineering, business, and social science fields, as well as among migrants from developing countries. These findings highlight experiential learning in advanced host countries as a driver of returnee entrepreneurship and contributes to the literature on returnee entrepreneurship, the determinants of entrepreneurship, and transnational human capital transfer, with implications for emigration and immigration policies.

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1 Introduction

Skills and knowledge are key drivers of entrepreneurial activity. A substantial share of migrants in host countries—most of which are advanced economies—eventually return home, particularly high-skilled migrants who bring back valuable resources such as skills and knowledge gained through professional exposure in these advanced environments (OECD, 2008; Bijwaard and Wahba, 2014). Such resources can foster home-country entrepreneurship. Despite its importance, the influence of advanced-host-country professional exposure on returning migrants' entrepreneurial engagement remains underexplored. This paper fills this gap by examining how such exposure affects returning migrants' propensity to found startups.

An extensive body of literature has examined how skilled migrants promote entrepreneurship in advanced host countries (e.g., Kerr and Kerr, 2020; Azoulay et al., 2022; Dimmock et al., 2022). Much less attention, however, has been paid to how returning migrants' exposure in such countries shape entrepreneurial outcomes in their home countries. Recent work began to highlight several channels, including knowledge transfer to local firms (Liu et al., 2010; Filatotchev et al., 2011; Wang, 2015; Choudhury, 2016), returnees' contribution to firm innovation (Qiao et al., 2024), access to entrepreneurial resources via host-country networks (Nanda and Khanna, 2010; Wang, 2020), and returnees' startup performance in emerging markets (Dai and Liu, 2009; Li et al., 2012). While these studies advance our understanding of returnees' contributions to home-country entrepreneurship, the direct impact of host-country professional exposure on their own entrepreneurial activity remains insufficiently understood.

Rebellions, a fabless AI chip startup founded in Korea in 2020, illustrates this phenomenon. Its founders, Sunghyun Park, Ph.D., and Jinwook Oh, Ph.D., previously worked at US firms including Intel, IBM, Microsoft, and Google (Park earned his Ph.D. in electrical engineering and computer science from MIT). Rebellions has since received Series C funding and been recognized as a promising startup by Forbes Korea and CB Insights. While working as a quant trader at Morgan Stanley, Park recognized the semiconductor industry's trend towards

application-specific integrated circuits and decided to found Rebellions. Park noted in an interview with Forbes Korea, the importance of expertise acquired in the U.S.: "Dr. Oh experienced everything in AI chip development during his 7 years at IBM...there is still a shortage in Korea of personnel who truly know how to develop AI chips properly"(Jang, 2022). This case demonstrates how professional exposure in US firms can enable startup founding.

Advanced host countries are typically close to the global knowledge frontier (Romer, 1990), offering migrants exposure to cutting-edge expertise. Professional exposure in these environments provides access to such knowledge via two channels. First, migrants can build networks via interactions with local and other immigrant professionals. These networks serve as conduits of knowledge (Granovetter, 1973; Burt, 2004), and if maintained after return, they provide continued access to advanced knowledge. However, much knowledge, particularly its tacit components, cannot be fully transferred through networks alone (Kogut and Zander, 1992). Direct participation in professional activities allows migrants to acquire skills, knowledge, and practices through hands-on experience (Argote and Epple, 1990; Roca and Puga, 2017), making experiential learning a critical mechanism for knowledge acquisition. While network-building contributes to migrants' exposure, it is their direct engagement in advanced work environments that primarily drives the accumulation of human capital and, ultimately, enhances entrepreneurial capacity upon return.

Building on these theoretical channels, existing studies examine how these channels influence returnees' entrepreneurial activities. Returnees leverage their enhanced access to business-related knowledge through networks for startup founding and performance (Nanda and Khanna, 2010; Wang, 2020), benefit from skills and knowledge acquired in host countries (McCormick and Wahba, 2001; Li et al., 2012), and exploit both channels simultaneously (Dai and Liu, 2009). However, most of these studies compare returnees with local entrepreneurs who may differ in unobservable ways, focus on a single home-country context, or lack causal identification. Consequently, while these studies document the importance of both net-

works and expertise acquired abroad, the causal effect of professional exposure—particularly the accumulation of human capital through direct participation in advanced work environments—remains unclear.

In this paper, I investigate how returning migrants' professional exposure in the United States affects their likelihood of founding a startup upon return. The United States, positioned at the global knowledge frontier and home to a highly active entrepreneurial ecosystem, offers migrants exceptional exposure to advanced work and entrepreneurial practices. Returnees with greater professional exposure in this environment are more likely to acquire valuable skills, knowledge, and networks, which in turn increases their propensity to found a startup in their home countries after return.

Examining the causal effects of returning migrants' prior U.S. professional exposure on their likelihood of founding a startup poses two empirical challenges: i) identifying an appropriate control group that is comparable to returnees with such exposure; and ii) addressing potential endogeneity in the relationship. I address the first challenge by comparing returnees with varying levels of U.S. professional experience. To address the second challenge, I implement an instrumental variable strategy that exploits immigration-system-driven variation in migrants' opportunities to accumulate U.S. professional experience. Specifically, the 2004 H-1B cap reduction, combined with the introduction of home-country-specific U.S. visa categories, increased opportunities for U.S. professional employment among nationals from countries with access to these special visa categories relative to those without. In addition, variation in green card waiting times at the time of graduation affects migrants' incentives to remain in the United States. Longer waiting times reduce the attractiveness of staying in the U.S., thereby decreasing the amount of U.S. professional experience migrants accumulate before returning home.

To track the career trajectories of returning migrants, I construct a sample of returnees identified through LinkedIn. Returnees are defined as individuals who earned their first bachelor's degree outside the United States, subsequently obtained a degree in the United

States between 1991 and 2020, and later returned to the country where they completed their first bachelor's degree. The country of the first bachelor's degree serves as a proxy for individuals' nationality. Using this sample, I estimate a linear probability model in which the outcome is an indicator for being a founder. The key explanatory variable is the length of prior U.S. professional experience—an empirical measure of professional exposure.

In baseline OLS estimates, I find a significantly positive correlation between prior U.S. professional experience and returnees' propensity to found startups in their home countries. This result is robust to the inclusion of additional controls for individual characteristics. Two-stage least squares (TSLS) estimates suggest a positive and statistically significant effect of prior U.S. professional experience on returnees' likelihood of founding a startup. A one-year increase in prior U.S. professional experience increases the probability of founding a startup by 3.11 percentage points, corresponding to a 63.5 percent increase relative to the mean.

I also find substantial heterogeneity in these effects. Returning migrants who worked in large U.S. firms obtain additional benefits, and the positive effects are concentrated among returnees in hard science & engineering, business, and social science fields, as well as among those from developing countries.

This paper makes several contributions. First, it provides the first causal estimate of how returnees' prior professional exposure in advanced host countries affects their likelihood of founding a startup at home. Research on this topic has been limited by the scarcity of large-scale data tracking returnees' career trajectories and by challenges in establishing causal inference due to difficulties in defining comparable control groups and addressing unobserved heterogeneity in migrants' return decisions. By leveraging a novel dataset and a research design that mitigates these issues, this paper overcomes these empirical constraints. Second, it contributes to the return migration literature by directly examining the role of host-country professional exposure—particularly hands-on experience—in shaping returnees' entrepreneurial outcomes. While such exposure is central to returnees' effects on their home

countries, prior work has typically assumed its importance or examined it indirectly through outcomes such as firm performance. Third, this paper contributes to the literature on the determinants of entrepreneurship by highlighting a previously overlooked mechanism: how professional exposure in advanced host countries shapes home-country entrepreneurial activity. Finally, the paper offers policy implications. Current U.S. employment-based immigration rules limit immigrants' entrepreneurial activities within the country. By showing that returnees with prior U.S. professional experience are more likely to found startups than peers with less or no such experience, the findings suggest that the United States could better harness migrants' accumulated human capital by enabling them to pursue entrepreneurship domestically. For home countries, the results highlight the potential benefits of policies that encourage citizens to gain experience in advanced economies before returning home, thereby maximizing the transfer of entrepreneurial capacity.

The rest of this paper is organized as follows. Section 2 connects this paper to related literature. Section 3 describes the data. Section 4 specifies the identification strategy. Section 5 presents the results of my empirical analysis. Section 6 concludes.

2 Related Literature

Several stands of literature are relevant. First, this paper contributes to the literature on return migration. While prior exposure in host countries is central to returnees' contributions to their home countries, existing research has largely emphasized host-country networks as the primary mechanism (Nanda and Khanna, 2010; Wang, 2015; Choudhury, 2016; Wang, 2020; Fry, 2023). Scholars have recognized the importance of returnees' direct professional experience, but it has typically been assumed or embedded in analyses of outcomes including firm performance (Dai and Liu, 2009; Li et al., 2012), firm innovation (Qiao et al., 2024), and knowledge dissemination (Filatotchev et al., 2011; Kahn and MacGarvie, 2016). Consequently, there has been relatively limited evidence about how such exposure directly affects

returnees' own activities including startup founding in their home countries. By directly examining how professional exposure in advanced host countries affects returnees' engagement in entrepreneurship, this paper clarifies the role of host-country professional exposure in shaping home-country economy.

Second, this paper relates to the literature on human capital accumulation and entrepreneurship. Existing work suggests that workers can acquire valuable skills and knowledge through direct participation in the workplace (Argote and Epple, 1990; Jovanovic and Nyarko, 1996), and the quality of expertise gained depends on the quality of the workplace and the surrounding city (Roca and Puga, 2017; Friedrich et al., 2019). By showing that returning migrants with greater professional exposure in the United States—a country at the global knowledge frontier—are more likely to found startups, this paper provides evidence that experiential learning in advanced host countries enhances migrants' entrepreneurial capabilities.

Third, this paper contributes to the literature on the determinants of entrepreneurship. Given its importance to economic growth, there have been extensive efforts to understand the drivers of entrepreneurship, including prior entrepreneurial experience (Hsu, 2007), prior knowledge (Shane, 2000), skills (Lazear, 2005), age (Azoulay et al., 2020), personal traits (Levine and Rubinstein, 2017), entrepreneurial peers (Nanda and Sørensen, 2010; Wallskog, 2025), and financial stability (Hombert et al., 2020). Gupta et al.'s (2024) paper is closest to this study, providing evidence on the effect of U.S. immigrant entrepreneurs' prior professional experience on their startups' performance, consistent with this paper's findings. By showing professional exposure in the U.S. boosts returning migrants' propensity to found startups at home, I highlight a new channel in this literature.

Fourth, this paper contributes to research on transnational human capital transfer (Saxenian, 2005). Migration to advanced economies often raises concerns about the loss of human capital, or brain drain, but subsequent return migration and circular mobility can partially offset these effects through reverse brain drain or brain circulation. Despite the importance of this debate, few studies empirically examine returnees' contributions to their home coun-

tries at scale, largely due to data limitations (with some exceptions, e.g., Amanzadeh et al., 2024). By showing that returnees with prior U.S. professional experience are more likely to found startups upon return, this paper demonstrates that such migrants—having acquired skills, knowledge, and networks—may help offset concerns about brain drain.

3 Data & Measurement

3.1 Data

A key empirical challenge in examining the impact of prior U.S. work experience on returning migrants' entrepreneurship is the absence of publicly available datasets that track migrants' career trajectories after return. To address this limitation, I use LinkedIn profile data from Revelio Labs, scraped in August 2024, which contain detailed education and employment histories across countries.

LinkedIn Profiles

LinkedIn is the largest professional networking and career development platform, with approximately one billion users across more than 200 countries as of 2024. The data provide self-reported, individual-level information on education—including university name, location, degree level, field of study, and dates attended—and on employment spells, including job title, company, location, and employment dates. Revelio Labs further infers individuals' gender from their first names. These records enable tracking of individuals' career trajectories and cross-border mobility.

The main sample consists of returning migrants from the United States registered on LinkedIn, defined as individuals who obtained their first bachelor's degree (if multiple were earned) outside the U.S., later earned a subsequent degree in the U.S. in years between 1991 and 2020, and subsequently returned to the country of their bachelor's degree.[1] Because

[1] I restrict the sample to individuals with no recorded U.S. work experience prior to their first U.S. degree. To ensure accurate classification of education records, I first exclude entries that reflect non-degree education or experiences—such as visiting or exchange programs, postdoctoral fellowships, and Massive Open Online

LinkedIn profiles do not report individuals' nationalities, I use the country of their first bachelor's degree as a proxy, following the common assumption that individuals typically pursue undergraduate education in their home country (Amanzadeh et al., 2024).

Table 1 reports the top 30 home countries by the number of unique returnees, along with their count and share. Returnees from China and India account for a substantial portion of the sample, reflecting the large numbers of students from these countries who pursue degrees in the U.S. Returning migrants from Canada and the United Kingdom also represent a relatively large share, likely due to the concentration of LinkedIn users in Western countries.

Classification of Instructional Programs

The LinkedIn data include individuals' degree fields of study as raw text. To group these majors into standardized categories, I use the Classification of Instructional Programs (CIP) taxonomy provided by National Center for Education Statistics (2020), which has three levels—2 digits, 4 digits, and 6 digits—with 6-digit codes being the most granular. Using CIP titles and descriptions, I mapped each degree field of study to a 6-digit CIP field through a combination of merge operations, string matching, and selection of highest cosine similarity pairs based on OpenAI's text-embedding model, with ChatGPT assisting in CIP field

Courses—by detecting related keywords (e.g., "exchange student," "MOOC") in both university name and degree field. Some individuals also list multiple education records with identical start dates, likely because they are duplicates made by users by mistake, list two or more separate majors at the same degree level, or they started degrees of different levels on the same date (e.g., master's and doctorate). When these records refer to the same university, I collapse them into one unless they clearly correspond to distinct degree levels. Records referring to different universities are retained as originally reported. The first bachelor's degree is defined as a degree labeled "bachelor's" (excluding records without degree-level information) with a duration exceeding 30 months. If an individual earned a first bachelor's degree both in the U.S. and abroad, I use the one earned abroad. When multiple bachelor's degrees are earned in different countries with identical dates, I select the one with the longest duration; if ties remain, I keep the one listed first by the user. The subsequent U.S. degree is defined as a degree earned in the United States after the first bachelor's degree abroad and lasting longer than eight months, reflecting the typical minimum duration of master's programs. Many profiles lack university location information, often because users combined the institution name with additional text (e.g., "Harvard University Boston"), preventing LinkedIn's autofill function from identifying the correct location. To recover these, I match university names against a list of over 9,000 global universities from Gutiérrez (2020), using string matching on university name and, when necessary, location. This procedure may introduce some misclassification, since the university list is not exhaustive and string matches are imperfect, although it covers a large, representative set of institutions. To reduce the misclassification rate, I performed string matching for foreign region names using reference lists from the R packages *countrycode*, *maps*, and *datasets*, manually reviewing the matches and dropping any universities that were misclassified. This procedure allows the U.S. degree to be identified for roughly 40% of returning migrants in the estimation sample.

selection for a small number of edge cases.[2]

Table 2 presents the distribution of broad degree fields for the most recent U.S. degrees earned by returning migrants, showing both the count and share for each field. I created a crosswalk from 2-digit CIP fields to these broader categories, aggregating majors accordingly (see Table A1 for the mapping from 2-digit CIP fields to broad degree fields). A substantial share of returnees majored in Business, Hard Science and Engineering, and Social Sciences.

US School Ranking Group

To account for heterogeneity in individuals' abilities, I use the rankings of US schools attended by returnees. Specifically, I use Forbes's (2026) US college rankings, which provide a comprehensive list of 500 American institutions, including both universities and liberal arts colleges. Although the list is from 2026, it serves as a reasonable proxy for institutional quality, as university rankings are relatively stable over time. Approximately 75% of returning migrants in the sample attended a school within the top 500. I split the rankings of these individuals into 20 quantiles and categorize schools outside the top 500 into a single group, creating the variable *US School Ranking Group*.

Green Card Waiting Time

U.S. Department of State (2026) provides historical records of the latest priority dates of applications available for green card issuance for each fiscal year. Using this information, I estimate returning migrants' green card waiting time at the time of graduation. Section 4 explains how this variable is used as an instrument.

Quality of U.S. employers

To explore heterogeneity in the effect of prior U.S. work experience on startup founding

[2]There are 48 2-digit CIP fields in total. I excluded 9 2-digit CIP fields when matching degree fields of study with 6-digit CIP codes because these are likely irrelevant to higher education: BASIC SKILLS AND DEVELOPMENTAL/REMEDIAL EDUCATION; CITIZENSHIP ACTIVITIES; HEALTH-RELATED KNOWLEDGE AND SKILLS; INTERPERSONAL AND SOCIAL SKILLS; LEISURE AND RECREATIONAL ACTIVITIES; HIGH SCHOOL/SECONDARY DIPLOMAS AND CERTIFICATES; HEALTH PROFESSIONS RESIDENCY/FELLOWSHIP PROGRAMS; MEDICAL RESIDENCY/FELLOWSHIP PROGRAMS. Some individuals do not provide a valid string value for a degree field of study, or the text could not be classified; in such cases, I assigned "Unclassified" as the CIP field.

based on the size of U.S. employers, I use a list of firms in Arora et al. (2021).

Economic Development of Home Countries

To explore heterogeneity in the effect of prior U.S. work experience on startup founding based on the level of economic development in returnees' home countries, I use per capita GDP in constant 2015 U.S. dollars from the World Bank (2026). Because the World Bank does not provide this information for Taiwan, I obtain the data from International Monetary Fund (2025).[3] I also incorporate the list of OECD member countries and their accession years (OECD, 2026).

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3.2 Measurement

Prior U.S. Professional Experience

The focal explanatory variable in this paper is returning migrants' prior U.S. work experience, which serves as an empirical measure of their professional exposure in the country. Using information on returning migrants' employment spells in the U.S., I compute the following:

$$USEXP_{hci} = \sum_{k=t_0}^{y-1} \text{U.S. Tenure}_{i(y)}$$

[3]Taiwan's per capita GDP is reported in current U.S. dollars; I convert this to 2015 U.S. dollars using the GDP deflator from the Federal Reserve Bank of St. Louis (2026).

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where h indexes the home country, c a U.S. degree cohort, i a returning migrant, y the year of return, and k a prior calendar year between t_0—the first year of the individual's employment history—and $y-1$, the year preceding the return. This variable represents individual i's total cumulative U.S. professional tenure, in years, from home country h, who earned her most recent U.S. degree in year c and returned in year y.[5] Only post-graduation employment in the U.S. is included in the construction of this variable; on-campus jobs or employment during academic programs are excluded.

Engagement in Entrepreneurship

Using keywords in returning migrants' job titles, I define the outcome variable $Founder_{hci}$ as 1 if returnee i become a startup founder, and 0 otherwise. Individuals are classified as entrepreneurs if their job title includes any of the following keywords: *founder*, *originator*, *establisher*, or *initiator*.[6]

Summary statistics

I construct cross-sectional sample of 209,765 returnees from 153 home countries who earned a U.S. degree between 1991 and 2020 and returned to their home countries between 1991 and 2024.

Table 3 reports summary statistics of the data. About 4.9% of returning migrants in the sample found startups, and *USEXP*, prior U.S. professional experience, has a highly skewed distribution—the 75th percentile of the variable is 0. In fact, only about 21.2% of returning migrants have positive prior U.S. professional experience. It is also noteworthy

[5]Some employment spells do not have end dates. In many cases, this is because the positions are ongoing, which does not affect the construction of the variable or the estimation. In other cases, however, the spells are not the last position yet still have missing end dates. I imputed these missing end dates by subtracting one day from the start date of the subsequent position, assuming that individuals do not have a gap between employments and that the position with the imputed end date ended before the start of the subsequent position. Because some employment spells span multiple calendar years, I split each spell into the individual years it covers and then count the number of unique days of employment in the U.S. When individuals have overlapping employment spells, I count only unique days across overlapping periods to avoid double counting. About 3.5% of individuals in the sample that move between their home countries and the U.S. over time. For these cases, I use the maximum value of *USEXP*. The estimation results are robust to the inclusion of these individuals.

[6]A small number of observations have missing job titles, mostly because individuals did not enter a job title when listing their position on LinkedIn. In such cases, the variable is coded as 0.

that more than 80% of returning migrants hold a master's degree as their most recent U.S. degree. This reflects my definition of returning migrants—individuals who earn their first bachelor's degree outside the U.S. and subsequently obtain a degree in the United States before returning.

4 Identification Strategy

Estimating the impact of returning migrants' prior U.S. professional experience on their home-country entrepreneurship faces two empirical challenges. Causal inference is difficult due to i) challenges in selecting an appropriate comparison group, and ii) factors that are unobservable to the econometrician but affect the length of experience and, in turn, returnees' startup founding.

A basic approach to defining a comparison group is to compare entrepreneurial activity among returnees with locals—individuals in home countries who have never lived abroad. However, these groups differ in fundamental, unobservable ways that cannot be fully captured using observable characteristics. For example, returnees are likely more entrepreneurial than locals simply by virtue of having chosen to live and work abroad. To address this, I compare returnees with others who have similar observable characteristics but differ in the length of prior U.S. work experience. For example, I compare two returning migrants in India, both of whom earned a bachelor's degree in India and completed a master's degree in the U.S. Both eventually returned home, but one acquired three years of professional experience in the U.S. prior to return, while the other returned immediately after graduation. I examine whether the former is more likely to found a startup in India than the latter.

For the second challenge, I implement an instrumental-variable strategy that exogenously affects the length of returning migrants' professional experience in the U.S.; I describe this strategy in detail below. Together, these strategies allow me to assess whether prior U.S. work experience increases returnees' propensity to found a startup.

4.1 Baseline Estimation

Using the identification strategy, I estimate the following:

$$Founder_{hci} = \alpha + \beta USEXP_{hci} + \mu_h + \lambda_c + X'_{hci}\boldsymbol{\gamma} + \epsilon_{hci} \tag{1}$$

where h indexes the home country, c a U.S. degree cohort, i a returning migrant. The variable *USEXP* is the focal explanatory variable, representing a returning migrant's prior U.S. professional experience. Home country- and U.S.-cohort fixed effects are captured by μ_h and λ_c. The vector X_{hci} consists of control variables, including fixed effects for degree level of the most recent U.S. degree, 2-digit CIP field of the most recent U.S. degree, U.S. school ranking group, bachelor's degree year, gender, and home-country metropolitan area. The equation is estimated by OLS, with standard errors clustered at the home-country level. The coefficient β is a coefficient of interest, capturing the effect of prior U.S. professional experience on returnees' likelihood of ever becoming entrepreneurs.

4.2 Instrument variables

An ideal experiment for estimating Equation 1 would randomly assign different lengths of prior U.S. professional experience to returning migrants. However, this regression potentially suffers from endogeneity. For example, believing that U.S. work experience would benefit their future entrepreneurial activities at home, potential returnees might deliberately seek to remain in the U.S. longer before returning, creating a reverse causality problem. To address this concern, I instrument *USEXP* using two sources of variation: (i) a combination of the 2004 H-1B cap reduction and the introduction of home-country-specific U.S. visa categories, and (ii) migrants' estimated green card waiting time at the time of graduation.

4.2.1 U.S. Visa Policy Changes

The H-1B program, established in fiscal year 1992 under the Immigration Act of 1990, provides temporary work visas for high-skilled foreign workers. It is heavily used by individuals with higher education degrees: according to U.S. Citizenship and Immigration Services (2024), 92% of initial H-1B beneficiaries in 2024 hold a bachelor's degree or higher (100% among those with verified degree levels). The annual visa cap was initially set at 65,000 and was not binding until fiscal year 1997 and again in 1998. It was increased to 115,000 in fiscal years 1999 and 2000, and to 107,500 in fiscal year 2001 under the American Competitiveness and Workforce Improvement Act. The cap was again raised to 195,000 between 2001 and 2003 under the American Competitiveness in the 21st Century Act (AC21) and was not binding during this period.[7] AC21 included a provision to revert the cap to 65,000 without further legislation. Given the upward trend of the cap since the late 1990's, it is plausible that further increases were anticipated. However, by fall 2003 it had become clear that no such increase would occur, and the cap reverted in 2004. It has remained binding since, substantially limiting U.S. employment opportunities for high-skilled foreign workers.[8]

However, nationals of five countries—Australia, Canada, Chile, Mexico, and Singapore—have been able to use country-specific U.S. temporary work visas established through U.S. free trade agreements. Specifically, the TN visa was introduced for Canadian and Mexican citizens in 1994, the H-1B1 visa for Chilean and Singaporean nationals in 2004, and the E-3 visa for Australians in 2005. Although the durations of these visas vary, they are indefinitely renewable and either uncapped or capped at levels that have never been reached, effectively serving as substitutes for the H-1B visa.

Because these visa policies restricted work opportunities for some nationalities but not

[7] The 1999 cap was inadvertently surpassed by 22,000 due to an administrative error by the Immigration and Naturalization Service. These excess visas were neither revoked nor retroactively counted toward the 2000 cap.

[8] AC21 exempts higher education institutions and related nonprofit or governmental research organizations from the H-1B cap. Since 2006, an additional 20,000 H-1B visas have been allocated annually to individuals with a master's degree or higher under the H-1B Visa Reform Act.

others, they are correlated with the length of returning migrants' prior U.S. professional experience, satisfying the relevance condition. The policies operate at the country level, so they constitute an intent-to-treat–style instrument. Moreover, the policy changes were intended to regulate inflows of high-skilled workers to the U.S. and are plausibly unrelated to migrants' entrepreneurial activity in their home countries, except through their effect on the length of returning migrants' prior U.S. professional experience, satisfying the exclusion restriction.

Leveraging these cross-country differences in visa policy environments, I construct an instrumental variable, *Cap-Free* × *Post*, which equals 1 if individual i from a visa-cap-free country (Australia, Canada, Chile, Mexico, or Singapore) graduated in a U.S. cohort c from 2004 onward (2005 for Australia) and 0 otherwise. These five countries are classified as visa-cap-free because their nationals could access alternative temporary work visas that were effectively uncapped, whereas nationals of all other countries were subject to the H-1B cap.

4.2.2 Green Card Waiting Time

When graduating in the United States, international students decide whether to remain in the country. Because their stay depends on their visa status, immigration options play a central role in this decision. Empirical evidence shows that obtaining permanent residency or citizenship reduces the likelihood of leaving the host country (Gundel and Peters, 2008). Therefore, chances of obtaining a green card strongly influence international students' decisions to remain in the U.S. Consistent with this, a staff member at the Boston University International Students & Scholars Office noted:

> "There are at least two reflex points in international students' decision to stay in the country versus return home, and one is at the time of graduation... The biggest consideration for international students' decision to stay in the country is their future immigration options... Getting a green card is always an important

consideration—it is an endgame."

This anecdotal evidence suggests that difficulties in obtaining a green card discourage international students from remaining in the U.S. after graduation. Therefore, I construct an instrumental variable, *Green Card Waiting Time*, defined as the green card waiting time at graduation, which forms the basis for international students' evaluation of their likelihood of obtaining permanent residency. I compute this measure by subtracting the final action date from the corresponding fiscal year date (see Appendix A1 for details).

Green card waiting time largely determines their likelihood of obtaining one, as U.S. immigrants must secure permanent residency before their visas expire (e.g., H-1B). Because students can anticipate their chances based on green card waiting time at graduation, longer waiting times encourage more students to leave the country, whereas shorter waiting times do less. Thus, green card waiting time functions as an intent-to-treat–style instrument that is negatively correlated with the length of returning migrants' prior U.S. professional experience, satisfying the relevance condition.

Because green card waiting time at graduation is determined by the backlog of green card applications from other immigrants seeking permanent residency in the U.S., it plausibly affects returnees' entrepreneurial activities at home only through their US work experience, satisfying the exclusion restriction.

U.S. immigration law imposes an annual cap on the number of green cards processed in each category (fiscal year: Oct 1–Sept 30) and per-country limits, restricting any single country to at most 7% of the total green cards. Citizens from high-demand countries—China, India, Mexico, and the Philippines—are typically subject to the per-country limit. As a result, applications from these four countries are processed at the country level, while applications from other countries are pooled. These rules collectively generate across- and within-country variation in green card waiting times, which I exploit for all countries. Variation also arises by U.S. degree level, because different degree levels correspond to different green card categories, and by U.S. degree cohort, as different cohorts face different waiting times due to the annual

cap and the backlog of applications. Thus, the overall variation occurs at the country (or group) level, by degree cohort, and by degree level. See Appendix A1 for further details.

5 Results

5.1 Overview: Prior U.S. Professional Experience and Returnee Entrepreneurship

I first explore whether returning migrants who eventually become entrepreneurs differ from other returnees in terms of their prior U.S. professional experience. To do so, I compute the average of *USEXP* and its 95% confidence intervals by returnees' founder status.

Figure 1 presents the distribution of these groups. Returning migrants who eventually become entrepreneurs have, on average, substantially longer prior U.S. professional experience—about 40% longer than those who never become entrepreneurs. This pattern appears to suggest that returning migrants with greater prior U.S. professional experience are more likely to ever found a startup in their home countries.

Figure 2 further illustrates this pattern. It presents a binned scatter plot of average *USEXP* against average *Founder* across 20 bins. The plot indicates a positive relationship between prior U.S. professional experience and returnees' likelihood of founding startups.

5.2 Instrument validity

5.2.1 Instrument validity: U.S. Visa Policy Changes

To confirm whether the U.S. visa policy changes generate variation in *USEXP*, I plot trends in country-level average *USEXP* by visa cap-free status. Figure 3 presents these trends. The figure suggests that, after becoming visa cap-free, returning migrants from those countries have more prior U.S. professional experience than those from other countries.

I verify these visual patterns by estimating the following event study:

$$USEXP_{hci} = \alpha_1 + \sum_k \pi_k \mathbb{1}(t_{c(i)} - t_{h(i)} = k) + \mu_h + \lambda_c + X'_{hci}\boldsymbol{\gamma} + \eta_{hci} \tag{2}$$

where the indexes and variables are the same as in Equation 1 except for the summation term. The indicator $\mathbb{1}(t_{c(i)} - t_{h(i)} = k)$ equals 1 for returning migrant i from home country h whose latest U.S. degree year (cohort c) is k years after the year that citizens of that home country first became visa-cap-free and 0 otherwise. I set $t_{h(i)} = 2004$ for Canada, Chile, Mexico, and Singapore and $t_{h(i)} = 2005$ for Australia. For returning migrants from all other countries, k = -1. Standard errors are clustered at the home-country level as in Equation 1. The coefficients π_k's capture the dynamic treatment effects of the visa cap-free policy on prior U.S. professional experience of returning migrants from these five countries.

Figure 4 shows the event study results for the outcome variable *USEXP*. The figure indicates a sizeable increase in prior U.S. professional experience for returning migrants from visa-cap-free countries relative to others following the policy change. These results suggest that the instrument *Cap-Free* × *Post* satisfies the relevance condition.

5.2.2 Instrument validity: Green Card Waiting Time

To confirm whether green card waiting time is negatively related with returning migrants' prior U.S. professional experience, I plot a binned scatter of *Green Card Waiting Time* against residualized *USEXP*, where the latter is residualized by home-country and US degree-cohort fixed effects. Figure 5 shows a negative correlation, consistent with the mechanism discussed in Section 4.2.2. The pattern suggests that the instrument *Green Card Waiting Time* satisfies the relevance condition.

5.3 Baseline Results

Table 4 presents the results of Equation 1. Columns (1) and (2) present OLS estimates with prior U.S. professional experience (*USEXP*) as the main explanatory variable. Column (1) includes only home-country and U.S. degree-cohort fixed effects, while column (2) adds individual-level controls. The coefficient of *USEXP* is similar in magnitude across both columns and is positive and statistically significant, indicating a positive correlation between prior U.S. professional experience and returnees' likelihood of founding a startup.

Columns (3) and (4) report first-stage estimates in which *USEXP* is regressed on *Cap Free* × *Post* and *Green Card Waiting Time*, using different sets of control variables. The coefficient of *Cap Free* × *Post* is positive and statistically significant in both columns, indicating that visa cap-free status increases prior U.S. professional experience. The coefficient of *Green Card Waiting Time* is negative and statistically significant, suggesting that longer green card waiting times at graduation reduce the length of returnees' prior U.S. professional experience.

Columns (5) and (6) report reduced-form estimates in which *Founder* is regressed on *Cap Free* × *Post* and *Green Card Waiting Time*, using different sets of control variables. The coefficient of *Cap Free* × *Post* is positive and statistically significant, indicating that visa cap-free status increases returnees' likelihood of founding a startup. The coefficient of *Green Card Waiting Time* is negative and statistically significant, suggesting that longer green card waiting times at graduation reduce returnees' propensity to found a startup. Combined with the first stage results, these findings imply that TSLS estimates would be positive.

Columns (7) and (8) report the TSLS estimates, with varying sets of control variables. Consistent with the preceding results, the coefficient of *USEXP* is positive and statistically significant, indicating that prior U.S. professional experience increases returnees' likelihood of founding a startup. The clustering-robust first-stage F-statistics in both columns exceed 10, the rule-of-thumb threshold for strong instruments. Notably, the coefficient becomes larger with the addition of individual-level controls. The coefficient in column (8) is my

preferred estimate: a one-year increase in prior U.S. professional experience raises returning migrants' probability of founding a startup by 3.11 percentage points, corresponding to a 63.5 percent increase relative to the mean.

The TSLS estimates are substantially larger than the OLS estimates, highlighting the importance of addressing endogeneity. To formally test this, I conducted the endogeneity test. I reject the null hypothesis that *USEXP* is exogenous at the 10% level, which suggests instruments are necessary for estimation. Finally, the overidentification test fails to reject the null hypothesis of instrument validity.

5.4 Mechanism

5.4.1 Does Size of U.S. Employers Matter?

Returning migrants have worked in different U.S. employers. If U.S. professional experience allow them to acquire skills and knowledge during their tenure, working at established firms—those more likely to lead the market—could provide additional benefits, further increasing their propensity to found startups in their home countries. To operationalize this idea, I define a dummy variable, *DISCERN*, which equals 1 if a returning migrant ever worked at a firm listed in the DISCERN data (Arora et al., 2021), and 0 otherwise. This dummy serves as a proxy for professional experience at large, established U.S. firms.

Using *DISCERN*, I estimate the following reduced form regression:

$$\begin{aligned} Founder_{hci} = \alpha + \beta_1 Heterogeneity\ Source_{hci} \times Green\ Card\ Waiting\ Time_{hci} + \\ \beta_2 Green\ Card\ Waiting\ Time_{hci} + \beta_3 Heterogeneity\ Source_{hci} + \mu_h + \lambda_c + \boldsymbol{\gamma}'\boldsymbol{X} + \epsilon_{hci} \end{aligned} \tag{3}$$

where the indexes, the outcome variable, and controls are the same as in Equation 1. Here, *Green Card Waiting Time* is used in the reduced form, and the new variable *Heterogeneity Source* captures the source of heterogeneity. The new variable *Heterogeneity Source* is a source of heterogeneity. In this analysis, *DISCERN* is used in place of *Heterogeneity Source*.

The coefficient β_1 captures the effect of prior U.S. professional experience on the likelihood of founding startups for returnees who have worked in large U.S. firms, relative to those with the same length of experience in other firms.

Table 5 reports the results. Column (1) presents estimates with only home-country and U.S. degree-cohort fixed effects, while column (2) includes the full set of controls. The coefficient on Green Card Waiting Time is negative and significant in both columns, as in columns (5) and (6) of Table 4, reflecting the same directional effect observed in the baseline regressions. The coefficient of *DISCERN* $\times$ *Green Card Waiting Time* is also negative and significant. Notably, the magnitude of the interaction term's coefficient is similar to that of *Green Card Waiting Time*. These results suggest that prior professional experience at a large, established firm further increases returnees' propensity to found startups, supporting the idea that skills and knowledge relevant to entrepreneurship are acquired during U.S. professional experience.

5.4.2 Heterogeneous Effects across Fields of Knowledge

Migrants can benefit from their professional experience in advanced host countries by acquiring skills and knowledge in areas where these countries have a comparative advantage. The United States, in particular, has strengths in science, technology, and business-related know-how. Therefore, the positive effects of prior U.S. professional experience on returnees' likelihood of founding a startup are likely to be stronger in these fields.

Because U.S. immigration rules for highly skilled workers often require them to perform tasks related to their expertise, their most recent U.S. degree fields provide a good measure of their specialties. Using the broad degree field categories shown in Table 2, I split the sample and estimate Equation 1 in each subsample to examine how the effects of prior U.S. professional experience vary across fields.

Table 6 reports the results. I present TSLS estimates, but also reduced-form estimates because the first-stage F-statistics are below 10 in many subsamples. The TSLS estimates are

positive and statistically significant in columns (1)-(3), but insignificant in other columns. The reduced-form estimates generally align with the TSLS results. Overall, the results suggest that the positive effects of prior U.S. professional experience on returnees' startup founding are concentrated among returnees in hard science & engineering, business, and social science fields.

5.4.3 Do Returnees from Less Developed Economies Benefit More from Their U.S. Professional Exposure?

Section 5.3 shows that returning migrants with longer prior U.S. professional experience are more likely to found startups in their home countries. This suggests that advanced-host-country experience allows migrants to acquire skills, knowledge, and practices that are relatively scarce at home but enhance entrepreneurial capacity. Because the scarcity of these resources generally decreases with the level of home-country development, migrants from less developed economies are likely to benefit more from such exposure, exhibiting a higher propensity to found startups upon returning.

To operationalize this idea, I examine heterogeneity in the effects of prior U.S. professional exposure on returnees' likelihood of founding startups by the level of home-country economic development. Specifically, using GDP per capita data, I construct a continuous variable, *GDP Gap*, defined the difference in GDP per capita between the United States and the home country in the year of return. I also create a dummy variable, *Above-Median GDP Gap*, which equals 1 if *GDP Gap* is above the median in the year of return, and 0 otherwise. Finally, I create a dummy variable, *OECD*, which equals 1 if the home country is a member of the OECD in the year of return, and 0 otherwise.

Using these variables, I estimate Equation 3, replacing *Heterogeneity Source* with each variable in turn. Table 7 reports the results. In column (1), the coefficient of *GDP Gap* $\times$ *Green Card Waiting Time* is negative but significant, suggesting that the positive effects of prior U.S. professional experience are stronger for returnees from less developed countries. A

similar pattern appears in column (2): the coefficient of *Above-Median GDP Gap* × *Green Card Waiting Time* is negative and significant, while the coefficient of *Green Card Waiting Time* remains negative and significant.

Column (3) yields consistent evidence. The coefficient of *OECD* × *Green Card Waiting Time* is positive and significant, whereas the coefficient of *Green Card Waiting Time* is negative and significant, indicating that returning migrants from developed countries benefit less from prior U.S. professional experience in startup founding. The absolute magnitude of the two coefficients are also similar, implying that the effect is largely concentrated among returnees from less developed countries.

6 Conclusion

Many high-skilled migrants return to their home countries after acquiring valuable skills and knowledge through their professional exposure in advanced host economies, generating important impacts ranging from innovation and firm performance to entrepreneurship. Yet, despite the significance of such exposure, little is known about how it directly affects returning migrants' own entrepreneurial activities. Overcoming empirical challenges in tracking returnees' career trajectories at scale and identifying an appropriate control group, this paper provides novel evidence using returnees from the United States as an empirical context. I find that a one-year increase in prior U.S. professional experience raises the probability of founding a startup by 3.11 percentage points, corresponding to a 63.5 percent increase relative to the mean. I also find that returning migrants who worked in large U.S. firms obtain additional benefits, and that the positive effects of prior U.S. professional experience are concentrated among returnees in hard science & engineering, business, and social science fields, as well as among those from developing countries.

While returnees' host-country exposure includes both network formation and direct workplace participation, the latter has often been overlooked or assumed to have uniformly pos-

itive effects. By explicitly examining the length of prior U.S. professional experience, this paper contributes new evidence on the role of direct professional exposure in shaping returnees' entrepreneurial outcomes.

This work also links to the literature on human capital accumulation, which emphasizes skill acquisition through experiential learning in the workplace (Jovanovic and Nyarko, 1996) and the importance of the locus of learning (Roca and Puga, 2017). By showing that professional tenure in the United States enhances returnees' entrepreneurial capabilities, the paper highlights a novel channel of human capital formation. Future research could explore whether similar effects extend to other capabilities, such as inventive ability.

In addition, by identifying professional experience in advanced economies as a channel of entrepreneurship, this paper contributes to the broader literature on the determinants of entrepreneurship. While the empirical focus is on returnees from the United States, future work could examine returnees from other advanced host countries, such as the United Kingdom, to test the external validity of these findings. Comparative analyses could also assess whether the effects of professional exposure differ across host-country contexts.

Moreover, this paper contributes to the literature on transnational human capital transfer by showing that returnees can offset potential losses from brain drain through human capital accumulated during professional tenures abroad. As new data and methods emerge, further work should examine the extent to which returnees mitigate the negative effects of emigration on their home economies.

Finally, the findings offer policy implications. The results suggest that returning migrants can translate their professional experience in the United States into entrepreneurial activity upon return. Currently, employment-based visa requirements in the U.S. constrain migrants' opportunities to stay and start ventures domestically, potentially leading them to establish businesses in their home countries instead. Relaxing such restrictions—or offering grace periods for prospective entrepreneurs—could enable the U.S. to retain more high-skilled founders. For home countries, facilitating citizens' access to advanced host countries and

encouraging professional experience abroad could foster entrepreneurship upon return. Examples may include scholarship programs that support study and work abroad or bilateral visa agreements that enhance cross-border mobility of skilled workers.

Table 1: Top-30 Home Countries by the Number of Returnees

Home Country	Count	Share
China	47,349	22.57 %
Canada	23,302	11.11 %
India	18,581	8.86 %
United Kingdom	11,552	5.51 %
Saudi Arabia	10,557	5.03 %
Taiwan	9,901	4.72 %
South Korea	7,854	3.74 %
Japan	5,607	2.67 %
Brazil	5,505	2.62 %
Thailand	5,500	2.62 %
Turkiye	5,318	2.54 %
Australia	4,492	2.14 %
Mexico	3,968	1.89 %
Italy	2,525	1.2 %
Singapore	2,458	1.17 %
Germany	2,441	1.16 %
Egypt	2,179	1.04 %
Israel	2,111	1.01 %
Greece	1,994	0.95 %
Spain	1,898	0.9 %
Philippines	1,748	0.83 %
Nigeria	1,680	0.8 %
Indonesia	1,470	0.7 %
Jordan	1,462	0.7 %
Pakistan	1,316	0.63 %
Colombia	1,262	0.6 %
Chile	957	0.46 %
Ghana	900	0.43 %
Netherlands	888	0.42 %
Lebanon	857	0.41 %

Notes: This table reports the top 30 home countries of returnees who earned a U.S. degree between 1991 and 2020, based on the number of unique individuals. It presents each country's count and share, where the share denotes the proportion of returnees from that country relative to the total sample.

Table 2: Distribution of Broad Degree Fields

Broad Field	Count	Share
Business	66,952	34.35 %
Hard Science & Engineering	65,608	33.66 %
Social Sciences	26,653	13.67 %
Humanity	12,958	6.65 %
Health	8,543	4.38 %
Other	7,188	3.69 %
Education	7,007	3.6 %

Notes: This table shows the distribution of broad degree fields for the most recent U.S. degrees earned by returning migrants, along with the count and share for each field. The share represents the proportion of returnees with a classified major in that field relative to the total number of returnees with a classified major.

Table 3: Summary Statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Founder	0.0493	0.2166	0	0	0	0	1
USEXP	0.6075	1.9447	0.0000	0.0000	0.0000	0.0000	31.6932
Cap-Free × Post	0.1315	0.3379	0	0	0	0	1
Green Card Waiting Time	2.0390	2.7385	0.0000	0.0000	0.0000	4.3014	15.6767
Return Year	2,013.0670	6.5051	1,991	2,010	2,014	2,018	2,024
US Degree Year	2,010.8530	7.1512	1,991	2,007	2,013	2,016	2,020
Bachelor Year	2,005.1420	8.8054	1,945	1,999	2,007	2,012	2,020
Doctorate	0.1205	0.3255	0	0	0	0	1
Master	0.8387	0.3678	0	1	1	1	1
Bachelor	0.0409	0.1980	0	0	0	0	1
US School Ranking	112.9289	119.9526	1	28	69	156	500
Male	0.6030	0.4893	0	0	1	1	1
Discern	0.1255	0.3313	0	0	0	0	1
GDP Gap	34,698.6500	19,536.5300	−131,739.8000	18,718.2900	39,083.0700	50,279.0800	83,456.1300
Above-Median GDP Gap	0.4123	0.4922	0	0	0	1	1
OECD	0.3782	0.4849	0	0	0	1	1
Observations	209,765						

Notes: This table presents summary statistics for a cross-sectional sample of 209,765 returnees from 153 home countries who earned a U.S. degree between 1991 and 2020. The variable *Founder* is a dummy equal to 1 if the individual is a returnee entrepreneur. *USEXP* measures the total length of prior U.S. professional experience. *Cap* × *Post* is a dummy equal to 1 if an individual is from visa-cap-free country and earned a U.S. degree after the country became visa-cap-free. *Green Card Waiting Time* is the estimated waiting time to obtain a green card at the time of graduation in the United States. *Return Year*, *US Degree Year*, and *Bachelor Year* denote the year of return to the home country, the year of U.S. degree attainment, and the year of the first bachelor's degree, respectively. *Doctorate*, *Master*, and *Bachelor* are dummies equal to 1 if a corresponding degree is the individual's latest U.S. degree. *US School Ranking* is the ranking of the U.S. university attended by the returning migrant. The sample contains schools whose rankings are not in the top 500. *Male* equals 1 if the individual has a male-sounding first name (inferred by Revelio Labs). *DISCERN* is a dummy variable equal to 1 if a returning migrant ever worked at a firm listed in the DISCERN data. *GDP Gap* is the difference in GDP per capita between the United States and the home country in the year of return, and *Above-Median GDP Gap* is a dummy variable equal to 1 if *GDP Gap* is above the median in that year. *OECD* is a dummy variable equal to 1 if the home country is a member of the OECD in the year of return.

Table 4: Baseline Regression: The Impact of Prior U.S. Professional Work Experience on Returnee Entrepreneurship

Outcome Variable:	Founder (1)	Founder (2)	USEXP (3)	USEXP (4)	Founder (5)	Founder (6)	Founder (7)	Founder (8)
USEXP	0.0012*	0.0011*					0.0232***	0.0311***
	(0.0006)	(0.0005)					(0.0043)	(0.0059)
Cap Free × Post			0.4582*	0.4546*	0.0106*	0.0101*		
			(0.2184)	(0.2178)	(0.0046)	(0.0040)		
Green Card Waiting Time			-0.0886***	-0.0737***	-0.0021***	-0.0025***		
			(0.0137)	(0.0174)	(0.0004)	(0.0003)		
Constant	0.0486***	0.0487***	0.7133***	0.6834***	0.0518***	0.0529***		
	(0.0003)	(0.0003)	(0.0348)	(0.0444)	(0.0007)	(0.0007)		
Model	OLS	OLS	1st Stage	1st Stage	Reduced Form	Reduced Form	TSLS	TSLS
Home Country FE	Y	Y	Y	Y	Y	Y	Y	Y
US Degree Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
US Degree Level FE	N	Y	N	Y	Y	Y	Y	Y
US Degree Field FE	N	Y	N	Y	Y	Y	Y	Y
US School Ranking Group FE	N	Y	N	Y	Y	Y	Y	Y
Bachelor's Year FE	N	Y	N	Y	Y	Y	Y	Y
Gender FE	N	Y	N	Y	Y	Y	Y	Y
Metro Area FE	N	Y	N	Y	Y	Y	Y	Y
Clustered Std. Error	Home Country	Home Country	Home Country	Home Country	Home Country	Home Country	GC Waiting Line	Home Country
1st Stage F-Stat							21	10.6
Return Time Window	1991-2024	1991-2024	1991-2024	1991-2024	1991-2024	1991-2024	1991-2024	1991-2024
Observations	209,757	209,741	206,620	206,605	206,620	206,605	206,620	206,605
Mean	0.0493	0.0493	0.5937	0.5937	0.0490	0.0490	0.0490	0.0490

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents the results of Equation 1, using *Founder* as the outcome variable to examine the effects of prior U.S. professional experience on returnee entrepreneurship. The standard errors are clustered at the home-country level. Columns (1)-(2) reports OLS estimates, columns (3)-(4) report 1st stage estimates, columns (5)-(6) report reduced form estimates, and columns (7)-(8) report TSLS estimates.

Table 5: Employer Size-Based Heterogeneity

Outcome Variable:	Founder	Founder
	(1)	(2)
DISCERN × Green Card Waiting Time	-0.0018***	-0.0016***
	(0.0004)	(0.0004)
Green Card Waiting Time	-0.0018***	-0.0023***
	(0.0004)	(0.0003)
DISCERN	0.0081+	0.0061
	(0.0043)	(0.0046)
Constant	0.0522***	0.0535***
	(0.0006)	(0.0006)
Model	Reduced Form	Reduced Form
Home Country FE	Y	Y
US Degree Cohort FE	Y	Y
US Degree Level FE	N	Y
US Degree Field FE	N	Y
US School Ranking Group FE	N	Y
Bachelor's Year FE	N	Y
Gender FE	N	Y
Metro Area FE	N	Y
Clustered Std. Error	Home Country	Home Country
Observations	206,620	206,605
Mean	0.0490	0.0490

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents the results of Equation 3, using *Founder* as the outcome variable to examine the heterogeneous effects of prior U.S. professional experience on returnee entrepreneurship by the size of former U.S. employers. Standard errors are clustered at the home-country level.

Table 6: Heterogeneous Effects across Fields of Knowledge

Outcome Variable:	Founder (1)	Founder (2)	Founder (3)	Founder (4)	Founder (5)	Founder (6)
TSLS						
USEXP	0.0276***	0.0437*	0.0407*	0.0916	-0.0068	0.0119
	(0.0041)	(0.0199)	(0.0157)	(0.0625)	(0.0146)	(0.0206)
Reduced Form						
Exempt Post	0.0154*	0.0018	0.0015	0.0208*	-0.0084	0.0001
	(0.0068)	(0.0060)	(0.0102)	(0.0100)	(0.0093)	(0.0121)
Green Card Waiting Time	-0.0029***	-0.0024***	-0.0023*	-0.0009	0.0000	-0.0013
	(0.0005)	(0.0007)	(0.0010)	(0.0013)	(0.0019)	(0.0016)
Constant	0.0541***	0.0552***	0.0470***	0.0513***	0.0464***	0.0424***
	(0.0014)	(0.0016)	(0.0026)	(0.0034)	(0.0045)	(0.0039)
Broad Degree Field	Hard Science & Engineering	Business	Social Sciences	Humanity	Health	Education
Model	TSLS	TSLS	TSLS	TSLS	TSLS	TSLS
Home Country FE	Y	Y	Y	Y	Y	Y
US Degree Cohort FE	Y	Y	Y	Y	Y	Y
US Degree Level FE	Y	Y	Y	Y	Y	Y
US Degree Field FE	Y	Y	Y	Y	Y	Y
US School Ranking Group FE	Y	Y	Y	Y	Y	Y
Bachelor's Year FE	Y	Y	Y	Y	Y	Y
Gender FE	Y	Y	Y	Y	Y	Y
Metro Area FE	Y	Y	Y	Y	Y	Y
Clustered Std. Error	Home Country	Home Country	Home Country	Home Country	Home Country	Home Country
1st Stage F-Stat	58.8	7.5	3.2	2	4.8	2.5
Observations	64,398	66,050	26,213	12,670	8,320	6,793
Mean	0.0491	0.0503	0.0431	0.0534	0.0439	0.0405

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents the results of Equation 1 estimated on subsamples by broad degree fields, using *Founder* as the outcome variable to examine the heterogeneous effects of prior U.S. professional experience on returnee entrepreneurship across fields of knowledge. Standard errors are clustered at the home-country level. Table A1 shows 2-digit CIP fields within each broad degree field category.

Table 7: Heterogeneity by Home-Country Economic Development

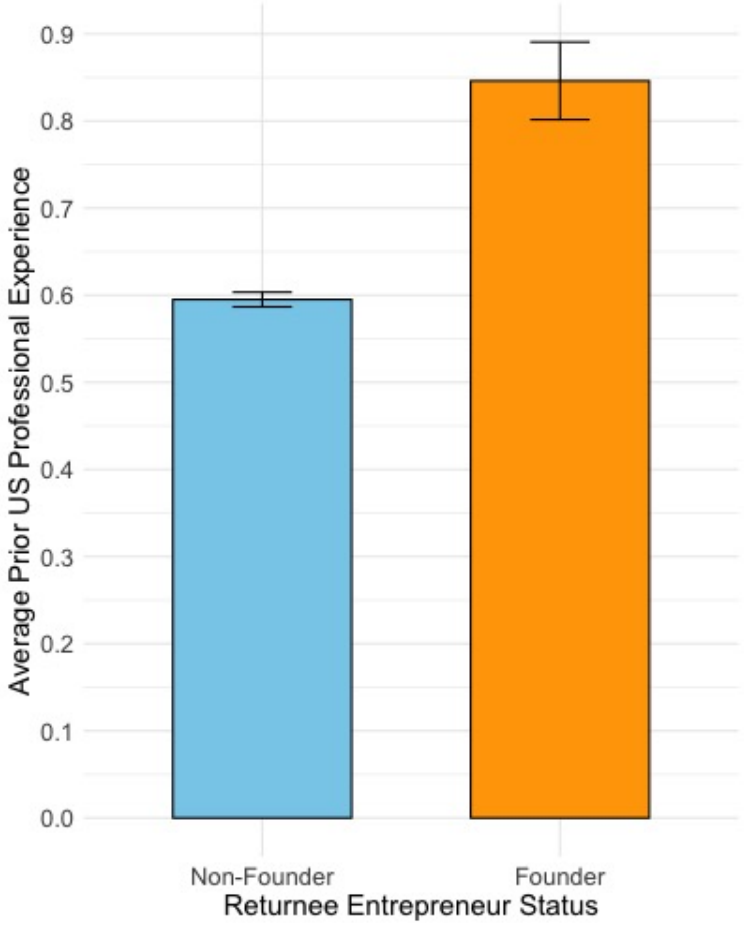
Outcome Variable:	Founder (1)	Founder (2)	Founder (3)
GDP Gap × Green Card Waiting Time	-0.0000**		
	(0.0000)		
Above-Median GDP Gap × Green Card Waiting Time		-0.0012*	
		(0.0006)	
OECD × Green Card Waiting Time			0.0027**
			(0.0009)
Green Card Waiting Time	-0.0007	-0.0018***	-0.0029***
	(0.0008)	(0.0005)	(0.0004)
GDP Gap	-0.0000		
	(0.0000)		
Above-Median GDP Gap		0.0080*	
		(0.0038)	
OECD			-0.0258**
			(0.0079)
Constant	0.0624***	0.0508***	0.0639***
	(0.0061)	(0.0018)	(0.0030)
Model	Reduced Form	Reduced Form	Reduced Form
Home Country FE	Y	Y	Y
US Degree Cohort FE	Y	Y	Y
US Degree Level FE	Y	Y	Y
US Degree Field FE	Y	Y	Y
US School Ranking Group FE	Y	Y	Y
Bachelor's Year FE	Y	Y	Y
Gender FE	Y	Y	Y
Metro Area FE	Y	Y	Y
Clustered Std. Error	Home Country	Home Country	Home Country
Observations	206,591	206,591	206,605
Mean	0.0490	0.0490	0.0490

Standard errors in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents the results of Equation 3, using *Founder* as the outcome variable to examine the heterogeneous effects of prior U.S. professional experience on returnee entrepreneurship across levels of home-country economic development. Standard errors are clustered at the home-country level.

Figure 1: Difference in *USEXP* by Returnee Entrepreneurship Status



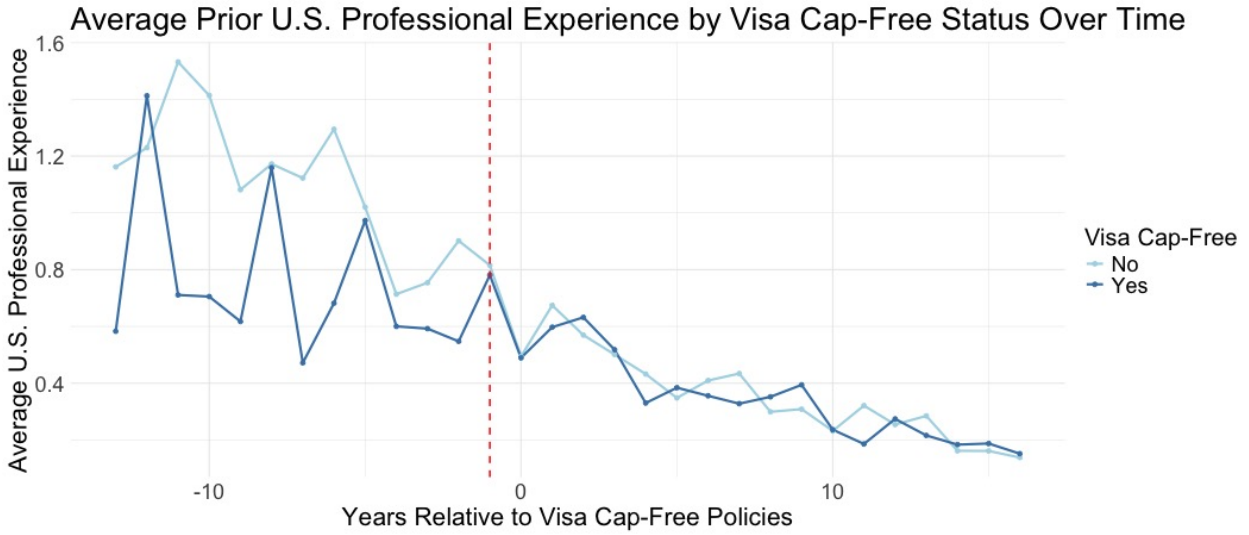
Notes: This figure show the group average and 95% confidence intervals of *USEXP*, prior U.S. professional experience, by returning migrants' entrepreneur status in their home countries.

Figure 2: Correlation between *USEXP* and Returnee Entrepreneurship



Notes: This figure illustrates the relationship between *USEXP* (prior U.S. professional experience) and returning migrants' propensity to found startups in their home countries. The plot shows binned averages of *USEXP* and *Founder*—the main outcome of this paper—across 20 bins, along with a linear fit and its confidence interval. Observations with $USEXP = 0$ are pooled into a single bin due to the large number of zeros in the variable.

Figure 3: Trend in Prior U.S. Professional Experience of Returning Migrants by Visa Cap-Free Status



Notes: This figure depicts the average *USEXP* (prior U.S. professional experience) of returning migrants by their home countries' visa cap-free status and U.S. graduation year, relative to the effective introduction of visa cap-free policies. The averages are constructed by first computing country-level means and then averaging these means within each visa cap-free status group. The visa cap-free group includes citizens of Australia, Canada, Chile, Mexico, and Singapore. Citizens of Canada, Chile, Mexico, and Singapore became visa cap-free in 2004, while Australians became visa cap-free in 2005.

Figure 4: Instrument Validity: U.S. Visa Policy Changes



Notes: This figure presents coefficient estimates and 95% confidence intervals from Equation 2, using *USEXP* as the outcome variable. The estimates examine the yearly average treatment effect of the visa cap-free policy on prior U.S. professional experience among returning migrants from five visa-cap-free countries (Australia, Canada, Chile, Mexico, or Singapore). Standard errors are clustered at the home-country level.

Figure 5: Instrument Validity: Green Card Waiting Time



Notes: This figure shows the correlation between residualized *USEXP* (prior U.S. professional experience) and Green Card Waiting Time. *USEXP* is residualized by home-country and U.S. degree-cohort fixed effects.

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Appendix

A1 Computation of Green Card Waiting Time

There are 3 typical categories for high-skilled migrants: EB-1, EB-2, and EB-3. EB-1 is for individuals that can demonstrate their extraordinary ability in their fields (e.g., Nobel Prize), are outstanding professors and researchers, or multinational managers of executives. The last subcategory unlikely applies to my research context.

EB-2 is for those with a graduate degree, bachelor's degree + 5 years of professional experience, or those who can additionally prove to have substantial merit and national importance. The last subcategory is different from other EB-2 subcategories in that it waives the Program Electronic Review Management" (PERM) labor certification process that requires the Department of Labor to verify no qualified U.S. workers are available for the role. Despite this waiver, EB-2 NIW applicants share the same green card waiting queue with other EB-2 applicants (the waiting queue will be explained below). PhD holders are common applicants for EB-2 NIW.

EB-3 is for those with a bachelor's degree, skilled workers with + 2 years of professional experience, or unskilled workers who fill jobs that cannot be filled with native workforce.

Applicants to green cards receive a priority date, which is either the date the Department of Labor receives the labor certification application, or the date USCIS receives Form I-140 if no labor certification is required. USCIS also sets a final action date for each category, indicating the priority date of applications that are currently available for approval. The final action date serves as a cutoff: if an applicant's priority date is earlier than the final action date, a visa is available. Green card applications within each category are processed on a first-come, first-served basis; when demand exceeds processing capacity, only applications that can be handled are processed, and the latest priority date among these processed applications becomes the final action date. The US government publishes the final action date monthly in its Visa Bulletin, allowing applicants to track their status U.S. Department of State (2026).[9]

Figure A1 shows the final action dates for Chinese citizens across different categories for each fiscal month of 2007. The column under the name "1st" shows the final action date for EB-1, "2nd" for EB-2, and "3rd" for EB-3. Columns labeled "1st," "2nd," and "3rd" correspond to EB-1, EB-2, and EB-3 categories, respectively. Table entries can take one of three forms: "C," "U," or an actual date. "C" (current) indicates no backlog; applications submitted that month are immediately available for visa issuance, conditional on completing paperwork. For example, in February 2007, the final action date was "C." "U" (unavailable) indicates that the annual cap has been reached, and no visas are available for issuance. An actual date represents the latest priority date of an application that was available for issuance. Occasionally, final action dates retrogress due to updated government estimates of demand, and in some cases, dates change from "U" to an actual date in subsequent months, though this is rare.

This table provides insight into the typical waiting period for applicants. For instance, in April 2007, the final action date for EB-2 was April 22, 2005. Subtracting this from April 2007 suggests that an applicant with a priority date of April 22, 2005, waited approximately

[9]Because of high demand for green cards among citizens of China, India, Mexico, and the Philippines, each country has a separate table.

two years for their green card. While issuance also requires paperwork and interviews, this analysis abstracts from those additional steps.

i) Picking the final action date for each fiscal year

I compute green card waiting times at the category- and fiscal-year level based on the final action date for each category-year. For each category, I use the following algorithm to select the final action date for each fiscal year:

1) If the final action date in September (the last month of the fiscal year) is neither "U" nor "C," use that date.
2) If the final action date in September is "C," use "C" only if the final action dates in the previous two months were either "C" or "U." Otherwise, use the most recent fiscal month's final action date that is an actual date.
3) If the final action date in September is "U," select the last month in the fiscal year with a final action date that is not "U." This can be either "C" or an actual date. If the selected date is "C," apply the rule in 2). Otherwise, use the most recent fiscal month's actual date.
4) If a month with final action date "C" has fewer than two preceding months (e.g., October or November), use "C" only if the current and previous month (if any) are both "C." Otherwise, use the most recent available actual date.

ii) Computing the difference between fiscal month and final action date

After selecting the final action date for each fiscal year, there is only one observation per fiscal month. Using this data, I compute green card waiting time for each category and fiscal year by subtracting the final action date from the fiscal month. For example, if the final action date and fiscal month in fiscal year 2009 are November 1, 2001, and April 2009, respectively, the estimated waiting time is April 1, 2009 – November 1, 2001 = 7 years and 5 months.[10]

ii) Connecting to the LinkedIn data

Two assumptions are made:

i) International students refer to the most recent green card waiting time when deciding whether to stay and work in the U.S.
ii) In doing so, they consider the waiting time for the most common category corresponding to their degree level.

The first assumption implies that students look at the previous year's green card waiting time. For example, the 2005 cohort would consider the waiting time from fiscal year 2004. Under the second assumption, doctorate degree holders refer to EB-1, master's degree holders to EB-2, and bachelor's degree holders to EB-3. Some doctorate holders may apply under EB-2 NIW; when I matched these individuals with EB-2 waiting times, the results were unchanged.

[10]For simplicity, I use the 1st day of the month. The USCIS final action date table reports only year and month.

Table A1: Broad Degree Field Mapping

Hyper Field	CIP Title (2-digit)
Hard Science & Engingeering	AGRICULTURAL/ANIMAL/PLANT/VETERINARY SCIENCE AND RELATED FIELDS.; NATURAL RESOURCES AND CONSERVATION.; ARCHITECTURE AND RELATED SERVICES.; COMMUNICATIONS TECHNOLOGIES/TECHNICIANS AND SUPPORT SERVICES.; COMPUTER AND INFORMATION SCIENCES AND SUPPORT SERVICES.; ENGINEERING.; ENGINEERING/ENGINEERING-RELATED TECHNOLOGIES/TECHNICIANS.; BIOLOGICAL AND BIOMEDICAL SCIENCES.; MATHEMATICS AND STATISTICS.; PHYSICAL SCIENCES.; SCIENCE TECHNOLOGIES/TECHNICIANS.; CONSTRUCTION TRADES.; MECHANIC AND REPAIR TECHNOLOGIES/TECHNICIANS.; PRECISION PRODUCTION.; TRANSPORTATION AND MATERIALS MOVING.
Business	BUSINESS, MANAGEMENT, MARKETING, AND RELATED SUPPORT SERVICES.
Social Sciences	COMMUNICATION, JOURNALISM, AND RELATED PROGRAMS.; LEGAL PROFESSIONS AND STUDIES.; PSYCHOLOGY.; PUBLIC ADMINISTRATION AND SOCIAL SERVICE PROFESSIONS.; SOCIAL SCIENCES.
Humanity	AREA, ETHNIC, CULTURAL, GENDER, AND GROUP STUDIES.; FOREIGN LANGUAGES, LITERATURES, AND LINGUISTICS.; FAMILY AND CONSUMER SCIENCES/HUMAN SCIENCES.; ENGLISH LANGUAGE AND LITERATURE/LETTERS.; LIBERAL ARTS AND SCIENCES, GENERAL STUDIES AND HUMANITIES.; LIBRARY SCIENCE.; PHILOSOPHY AND RELIGIOUS STUDIES.; THEOLOGY AND RELIGIOUS VOCATIONS.; VISUAL AND PERFORMING ARTS.; HISTORY.
Health	HEALTH PROFESSIONS AND RELATED PROGRAMS.
Education	EDUCATION.
Other	CULINARY, ENTERTAINMENT, AND PERSONAL SERVICES.; MILITARY SCIENCE, LEADERSHIP AND OPERATIONAL ART.; MILITARY TECHNOLOGIES AND APPLIED SCIENCES.; MULTI/INTERDISCIPLINARY STUDIES.; PARKS, RECREATION, LEISURE, FITNESS, AND KINESIOLOGY.; HOMELAND SECURITY, LAW ENFORCEMENT, FIREFIGHTING AND RELATED PROTECTIVE SERVICES.

Notes: This table presents the mapping between broad degree fields and 2-digit CIP fields used for aggregation.

Figure A1: Example of Green Card Final Action Date Table

FY-2007	1st	2nd	3rd
Oct.	C	1-Apr-05	1-May-02
Nov.	C	15-Apr-05	1-Jul-02
Dec.	C	22-Apr-05	1-Aug-02
Jan.	C	22-Apr-05	1-Aug-02
Feb.	C	22-Apr-05	1-Aug-02
Mar.	C	22-Apr-05	1-Aug-02
Apr.	C	22-Apr-05	1-Aug-02
May	C	22-Apr-05	1-Aug-02
June	C	1-Jan-06	1-Jun-03
July	C	C	C
Aug.	U	U	U
Sept.	1-Jan-07	1-Jan-06	U

Notes: This figure shows a portion of the final action date table for Chinese applicants, as provided by U.S. Department of State (2026).