Skilled Immigration Frictions as a Barrier for Young Firms*

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Abstract

This paper examines the impact of immigration policy frictions on technology-intensive firms by age cohort. The firm-level empirical evidence shows that H-1B policy restrictions on skilled immigrants directly affect the survival of young firms in technology-intensive sectors. We develop a novel general equilibrium model with firm entry and exit that mimics the policy frictions in the H-1B program. The model matches the age distribution of firms in high-technology sectors and shows that immigration policy reforms that increase the entry of younger firms induce greater exit of older, less productive firms, thereby increasing efficiency.

Keywords: Skilled immigration, start-ups, high-technology firms, firm dynamics

JEL Classification: F22, M13

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1. Introduction

Skilled immigration policies in the United States, particularly those related to the H-1B visa program, impose stiff constraints on firms. This program, the largest channel for hiring temporary foreign workers with at least a bachelor's degree, entails several implicit and explicit costs. Most notably, each fiscal year, private firms are subject to an aggregate quota of H-1B visas. When this quota is reached, visas are allocated through a random lottery.[1] The potentially large impact of these immigration barriers on young, emerging firms in technology-intensive sectors has often been overlooked.

Firms in high-tech sectors account for 65 percent of the demand for skilled foreign workers as measured by the number of Labor Condition Applications (LCAs).[2] In multiple surveys, entrepreneurs have mentioned that H-1B policy restrictions are particularly burdensome for new firms. GAO (2011) reports that in years when visas were limited by the cap, most of the established firms found alternative ways to hire their preferred candidates. For instance, multinational firms can hire skilled foreign workers in offshore subsidiaries (Glennon, 2020) and have them reapply to the lottery in subsequent years if necessary. In contrast, small tech startups are more likely to fill their positions with second-best candidates in the face of pervasive labor shortages. This often leads to delays and economic losses, especially for firms considering entry into rapidly changing technology fields that require highly specialized skills.

Taken together, this may have contributed to a striking observation: Despite breakthrough technological advances in recent decades, the share of high-tech firms among all existing new firms has declined since the early 2000s. See Figure 1a.[3] Important for our analysis, this decline in the share of high-tech startups cannot be explained by business consolidation driven by an increase in the market power of *big-tech* firms. In fact, there has been an increase in the share of small, less productive firms (with 1–19 employees) in the oldest age cohort of high-tech firms (ages 11 and

[1] Appendix A describes the H-1B visa policy.

[2] This is the first step for hiring via the H-1B program. Firms need to specify the number of foreign workers they would like to hire. These are level-1 high-tech firms, of which 74 percent are from information technology (IT) services high-tech sectors, and the rest are manufacturing high-tech firms. Our definitions of manufacturing versus IT high-tech firms follow Decker et al. (2016b).

[3] Appendix Figure D.13 shows that the number of young non-high-tech and high-tech sectors have faced different trends since the 2000s. Appendix Figure D.14 confirms the faster decline in the share of young high-tech firms compared to young non-high-tech firms in recent years.

older), which could arguably be the byproduct of a less competitive environment. See Figure 1b. In contrast, in the non-high-tech sector, there is a clear downward trend in the share of the smallest firms among the oldest firms, which is consistent with higher market concentration (Appendix Figure D.15). This aging of the high-tech sector firms and the increase in the share of smaller firms within older firms coincided with a period of more restrictive immigration policy for skilled workers. As shown in Appendix Figure D.12, the H-1B cap fell from 195,000 in 2003 to 85,000 in 2005 and has remained constant since then. At the same time, there has been a notable increase in the demand for skilled foreign workers during this period (as shown by the number of LCAs).

While there is extensive literature on the impact of US skilled immigration policy, to our knowledge, no study has specifically examined the direct impact of current policy frictions on younger firms in technology-intensive sectors and their spillovers to the broader economy. This paper aims to fill this gap by measuring the direct impact of migration frictions with firm-level data, while assessing their general equilibrium implications for different firm-age cohorts through the lens of a quantitative model that is also disciplined by the data.

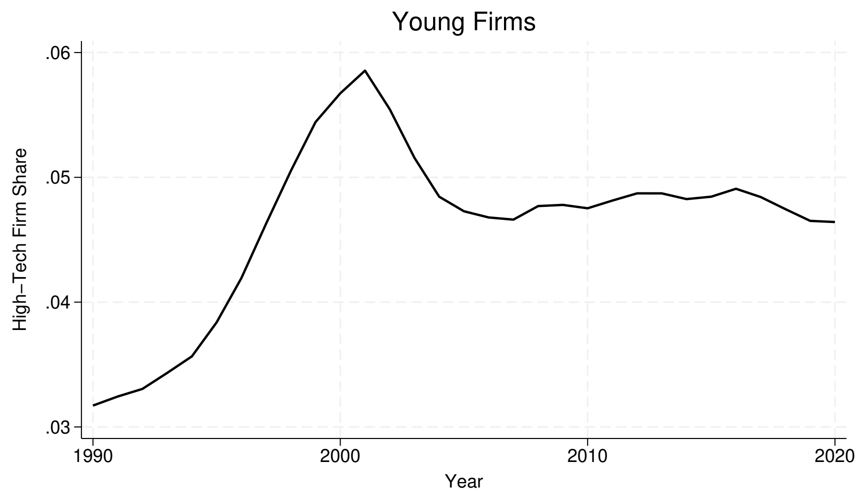
For our motivating evidence, we estimate the impact of H-1B visa lottery win rates on firm survival in subsequent years.[4] To do this, we combine proprietary establishment-level data from the National Establishment Time Series (NETS) with firm-level data on LCAs and H-1B petitions. Our findings confirm that higher H-1B visa lottery win rates significantly increase the survival of young firms (less than 5 years of age) in technology-intensive sectors, while this impact is not significant for older firms.

We then incorporate skilled immigration policy frictions that mimic the actual H-1B policy into a general equilibrium model based on Hopenhayn and Rogerson (1993) to show that eliminating these frictions increases average productivity in the high-tech sector. The main mechanism is through the increased entry and survival of younger firms, which induces a greater exit of older, less productive firms.

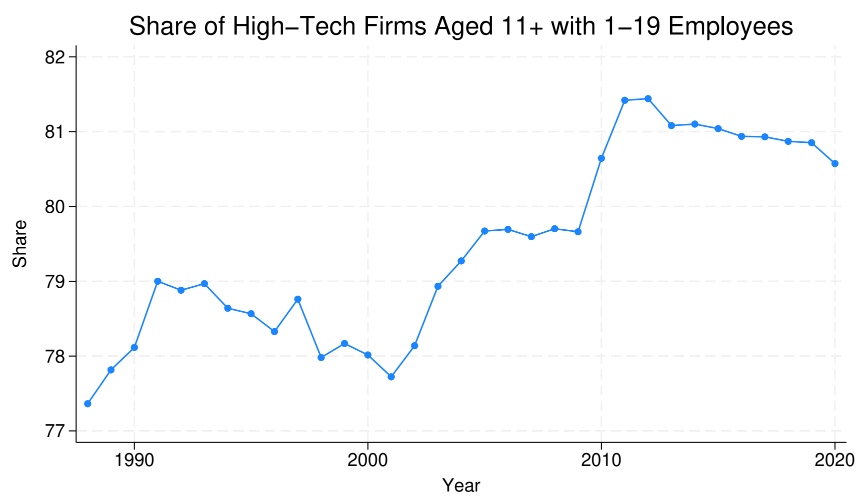
To account for the complexities of the actual H-1B visa policy, our model includes three immigration policy-related frictions for firms seeking to hire skilled foreign workers. First, there is a one-time sunk cost, which represents the cost of learning the immigration rules for skilled workers

[4]We measure H-1B lottery win rates using a similar approach to Dimmock et al. (2021) and recently Mahajan et al. (2024).

Figure 1. Shares of High-Tech Firms over Time



(a) Share of High-Tech Young Firms in All Young Firms



(b) Share of Small Firms within Older Firms: High-Tech

Notes: Figures 1(a) and 1 (b) are compiled using the US Census Bureau's Business Dynamics Statistics (BDS). High-tech firms are computed using four-digit NAICS codes and the BLS classification (Heckler, 2005). Young firms are defined as those with ages between 0 and 5.

and building relationships with law firms that can help with the legal process of hiring foreign workers. Any policy change that would make it easier for firms to submit their applications would lower such costs. Second, firms that have paid the sunk cost may face a negative idiosyncratic hiring shock that prevents them from hiring additional skilled foreign workers. This hiring shock captures the H-1B lottery in a closed-form manner, as some firms cannot hire foreign workers even if they are willing to pay the cost. Third, there is a per-employee hiring fee paid by firms that have overcome the first two frictions and end up hiring skilled foreign workers in a given period. This mimics the H-1B petition fee required for each worker.[5]

The model is calibrated to the US economy between 2005 and 2020 using data from the Business Dynamics Statistics (BDS), the Current Population Survey (CPS), and the US Citizenship and Immigration Services (USCIS). The distribution of firms in the model by age cohort matches the corresponding distribution in the data. Using the value function iteration method to solve for the decentralized equilibrium, our model demonstrates how changes in immigration policy can affect firm dynamics and changes in average firm productivity.

The removal of all migration barriers in the model leads to a higher mass of entrants, a lower exit rate of younger firms, a larger stock of foreign workers, and higher aggregate skill-intensive output, but with lower average output per firm. The presence of a higher mass of firms in the economy increases competition and reduces the profits of incumbents. Over time, older and less productive incumbents are forced out of the market, raising the average productivity of all firms.

Removing all barriers to high-skilled immigration would be an unrealistic policy scenario in practice. Therefore, we use our model as a laboratory to evaluate more nuanced immigration policy alternatives that could potentially boost firm dynamism in the economy while limiting the impact on the domestic labor force. We first consider an increase in the immigration cap that specifically targets young firms for only the first few years of their life, and then a policy that does not change the total number of new skilled immigrants, but simply reallocates the existing cap from older firms to younger firms. We show that these limited policy interventions can generate relatively more firm entry while inducing old and unproductive firms to exit the market, thereby raising average firm productivity. Such limited policy interventions would be more feasible to implement in a realistic

[5]Note that only employers of approved petitions have to pay this fee, which is similar to our model assumption.

institutional setting.

Next, we consider other policies that do not change the immigration cap but lower the hiring costs of immigrants (e.g., by streamlining the application process) or lower the entry costs of new firms (e.g., by making it less costly for foreign workers to obtain a start-up visa to start a new firm in technology-intensive sectors). We show that these policies can also significantly increase firm entry and raise average productivity, again with limited losses to domestic skilled workers.

All these results indicate that the general equilibrium effects of skilled immigration policy frictions on different firm age cohorts are powerful and key to understanding the far-reaching effects of immigration in the economy. This is the main contribution of our study.

2. Related Literature

Our main contribution is theoretical. To the best of our knowledge, this is the first quantitative model to assess the misallocation effect of immigration policy on the entry, survival, and productivity of firms in skill-intensive sectors and its implications for the broader economy. As such, our study adds to the extensive list of papers studying the general equilibrium impacts of US skilled immigration. Notable contributions include, Bound et al. (2015); Waugh (2018); Bound et al. (2017); and Mehra and Shen (2022).[6] None of these papers focus on the general equilibrium impacts of skilled immigration policy frictions on firms by different age cohorts. Our model is also closely related to the literature studying the role of firm entry and exit dynamics in response to aggregate shocks (e.g., Hopenhayn 1992 and Clementi and Palazzo 2016). Using BDS data, Sedláček (2020) also finds that changes in firm entry impact the economy both directly and indirectly as start-up cohorts age. While these firm-dynamics papers focus on the aggregate impacts of productivity shocks and recessions, ours highlights instead the distortions imposed by skilled immigration policies.

Our model is also related to a nascent literature that examines the link between ageing societies and the firm entry deficit. Notable contributions include Hopenhayn et al. (2022); Karahan et al. (2022); and Pugsley and Şahin (2019). Our results not only show that increased immigration

[6] Waugh (2018) uses a model with firm heterogeneity and skilled-biased productivity. The author shows that an expansion of H-1B visas causes new firms to enter the market, due to an anticipated increase in skilled labor availability and market size. Mehra and Kim (2023) study the general equilibrium impacts of the offshoring mechanism.

can offset the effects of demographic transitions on business formation, but we also identify in the microdata a direct link between high-skilled immigration frictions and firm survival for tech start-ups. The paper also relates to the literature studying policy distortions and the aggregate impacts of allocative efficiency across heterogeneous firms. Hopenhayn and Rogerson (1993) evaluate the equilibrium effects of tax policies on the labor market. Gabler and Poschke (2013) build a model with endogenous risky experimentation decisions chosen by firms. Bento and Restuccia (2017) and Ranasinghe (2014) assess the quantitative impact of policy distortions.[7]

The literature examining the impact of immigration policy on the performance of new firms is largely empirical. Dimmock et al. (2021) show that start-ups with higher win rates of H-1B visas were more likely to access credit, implement successful initial public offerings, and file patents. In contrast, our new empirical evidence focuses on the firm dynamics of young high-tech firms. Consistent with the evidence motivating our analysis, Haltiwanger et al. (2014) emphasizes the important role of young (ages 0–5), high-tech businesses in job creation and productivity and document the secular decline in the number of young high-tech firms after 2002.[8]

Mahajan (2022) shows that inflows of immigrant workers lead to an increased exit of establishments in smaller (less productive) firms. This evidence is consistent with our model's main mechanism—higher immigrant inflows cause new firms to enter the market, leading to the exit of older, less productive firms. Mahajan et al. (2024) find that skilled-intensive firms expand the most after winning the H-1B lottery. Orrenius et al. (2020) use the NETS database (from 1997 to 2013) and CPS data and find that immigration (particularly of less-educated individuals) boosts business survival and raises employment by reducing job destruction. Similarly, Olney (2013) uses data from the CPS and US Businesses' statistics to find that an increase in unskilled immigrants raised the number of establishments between 1998 and 2008. Finally, this paper is related to the empirical literature on the impact of skilled immigration in the United States (via the H-1B policy) on firms, cities, productivity, and hiring practices (Kerr et al., 2014; Kerr and Lincoln, 2010; Kerr

[7] Mukoyama and Osotimehin (2019) study the effects of firing taxes on reallocation, innovation, and productivity growth. Last, Sedlacek and Sterk (2019) investigate the long-run effect of the 2017 tax reforms on firm dynamics.

[8] Decker et al. (2016a) review the overall declining trends in business dynamism. Decker et al. (2016b) also highlight that since 2000, the decline in business dynamism and entrepreneurship has been accompanied by a decline in young high-growth firms, which have conventionally played an important role in boosting US job and productivity growth.

et al., 2013; Doran et al., 2016; Peri et al., 2014; Peri et al., 2015a; Ottaviano et al., 2018; Glennon, 2020; Raux, 2023).

3. Empirical Evidence

To further motivate our focus on young firms in technology-intensive sectors, we first use firm-level data to show that skilled immigration policy frictions (via the H-1B visa policy) affect young firms in technology-intensive sectors. We evaluate the impact of H-1B lottery win rates on firm survival in the years following the lottery. Our identification strategy exploits the exogenous variation in firms' H-1B visa lottery outcomes to establish whether access to skilled foreign workers constrains a firm's ability to continue operations.

3.1. Data

H-1B visas were allocated through a lottery in fiscal years 2008 and 2009 and in each fiscal year from 2014 onward.[9] We use the lottery years from fiscal years 2014 and 2015 and compute an average H-1B lottery win-rate measure in these years. By focusing on these fiscal years, we avoid the need to address the impact of the Great Recession in the first years in which the lottery was used. The H-1B visa win rate for each firm is measured as the ratio of approved petitions for new workers to the demand for visas, therefore indicating firm-level hiring constraints or firm-level frictions due to H-1B immigration policies.

Our H-1B win-rate measure is similar to Dimmock et al. (2021) and, recently, Mahajan et al. (2024).[10] Appendix B gives details on the datasets used, construction of key variables, existing omissions in the data and how we address them.[11]

We then match the firm-level win rates to firm outcomes using the National Establishment Time-Series (NETS) database by probabilistically matching firms by names and location (city) to create a panel data set from 2011 to 2020. NETS is a proprietary source of US business microdata

[9] In other years, visas were granted on a first-come-first-served basis since the cap was reached after the filing period.

[10] The latter use the fiscal year 2008 lottery year. Similar to them, we remove outliers in the LCA data.

[11] As discussed in Mahajan et al. (2024), LCAs do not accurately reflect the number of H-1B petitions each company files. While LCAs signal vacancies or firm demand for skilled foreign labor, it is not necessary that firms with approved LCAs actually file H-1B petitions for the number of workers indicated in the LCAs. To address this issue, we remove outliers in the LCAs by winsorizing the data. A description can be found in the Appendix.

based on Dun and Bradstreet (D&B) data. Our final sample includes 15,200 unique firms with win-rate measures matched with the NETS database. Appendix Table B.7 displays the summary statistics of key variables in our sample.

To the best of our knowledge, no previous study has matched H-1B data to the NETS database to evaluate the impacts of the H-1B lottery. Barnatchez et al. (2017) shows that although it does not cover the entire US Census-based employer universe, NETS mimics administrative employer data with reasonable accuracy.[12]

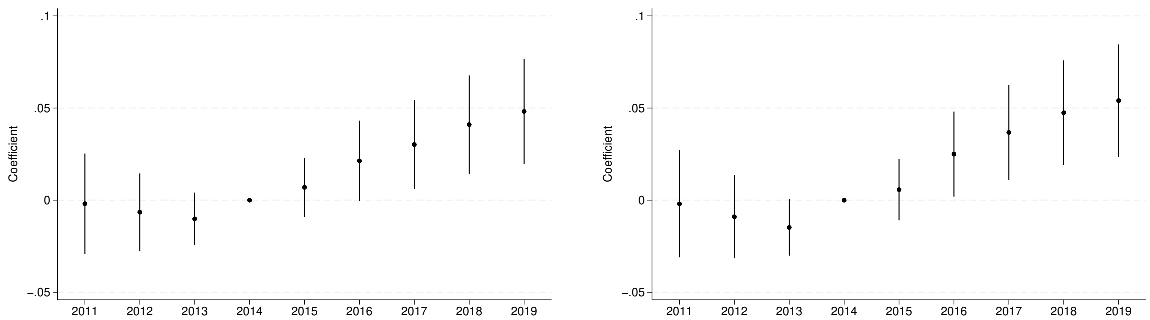
For our main dependent variable, we define $Survive_{i,t} = 1$ if a firm remains active in calendar year t. Note that H-1B lottery outcomes for fiscal years 2014 and 2015 were announced in April 2013 and April 2014, with an employment start date in October 2013 and October 2014, respectively. Therefore, the lottery outcomes in fiscal years 2014 and 2015 correspond to outcomes in calendar years 2013 and 2014, respectively. We define $Survive_{i,t} = 0$ if a firm both became inactive and did not undergo a merger/acquisition. The latter ensures that our firm survival variable does not mistakenly count a merger as a closure. While mergers/acquisitions may be a positive outcome for young firms in technology sectors, we exclude such outcomes given the lack of detailed data in NETS on the values of the mergers/acquisitions.

Next, we check pre-trends in key firm outcomes to make sure that the average lottery win rate was exogenous and unrelated to pre-lottery year firm outcomes. By construction, our key dependent variable, $Survive_{i,t}$ is equal to 1 in pre-lottery years 2011-2013 since firms in our sample had to be active to have submitted applications in at least one of the relevant lottery years.[13] Therefore, we instead analyze pre-trends in other firm outcomes — sales and employment. We use an event study approach to illustrate pre- and post-trends for these outcomes. Appendix B.1 gives details of the event study specification. Figures 2a and 2b shows that both pre-lottery firm sales and employment are uncorrelated with the average 2014-15 win rate, and Appendix B.1 further shows that these results hold when we consider only young firms. The results support our hypothesis that the win rate was not correlated with key firm outcomes in pre-lottery years (2011-2013), while it

[12]According to them, "the largest differences between NETS employer data and official sources are for small establishments, where imputation is prevalent in NETS." This is one reason why we do not use the NETS "sales" and "employees" variables as our dependent variables in our main empirical analysis.

[13]There are some exceptions, for example, new firms that became active in 2013 (or 2012) would be inactive in 2011.

Figure 2. Event Study: Employment and Sales



(a) Employment

(b) Sales

Notes: Coefficient estimates and their 95% confidence intervals for WinRate × Year are reported. Includes firm and year fixed effects.

did impact these outcomes in post-lottery years.

3.2. Main Empirical Specification

To test the impacts of a firm's average lottery win rate in fiscal years 2014 and 2015 on survival in the post-lottery calendar years (2015-2019), we use a difference-in-difference panel regression as follows,

$$Survive_{i,t} = \beta[WinRate_i \times post_t] + \gamma_i + \gamma_t + \epsilon_{i,t}, \tag{1}$$

where $post_t = 1$ if calendar year $t = 2015 - 2019$. γ_i captures firm fixed effects and γ_t captures time-fixed effects.

The results in Table 1 establish that higher average H-1B lottery win rates positively and significantly impact the survival of all firms in the 5 years following the lottery. For the full sample (column 1), firms that won the lottery for 100 percent of the workers they applied for increased their average survival by 2.2 percentage points, compared to those that had all their H-1B applications rejected.[14] The results for "all firms" and "high tech" firms look similar because the large majority of the H-1B applications come from the technology-intensive sectors. When comparing the results across different subsamples of firms, a 100 percent win for a young high-tech firm means, on average, a higher survival by 3.3 percentage points (column 3) compared to a win rate

[14] The results for all firms are similar to that of Mahajan et al. (2024), who find an impact of 2.4 percentage points.

Table 1. Survive

	(1) All Firms	(2) High Tech (HT)	(3) Age < 5 (HT)	(4) Age ≥ 5 (HT)
post× WinRate	0.022***	0.020**	0.033**	0.007
	(0.004)	(0.008)	(0.016)	(0.009)
FE	Yes	Yes	Yes	Yes
Obs.	136603	26565	10380	15522

Standard errors in parentheses

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

Notes: Standard errors (clustered at the firm level) are in parentheses. Post-lottery calendar years include 2015–2019. WinRate is the average H-1B lottery win rate in fiscal years 2014 and 2015.

of 0. In contrast, the impact of the win rate on older firms (aged 5+) is not significant (column 4).

In Appendix B.3, we also analyze the dynamic impacts on firm survival and Appendix Figures B.9 and B.10 indicate a persistent impact of the H-1B lottery win-rate on firm survival for all firms and young high-tech firms but not for older firms (Appendix Figure B.11). In summary, the results confirm our intuition that young firms in technology-intensive sectors are more likely to face constraints of immigration policy frictions relative to older firms.

Next, we try to isolate some potential mechanisms. Is the larger impact of the win rate on young firms solely due to their smaller size relative to older firms? To analyze this, we disentangle the results on firms by firm age and size.

3.2.1. Small vs Young Firms

We run our baseline regression for a separate sub-sample of young firms by size. In the regressions in Table 2, $Young = 1$ for firms that were less than 5 years old in 2013, and $Small = 1$ if the firm had $1 - 10$ employees in 2013.

The results indicate that the larger impact of the win rate on young high-tech firms in our baseline results does not merely stem from the fact that these are small firms. In fact, if a firm is both young and small, then the average impact of the win rate on firm survival is not significant. The results for young high-tech firms are driven by firms that are relatively larger (more than 10 employees).

These results indicate that it is important to consider both age and size in order to understand the impacts of the H-1B lottery win rate in the high-tech sector. Particularly, for younger firms, a relatively larger productive capacity at the time of the lottery seems to increase the impact of the

Table 2. Results by Age and Size for High-Tech Firms

	(1) Age<5	(2) Age<5, Size ≤ 10	(3) Age <5, Size > 10
post$\times$ WinRate	0.033**	0.016	0.086**
	(0.016)	(0.018)	(0.034)
FE	Yes	Yes	Yes
Obs.	10380	8265	2115

Standard errors in parentheses

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

Notes: Standard errors (clustered at the firm level) are in parentheses. Post-lottery calendar years include 2015–2019. WinRate is the average H-1B lottery win rate in fiscal years 2014 and 2015. A firm aged less than 5 years in 2013 is classified to be young and a firm with less than 10 workers in 2013 to be small.

lottery win rate on a younger firm's survival. These results are robust to using a triple difference regression with size interactions. See the Appendix B.2 for details.

To summarize, our results indicate that younger firms in the high-tech sector were more likely to gain from getting a foreign skilled worker on an H-1B visa. This is not only due to the fact that young firms are smaller on average. On the contrary, the impact of the win rate is greater for relatively larger younger firms. This seems to indicate that even within younger high-tech firms, those that are relatively larger or more productive to begin with, gain more from winning the lottery.

Next, we incorporate a more general set of immigration policy frictions that are similar to US policies into a general equilibrium model. This approach allows us to study the impacts of these frictions on high-technology firms by age and on average productivity.

4. Model

The model features a two-sector economy populated by skilled and unskilled households. Sector 1 (the skilled-intensive sector) consists of an endogenous measure of firms subject to optimal entry and exit decisions. This sector is interpreted as the high-tech industry and hires only domestic and foreign skilled workers.

There are two key distinctions between a domestic skilled worker and a foreign skilled worker in the model. First, domestic and foreign skilled workers are imperfectly substitutable as documented in the literature (Ottaviano and Peri 2012).[15] Second, foreign skilled workers have a higher relative productivity than domestic skilled workers. It has been noted that foreign workers foster additional productivity gains (for instance, see Bernstein et al. 2022, Ghosh et al. 2014, and Peri et al. 2015b). In our model, $a > 1$ represents the relative productivity difference between foreign and domestic skilled workers. Apart from the empirical evidence, this assumption is also reasonable because by law, firms must pay a cost for hiring skilled immigrant workers and they also must pay the same prevailing skilled wages to workers.[16] These conditions would generate limited incentives for hiring skilled foreign workers, which is inconsistent with the data on the number of applications submitted for skilled immigrant workers that indicate a sizable demand for such workers. This assumption is also similar to Mehra and Shen (2022). The parameter a will be calibrated to match data moments related to foreign worker demand in Section 4.4.1. Once foreign workers are hired, they remain with the firm until an exogenous separation shock occurs or the firm decides to fire them.

Firms in sector 1 are subject to idiosyncratic productivity shocks and shocks to the hiring of foreign workers. In each period, only an endogenous subset of sector 1 firms hire skilled foreign workers. Skilled immigration policy in the United States imposes regulatory frictions and legal fees that are borne by the firm. To capture this, we assume that sector 1 firms must pay a one-time sunk cost if they want to have the ability to hire skilled foreign workers. This cost captures the time and money spent in gaining knowledge of immigration policies, building relationships with lawyers, and so on. Since not all firms pay this sunk cost, a subset of sector 1 firms produce output using only skilled domestic workers.

In each period, all sector 1 firms hire skilled domestic workers. While sector 1 firms that have already incurred the sunk hiring cost would like to hire foreign workers, additional immigration policy frictions prevent them from doing so each period. We assume that these firms face an idiosyncratic shock in each period that prevents them from hiring additional foreign workers in that period. If an unfavorable hiring shock hits a firm, it can hire at most the foreign workers carried over from the previous period, minus the foreign workers who exogenously leave the country. In

[15]For example, natives may specialize in communication tasks that require more social interaction, while foreigners may have a comparative advantage in mathematical tasks.

[16]When sponsoring a worker for an H-1B visa, a company must attest that it will pay the worker the prevailing wage for that occupation.

contrast, if a favorable shock is realized, the firm can increase the number of foreign workers hired by paying an adjustment cost, i.e., a hiring cost for each foreign worker. The idiosyncratic hiring shock is a simple way of capturing the H-1B lottery.

Firms in sector 2 (the unskilled-intensive sector) are interpreted as other firms that hire relatively low-skilled domestic workers to produce output. This sector consists of one representative firm. The model features complementarities between skilled and unskilled workers through the household consumption bundle, which includes output from both the skilled and unskilled sectors.

We focus on the domestic economy and do not explicitly model the rest of the world. Instead, we assume that there is a foreign country with a large elastic supply of skilled workers that domestic firms can hire. Finally, all prices are expressed in units of the final consumption basket.

4.1. Firms

In this section, we describe the challenges faced by firms in our model, beginning with skilled-intensive firms due to the key role their dynamics play in our framework. We then discuss the issues pertaining to unskilled-intensive firms. Since we write the firms' problems recursively, we suppress the time notation when describing them.

4.1.1. Skilled-Intensive Sector (Sector 1)

The skilled-intensive firms in our model represent the high-tech firms we focus on in this paper, and therefore, we explicitly model their entry and exit decisions. They are owned by skilled domestic households and produce a homogeneous good, maximizing the present discounted value of profits. They use a decreasing returns-to-scale production function $y = f(z, l^s)$, where y is the output and z is the firm-specific productivity and follows a Markov process. l^s is the composite of domestic (l^d) and foreign (l^f) skilled labor. Only firms that have paid the one-time sunk cost, c_s, can hire foreign workers. We refer to firms that hire only domestic skilled workers as type-d firms, and those that hire both domestic and foreign skilled workers as type-f firms. Both types of firms also face an operation cost of c_f in every period.

Hired foreign workers leave their jobs at an exogenous rate of $\delta \in (0, 1)$, and new hires are denoted by $n = l^f - (1-\delta)l^f_{-1}$, where l^f_{-1} is the stock of foreign workers from the last period. New foreign workers start producing in the same period of hire. Because firms must pay the filing cost of H-1B visas, they face a hiring cost when hiring foreign workers, denoted as $\psi(l^f, l^f_{-1})$. The hiring cost, the sunk cost, and, the operation cost are all denominated in units of the skilled-intensive sector good.

Incumbent firms. At the beginning of each period, an incumbent firm, whether type d or type f, decides on whether to exit the market or continue operations. The decision is based on the firm-specific stock of foreign workers, l^f_{-1} (0 for type d), and productivity from the last period, z_{-1}. If the firm decides to exit the market, it receives an outside value of 0 and fires all remaining foreign workers. If the firm decides to continue operations, a type-d firm may pay the sunk cost, c_s, to become a type-f firm in the same period.

Next, both types of firms learn their new productivity, which evolves based on a log AR(1) process

$$\log(z) = (1 - \rho_z)\mu_z + \rho_z \log(z_{-1}) + \varepsilon, \tag{2}$$

where ε is a firm-specific productivity shock. After learning about its productivity, a type-f firm faces an idiosyncratic hiring shock, which determines if it can hire additional foreign workers in the same period.

Both types of firms then make hiring decisions. Type-d firms only hire domestic workers, while type-f firms can hire foreign workers by paying hiring costs ($\psi(l^f, l^f_{-1})$). If a type-f firm receives an unfavorable hiring shock, it can produce with at most $(1 - \delta)l^f_{-1}$ foreign workers and as many domestic workers as it wants. With a favorable hiring shock, a type-f firm can hire as many domestic and foreign workers as it wants. All firms pay the operation cost, c_f, and produce the sector 1 good. Each firm is also small, so it takes the prices and wages as given when deciding. Denote $V^{ID}(z_{-1})$ and $V^{IF}(l^f_{-1}, z_{-1})$ as the beginning-of-period values for the incumbent type-d and type-f firms. The value of a type-d firm that decides to stay but does not become a type-f firm is given by

$$W^d(z) = \max_{l^d} \left\{ \left[p_1 f(z, l^s) - p_1 c_f - w_s l^d \right] + \beta V^{ID}(z) \right\} \tag{3}$$

$$\text{s.t. } l^s = l^d. \tag{4}$$

The value of a type-f firm that decides to remain in the market but is adversely affected by an unfavorable hiring shock (i.e., the firm loses the lottery) is given by

$$W^{fu}(l_{-1}^f, z) = \max_{n, l^f, l^d} \left\{ \left[p_1 f(z, l^s) - p_1(\psi(l^f, l_{-1}^f) + c_f) - w_s(l^d + l^f) \right] + \beta V^{IF}(l^f, z) \right\} \tag{5}$$

$$\text{s.t. } l^f = n + (1-\delta) l_{-1}^f, \tag{6}$$

$$n \leq 0, \tag{7}$$

$$l^s = \left[\left(l^d\right)^\gamma + \left(a l^f\right)^\gamma \right]^{\frac{1}{\gamma}}, \tag{8}$$

where $\psi(l^f, l_{-1}^f)$ is the hiring cost of an additional foreign worker, with $\psi(l^f, l_{-1}^f) > 0$ if $l^f > (1-\delta) l_{-1}^f$ and 0 otherwise. p_1 is the price of the skilled-intensive sector good. l^s is the aggregate skilled labor hired by the firm, and $1/(1-\gamma)$ is the elasticity of substitution between skilled domestic and foreign workers. $\beta \in (0, 1)$ is the subjective discount factor for the skilled domestic households, who are the owners of the skilled-intensive sector firms.[17]

A type-f firm that decides to stay but receives a favorable hiring shock (i.e., wins the lottery) can hire additional skilled foreign workers and face the following problem:

$$W^{ff}(l_{-1}^f, z) = \max_{n, l^f, l^d} \left\{ \left[p_1 f(z, l^s) - p_1(\psi(l^f, l_{-1}^f) + c_f) - w_s(l^d + l^f) \right] + \beta V^{IF}(l^f, z) \right\} \tag{9}$$

$$\text{s.t. } l^f = n + (1-\delta) l_{-1}^f, \tag{10}$$

$$l^s = \left[\left(l^d\right)^\gamma + \left(a l^f\right)^\gamma \right]^{\frac{1}{\gamma}}. \tag{11}$$

At the beginning of the period, firms decide whether to exit the market or continue operations. Specifically, firms that have foreign workers at the beginning of the period solve

$$V^{IF}(l_{-1}^f, z_{-1}) = \max \left\{ W^F(l_{-1}^f, z_{-1}), 0 \right\}, \tag{12}$$

where $W^F(l_{-1}^f, z_{-1}) = \mathbb{E}_{z|z_{-1}} \left[q \times W^{ff}(l_{-1}^f, z) + (1-q) \times W^{fu}(l_{-1}^f, z) \right]$ and q is the probability

[17] The model is constructed in such a way that the only sources of uncertainty are the idiosyncratic productivity shock and the foreign worker hiring cost. There are no aggregate shocks, and as a result, the model admits a stationary distribution. This implies that households' consumption is constant over time. Consequently, it is equivalent to assuming that the firm discounts the future using the skilled households' stochastic discount factor.

that an incumbent type-f firm receives a favorable hiring shock. We normalize the value of exiting the market to 0.

Here, we can note the intuition behind why higher q (or lower frictions imposed by the hiring cap) would indicate that type-f firms are more likely to continue operations, all else equal, consistent with our empirical results. The gains from hiring foreign workers implies that the continuation value of firms that receive a favorable shock is greater than the continuation value if a firm does not receive that favorable shock ($W^{ff} > W^{fu}$). Therefore, in the presence of lower hiring frictions (higher q), the expected value of continuing operations $W^F(l_{-1}^f, z_{-1})$ would be higher, thus allowing more firms to continue operations, all else equal. This could potentially be more beneficial for younger firms that may have a lower z in the beginning stages of their life-cycle.

For an incumbent type-d firm, it can choose to either exit the market, stay in the market and continue to be type d, or stay in the market and pay a sunk cost c_s to become type f. Specifically, its value function is

$$V^{ID}(z_{-1}) = \max\left\{\mathbb{E}_{z|z_{-1}} W^d(z), W^F(0, z_{-1}) - p_1 c_s, 0\right\}. \tag{13}$$

Since the value function $V^{IF}(l_{-1}^f, z_{-1})$ is increasing in the productivity z_{-1}, there exists a productivity cutoff point $z^{I*}(l_{-1}^f)$ for each level of l_{-1}^f such that firms with a productivity $z_{-1} \geq (<) z_f^{I*}(l_{-1}^f)$ will choose to continue operations (exit the market). A similar argument applies to type-d firms.

New entries. There is free entry of firms. After paying a cost of c_e, an entrant may enter the market and draw a z_{-1} from a distribution.[18] Then, the new entrant, just like incumbents, can choose to immediately exit or continue operations. Similar to Hopenhayn and Rogerson (1993) and Sedlacek and Sterk (2019), we assume the entrants start as type-d firms.

Denote $V^e(z_{-1})$ as the value of the new entry with a productivity z_{-1} drawn. Free entry implies that firms keep entering the market until $\mathbb{E}_e V^e(z_{-1}) = p_1 c_e$. The endogenous entry decisions allow us to quantitatively evaluate the effects of immigration policies on new firm formation.

Since the entering firms face the same problem as the incumbent type-d firms, the continuing

[18] The entry cost is also denominated in units of the sector 1 good.

entering firm's problem is given by

$$W^e(z) = W^d(z). \tag{14}$$

Then, the value of the newly entered firm $V^e(z)$ is defined as

$$V^e(z_{-1}) = V^{ID}(z_{-1}). \tag{15}$$

4.1.2. Unskilled Sector (Sector 2)

Sector 2 represents the non-high-tech industries, and its output is produced by a continuum of identical firms with a production function

$$Y_2 = L_u, \tag{16}$$

where L_u is the unskilled labor supplied by the unskilled households, which will be discussed in the next section. The firm's marginal cost of production is w_u, which is the wage paid to domestic unskilled labor. Therefore, the price of the representative sector 2 good in units of the consumption basket is given by $p_2 = w_u$.

4.2. Households

There are three types of representative infinite-lived households: skilled domestic (s), unskilled domestic (u), and skilled immigrants or foreign workers (f). We have foreign workers as a separate type of household in the model to capture the fact that foreign-born workers are a non-negligible component of the US labor force.[19] Moreover, by including separate domestic skilled and unskilled households, our model allows us to perform welfare analysis related to current policy discussions as shown in section 5. We assume that all households supply labor inelastically. The lifetime utility of unskilled domestic, skilled domestic, and skilled foreign households are

$$\max_{\{C_{j,t}\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \ln(C_{j,t}), \quad j \in \{u, s, f\}, \tag{17}$$

[19] In 2023, the foreign-born accounted for 18.6 percent of the US civilian labor force and more than 40% of foreign-born had a bachelor's degree or higher. Data source: https://www.bls.gov/news.release/forbrn.htm.

where $\beta \in (0, 1)$ is the subjective discount factor and $C_{j,t}$ represents the consumption basket for household j in period t. Denote L_u, L_s, and L_f as the measures of the unskilled domestic, skilled domestic, and skilled foreign households, and assume they supply one unit of labor.

The aggregate consumption baskets $C_{j,t}$ for each household $j \in \{u, s, f\}$ include sub-baskets of outputs from the skilled labor-intensive (sector 1) and unskilled labor-intensive (sector 2) firms:

$$C_{j,t} = \left(\frac{C^1_{j,t}}{\alpha_y}\right)^{\alpha_y} \left(\frac{C^2_{j,t}}{1-\alpha_y}\right)^{1-\alpha_y}, \tag{18}$$

where $C^1_{j,t}$ and $C^2_{j,t}$ are the basket of goods produced by firms in sectors 1 and 2, respectively. The weight of the sector 1 good in consumption is $\alpha_y \in (0, 1)$.

Since the representative skilled domestic household owns all the firms in the skilled-intensive sector, its budget constraint is given by

$$C_{s,t} = w_{s,t} L_{s,t} + D_t, \tag{19}$$

where D_t is the aggregate profit from all the sector 1 firms. On the other hand, the domestic unskilled and skilled foreign households consume their labor income each period, yielding the budget constraints

$$C_{u,t} = w_{u,t} L_{u,t}, \tag{20}$$

$$C_{f,t} = w_{s,t} L_{f,t}. \tag{21}$$

The demand for each type of good by the households is given by

$$C^1_{j,t} = \alpha_y \frac{C_{j,t}}{p_{1,t}}, \tag{22}$$

$$C^2_{j,t} = (1-\alpha_y) \frac{C_{j,t}}{p_{2,t}}, \tag{23}$$

where $j \in \{u, s, f\}$. $p_{1,t}$ and $p_{2,t}$ are the prices of sector 1 and 2 goods, respectively, in units of the final consumption basket. Last, the consumption-based price index can be expressed as

$$1 = (p_{1,t})^{\alpha_y} (p_{2,t})^{1-\alpha_y}. \tag{24}$$

4.3. Aggregation

Due to the idiosyncratic productivity and hiring costs, the firms in sector 1 are heterogeneous in the sense that they have different foreign workers and productivity. Since all the uncertainties are idiosyncratic shocks in the skilled-intensive sector, this economy admits stationary distributions of firms. On the other hand, all the aggregate variables are constant over time. We denote the distributions of type-d and type-f firms as $\mu_d(z)$ and $\mu_f(l^f, z)$. The productivity distribution of new entrants is denoted as $\mu_e(z)$. In the interest of space, the aggregate variables are defined in Appendix C.

4.4. Numerical Results

We solve the model numerically using a two-step method. In the first step, we solve for the w_s/p_1 ratio in sector 1 that satisfies the free entry condition. Specifically, given the w_s/p_1 ratio, we iterate the firms' value functions until the distance between two successive iterations becomes smaller than 10^{-6}. Then, if the free entry condition does not hold (e.g., $|\mathbb{E}_e V^e(z_{-1}) - p_1 c_e| > 10^{-6}$), we revise w_s/p_1 and repeat the above step until the free entry condition is satisfied. In the second step, we use the firms' policy functions we found in the first step to simulate the distribution of sector-1 firms, calculate the aggregate variables, and check whether the skilled domestic labor market clears. If it does not, we revise the entering mass N_e and repeat the second step until the labor market clears. We calculate expectations using 80 quadrature points for the productivity shock.

4.4.1. Calibration and Functional Forms

We specify the functional form of productivity in sector 1 as $y = f(z, l^s) = z l^{s\theta}$, where θ is the span of control. The foreign labor adjustment cost is set to $\psi(l^f, l^f_{-1}) = f_r \max\{l^f - (1-\delta) l^f_{-1}, 0\}$. Therefore, the cost is only incurred for the new hiring each period.

For calibrating the model parameters, we adopt an annual calibration such that the stationary equilibrium in the model matches the US economy during 2005–2020. Several parameters are calibrated directly from the data or from findings from prior literature. We set $\beta = 0.96$, which implies an annual real interest rate of 4 percent. The exogenous return shock to foreign skilled labor is set to $\delta = 0.1$, to match the annual return migration rate of 10 percent (North 2011). We normalize the aggregate skilled domestic labor supply to 1 ($L_s = 1$). Given this normalization of skilled domestic labor supply, we then calibrate the unskilled domestic labor supply to $L_u = 1.92$ to match the average share of domestic workers with less than a bachelor's degree, approximately 52 percent, over this time period (Current Population Survey).

Additionally, we set $q = 0.35$ to match the average fraction of accepted petitions for skilled foreign workers. γ is set to be 0.9167 to target an elasticity of substitution between domestic and foreign workers of 12 (Ottaviano and Peri 2012). The span of control θ is set to 0.97, which is consistent with the estimates in Basu and Fernald (1997) and more recently Gao and Kehrig (2017). Note that $\theta > \gamma$ implies that skilled domestic workers increase the marginal product of skilled foreign workers and vice versa. We set the persistence of the productivity process to $\rho_z = 0.6$ and the standard deviation of shocks to $\sigma = 0.3$, consistent with the evidence in Foster et al. (2008) for the high-tech sector, and normalize the average productivity μ_z to 1.

We calibrate $\alpha = 0.485$, $f_r = 0.3$, $a = 1.345$, $c_e = 8.1$, $c_f = 3.41$, and $c_s = 14.3$ to jointly match the targets specified in Table 3. Note that the ratio of regulatory cost f_r to skilled wages w_s is computed using data from USCIS on average filing costs and data from the CPS on average skilled wages. The average employment in the high-tech sector and the average exit rate for firms in this sector are computed from the BDS data. The fraction of type-f firms in the high-tech sector that hire skilled foreign workers is computed as the average proportion of high-tech firms that submit LCAs, and the type-d fraction is just $1-$ the type-f fraction.[20] L_f^{demand} refers to the total demand for skilled foreign workers, that is, the sum of demand by the type-f firms that are facing favorable and unfavorable hiring shocks (referred to as type-ff and fu firms) in the model. The corresponding target in the data is computed as the total number of LCAs filed by firms in the high-tech sector (USCIS) as a proportion of total employment in the high-tech sector (BDS).[21] Last, w_s/w_u represents the wage skill premium and is measured using the CPS accessed via IPUMs (Ruggles et al., 2003).

To further evaluate our model, we compare the model-implied distribution of firms across age cohorts with the corresponding distribution in the data for high-tech firms. Note that the distribution was not directly targeted in the calibration. Table 4 shows that our model generates a firm age

[20] We use the total number of high-tech firms from the BDS and the total number of firms submitting LCAs in the high-tech sectors using our cleaned LCA dataset. As long as a firm submits an LCA, it is a type-f firm even if it does not receive approval for an H-1B worker.

[21] The parameter a is most directly related to this data target.

Table 3. Data and Model Moments

Targets	Data	Model
f_r/w_s	0.13	0.13
Average employment	28.18	28.14
Type-d fraction	0.85	0.83
Average exit rate	0.099	0.1
L_f^{demand}/L_s	0.047	0.043
w_s/w_u	1.8	1.8

Table 4. Distribution of Firms and Employees by Age in High-Tech Sector: Data and Model

Firm age	0	1-5	6-10	11+
Share of firms % (data)	10.28	31.15	20.64	37.92
Share of firms % (model)	10.44	35.62	19.92	34

Data source: BDS (2005–2020).

distribution that is close to the data.

4.5. Economy without Immigration Frictions

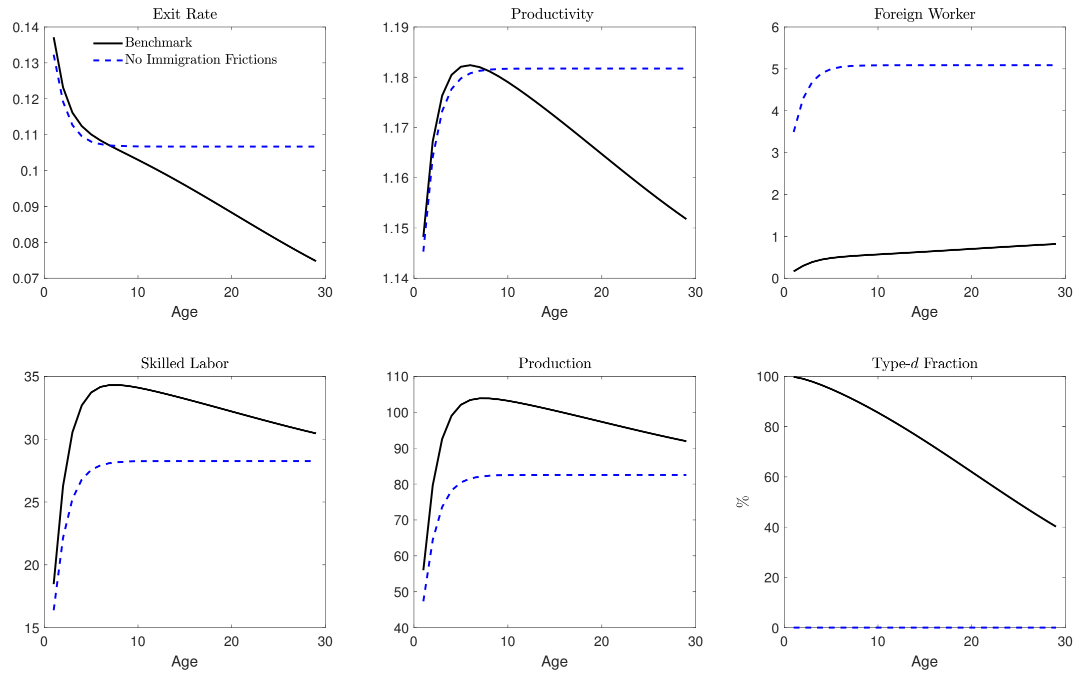
A novel contribution of our model is that we introduce a set of skilled immigration policies that mimic real-world frictions that firms face when hiring foreign workers. This section presents an economy with all the immigration frictions removed ($c_s = 0$, $f_r = 0$, and $q = 1$) and compares it to our baseline economy that includes all frictions. Figure 3 compares the average firm characteristics by age in the no immigration friction case and the baseline economy, and column (7) in Table 5 shows the aggregate variables in the no immigration friction case relative to the baseline case.

As shown in column (7) of Table 5, removing all immigration frictions significantly increases the number of foreign workers and improves firm dynamism in the economy. The removal of policy restrictions on skilled immigration attracts new entrants, which increase by 65%, and leads to an increase in firm mass by 57%. The heightened competition increases the average exit rate by 5.3%, and this exit of less productive firms causes the average productivity of all firms to improve by 0.4%.[22]

Figure 3 shows that removing all immigration frictions does not affect the young and older firms equally. Consistent with our empirical evidence, the first plot shows that removing immigra-

[22]In the firms' stationary distribution in equilibrium, the number of new entrants equals the number of firms exiting the market, which is calculated as the firm mass multiplied by the exit rate in each period.

Figure 3. Average Firm Characteristics by Age in the No Immigration Friction Case



Notes: This figure shows the firms' average exit rate, productivity, foreign worker, skilled labor, production, and the fraction of type-d firms by age in the no immigration friction case and benchmark case.

tion frictions makes young firms more likely to survive in the first few years of their lives, while the heightened competition induces the older and unproductive firms to exit the market at a higher rate. As a result, the second plot illustrates that the average productivity of old firms improves significantly in the no immigration friction case, therefore increasing the overall average productivity of all firms. Due to the increased firm mass, each firm becomes smaller, hires a smaller number of workers, and has lower production in the no immigration friction case, as shown in the fourth and fifth plots in figure 3.

Lastly, in terms of the welfare of domestic households, the higher number of foreign workers increases sector-1 output by 26.4%, which suppresses the price of sector-1 goods and the sector-1 wage. Consequently, the domestic skilled workers suffer a reduction in consumption of 9.4%. On the other hand, the higher number of foreign workers boosts the demand for unskilled sector output, leading to a 12% increase in both the wages and consumption of the unskilled workers.

While the no-immigration friction case presented in this section helps us understand the role of immigration frictions in our model, it is an extreme case that is unlikely to be implemented in reality. In section 5, we discuss the implications of various counterfactual policy changes that are related to current skilled immigration policy discussions.

5. Counterfactual Policy Exercises

Our model is flexible enough to evaluate the implications of various counterfactual policies that mitigate different sets of frictions. We divide our counterfactual exercises according to the following criteria. First, we evaluate policies related to the H-1B cap changes. As noted in Kerr et al. (2020), the most frequently proposed H-1B reform is to raise the annual cap on the H-1B program for for-profit firms. Many proposals fall in the range of 115,000 visas to 195,000 visas and some business leaders even advocate for an unlimited number of visas.[23] Therefore our first set of counterfactual exercises focus on doubling the probability of receiving a foreign skilled worker by increasing q to 0.7 and also $q = 1$ (no restriction on H-1B visas).

Next, we contrast the above cap change policy, which focuses on all firms, with an alternative cap change policy that favors younger firms. This is in line with our motivation that younger firms are more affected by H-1B policy restrictions. We focus on counterfactual policies that (i) increase the cap only for younger firms in their first few years, and (ii) reallocate visas from older firms to younger firms. While there has been no explicit policy proposal for such visa policies toward startups, some policy advocates have proposed that small businesses should have a special annual allocation of H-1B visas.[24] For each type of policy reform, we conduct two counterfactual analyses, one with a mild policy change and the other with a more aggressive policy change. The effects of these counterfactual analyses on aggregate variables are collected in Table 5. Figure 4 presents the firm distributions by age with cap changes, and Figure 5 shows the average firm characteristics by age with different cap changes. Our results show that policies that favor younger firms without changing the overall cap for all firms can have relatively large effects on average productivity without corresponding welfare losses for domestic skilled workers. Therefore, such policies may be important. We discuss the results of these cap-change policies in section 5.1.

In Section 5.2, we discuss counterfactual policies that focus on evaluating the impact of streamlining the H-1B process and making it less burdensome. In our framework, such policies can be evaluated by reducing the sunk cost c_s of hiring foreign workers. An example of such policies is

[23] https://money.cnn.com/2017/05/04/technology/eric-schmidt-h1b-visa/

[24] https://www.niskanencenter.org/small-business-employees-need-a-special-allocation-in-the-h-1b-lottery/

Table 5. Effect of Skilled Immigration Policy on Aggregate Variables (Relative to the Baseline Case)

	(1) $q = 0.7$ All firms	(2) $q = 1$ All firms	(3) $q = 1$ Age 0-1	(4) $q = 1$ Age 0-4	(5) Reallocate Cap (a)	(6) Reallocate Cap (b)	(7) Frictionless All firms
Y_1	1.044	1.082	1.005	1.019	0.998	0.995	1.264
p_1	0.978	0.960	0.997	0.991	1.001	1.002	0.886
p_2	1.021	1.039	1.002	1.009	0.999	0.998	1.12
w_s	0.980	0.964	0.997	0.992	1.001	1.0023	0.900
w_u	1.021	1.039	1.002	1.009	0.999	0.998	1.120
c_s	0.983	0.969	0.997	0.992	1.0007	1.0016	0.906
c_u	1.021	1.039	1.002	1.009	0.999	0.998	1.120
L^f	3.237	5.161	1.279	1.998	0.910	0.785	14.64
Firm mass	1.104	1.207	1.000	1.005	0.992	0.975	1.57
New entry	0.744	0.527	1.072	1.262	1.049	1.199	1.65
Avg. Exit Rate	0.674	0.437	1.073	1.256	1.057	1.229	1.053
Avg. z	0.976	0.958	1.0039	1.014	1.0035	1.013	1.004

Notes: All numbers in the table are relative to the values in the baseline case (with all immigration frictions). Cases (1) and (2) impose a higher foreign worker hiring probability for all firms, while cases (3) and (4) impose a corresponding probability increase in the first 2 and 5 years of a firm's life, respectively. In cases (5) and (6), we shift the hiring probability from old firms to old firms based on the firm distributions in the baseline case. The young (old) firms face hiring probabilities of 42.33% and 64.32% (30% and 15%) in cases (5) and (6), respectively. Case (7) represents the case that all immigration frictions are removed ($c_s = 0$, $f_r = 0$, and $q = 1$) for all firms.

the pre-registration process introduced in 2020, whereby an H-1B cap-subject petition may only be filed by a petitioner whose registration has been selected. Such policies reduce the time and effort required for employers to file H-1B petitions. We can also analyze the impact of policies that make it easier for foreign skilled workers to start businesses (e.g., start-up visas), which would effectively reduce the sunk entry costs in our framework.[25]

5.1. Counterfactual policies related to cap changes

Higher q for all firms. We first show the results when the cap is raised for all firms in the economy, while holding all other immigration frictions unchanged. Columns (1) and (2) in Table 5 show the model results when the probability of hiring foreign workers q is doubled to 0.7 or increased to 1. As shown in the table for both cases, having a higher probability of hiring increases the number of foreign workers, which increases output in sector 1 by 4.4% and 8.2%, respectively, and reduces the skilled labor wage by 2% and 3.6%. As a result, domestic skilled labor suffers a decrease in consumption of 1.7% and 3.1% from the mild and more aggressive policy reforms, respectively.

[25] Such policy proposals have received bipartisan support. See Kerr et al. (2020) for details.

On the other hand, unskilled workers enjoy a higher wage in the unskilled sector and an increase in consumption of 2.1% and 3.9%, respectively.

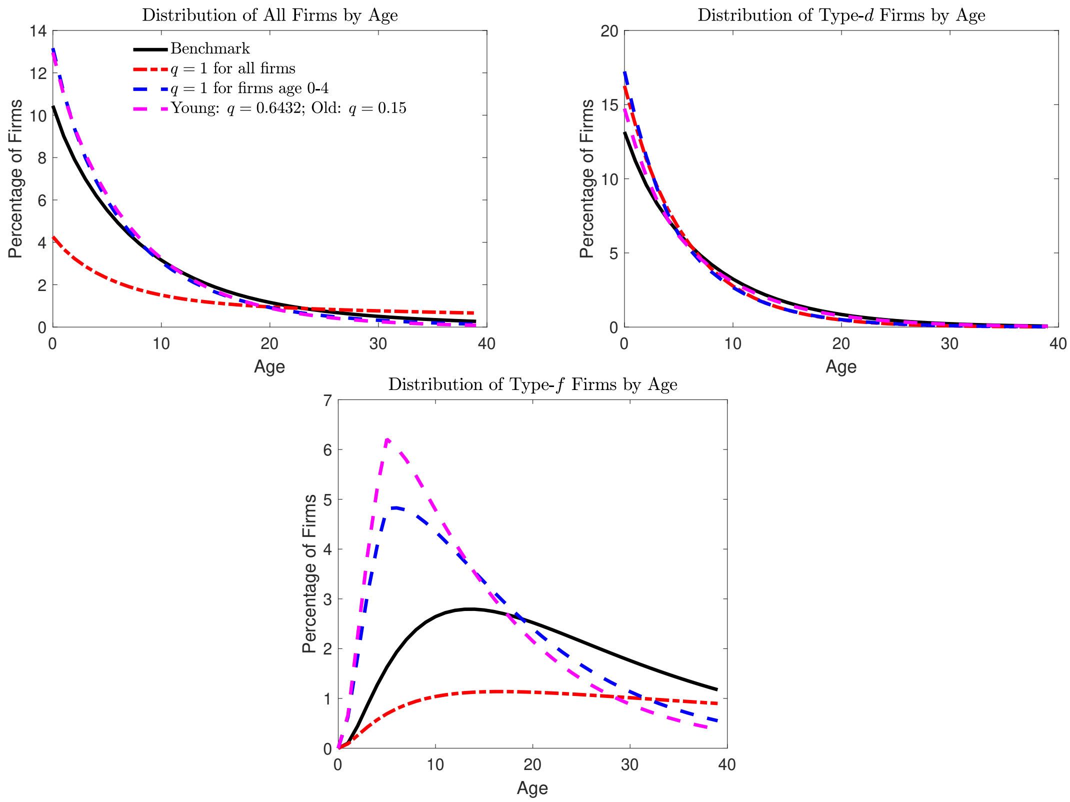
In terms of firm dynamics, the higher hiring probability q makes firms more likely to survive overall and reduces the average exit rate for all firms. Increasing q, without changing any other immigration frictions, disproportionately benefits older firms because they are already more likely to be type-f firms.[26] On average, these firms are large employers of foreign workers due to their relatively larger size. In contrast, a higher fraction of young firms in the model have not yet paid the switching cost c_s to become type-f firms. Moreover, on average, they also have a lower demand for foreign workers if they can hire them, as they may not be able to pay the per-worker hiring cost f_r for a large number of foreign workers due to their relatively smaller size. This result intuitively explains why young but relatively small firms may not benefit much from a reduction in the cap (as discussed earlier).

Higher q for younger firms. We next consider a policy change that allows younger firms to have a higher probability of hiring foreign workers. Specifically, columns (3) and (4) in Table 5 show the results when firms with ages 0-1, or firms with ages 0-4 are not subject to the lottery ($q = 1$ for them) and can hire as many foreign workers as they wish. Unlike the policy change that increases the cap for all firms, such a policy directly targets younger firms, in line with our motivation. Table 5 shows that such a policy change increases the number of foreign workers by 27.9% if it targets only firms aged 0-1, and by 99.8% if it targets firms aged 0-4. Similar to the policy proposal that increases q for all firms, the higher number of foreign workers hurts domestic skilled workers but by a lesser extent, as they only suffer a decline in consumption of 0.3% and 0.8% for the mild and more aggressive policy reforms. On the other hand, the domestic unskilled workers enjoy an increase in consumption by 0.2% and 0.9% in the mild and more aggressive policy reforms.

The policy reform that targets the younger firms attracts a larger mass of new entrants and makes the older firms more likely to exit than the younger firms due to the increased competition from new entrants. Figure 4 and the first plot in Figure 5 confirm this result, showing that the

[26] The empirical reduced-form *diff-in-diff* H-1B lottery coefficient in Table 1 should be strictly interpreted as partial equilibrium in nature and thus not directly comparable (in quantitative terms) to the model results that instead exhibit strong general equilibrium effects. In addition, the expectation channel is key in our model. A one-time unforeseen random lottery win in the data is different from a change in the cap for all firms that increases the winning chances for all firms in subsequent periods.

Figure 4. Firm Distributions by Age with Cap Changes

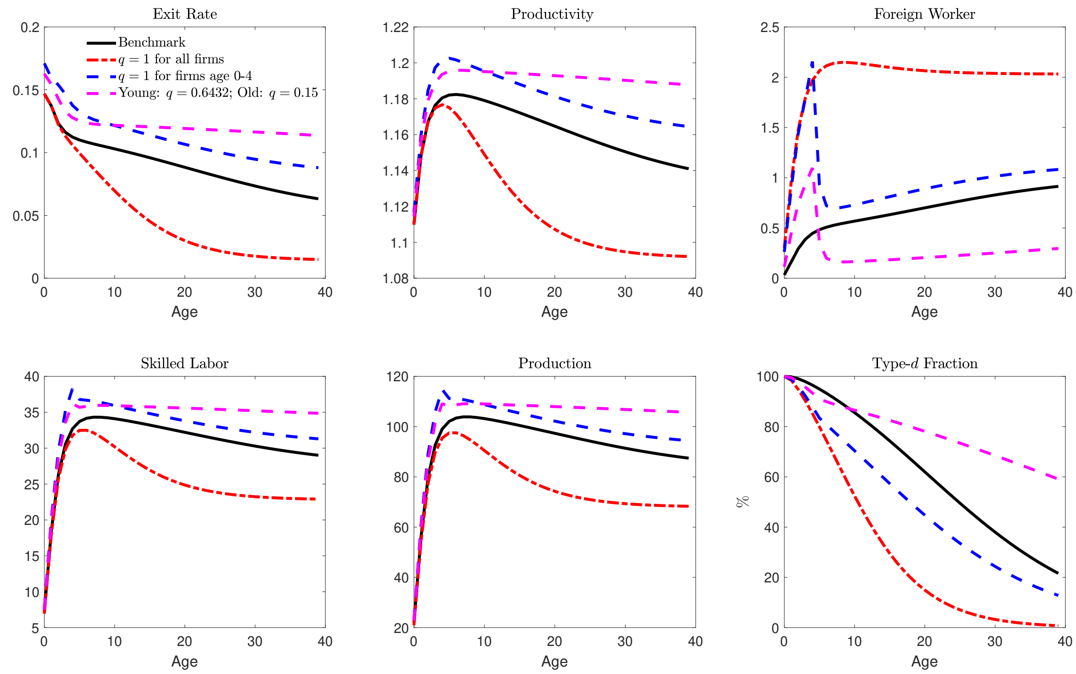


Notes: This figure shows the firms' distributions by age and firm types. We show the distributions for four cases: (1) Benchmark case, (2) unlimited cap ($q = 1$) for all firms, (3) unlimited cap ($q = 1$) for firms with ages 0-4, and (4) the priority is shifted from old firms to young firms so $q = 0.6432$ for firms with age 0-4 and $q = 0.15$ for firms with age 5 or older.

exit rates increase more for older firms and the distribution of firms become more concentrated among younger firms. Since such a policy reform drives older and low-productivity firms out of the market, average productivity and output increase after the policy change, as shown in Figure 5. Notably, the average productivity gains in the case of no frictions for firms aged 0-1 are comparable to those obtained by removing all immigration frictions (as seen in column 7), and are markedly larger when extended to firms aged 0-4.

Reallocate cap from older firms to younger firms. The previous two policy reforms increase the hiring probability q for some or all firms, while no firms suffer a reduced q. As a result, the relaxed skilled immigration policies result in more foreign workers in the economy and hurt the welfare of domestic skilled workers. We next consider a policy reform that reallocates the cap from older firms to younger firms. Specially, we change the hiring probabilities for old (age 5 and higher)

Figure 5. Average Firm Characteristics by Age with Cap Changes



Notes: This figure shows the firms' average exit rate, productivity, foreign worker, skilled labor, production, and the fraction of type-d firms by age. We show these variables for four cases: (1) Benchmark case, (2) unlimited cap ($q = 1$) for all firms, (3) unlimited cap ($q = 1$) for firms with ages 0-4, and (4) the probability is shifted from old firms to young firms so $q = 0.6432$ for firms with age 0-4 and $q = 0.15$ for firms with age 5 or older.

and young (ages 0-4) firms (q^{old} and q^{young}) so the average q remains the same as in the benchmark case:

$$q^{\text{benchmark}} = \text{frac}^{\text{old}} \times q^{\text{old}} + \text{frac}^{\text{young}} \times q^{\text{young}},$$

where frac^{old} and $\text{frac}^{\text{young}}$ are the fractions of old and young firms in the benchmark cases. For this type of reform, we conduct a mild, $q^{\text{old}} = 0.3$, and a relatively more aggressive, $q^{\text{old}} = 0.15$, policy change. Since $q = 0.35$ in the benchmark case, this implies that q^{young} is equal to 0.4233 and 0.6432 in the less and more aggressive cases, respectively. The results are reported in columns (5) and (6) in Table 5.

The first plot in Figure 5 shows that shifting the hiring probabilities toward younger firms increases the average exit rates, especially for the older firms, due to the larger mass of new entrants and increased competition. Figure 4 confirms this intuition and shows that the firm distribution becomes more concentrated among the younger firms after such a policy change. Similar to the policy reform that increases q only for young firms, average productivity and output for all ages increase after the shift in hiring probabilities, as shown in Figure 5. Importantly, the improvement in the average productivity is also comparable (when less aggressive) or greater (when more aggressive) than removing all immigration frictions.

The most important difference between this policy reform and the previous two is that it aims to help younger firms while not requiring an increase in the H-1B cap. Since the old firms are, on average, larger employers of foreign workers than the young firms in the benchmark case, the shifted hiring probabilities cause the total number of foreign workers to decrease by 9% and 21.5% in the mild and aggressive policy changes, respectively, as shown in Table 5. This highlights the importance of the general equilibrium effects. As a result, such a policy reform does not reduce the welfare of domestic skilled workers, in contrast to what we observed in the previous two types of reforms. Such a result implies that reallocating the cap to younger firms is more feasible and easier to implement than the previous two policy reforms since it can increase business dynamism while leading to smaller welfare costs for domestic skilled workers, the key group that directly competes with foreign skilled workers.

5.2. Lower sunk costs

In this section, we evaluate the impact of the following policy changes on all firms: (1) Sunk hiring costs are eliminated, i.e. ($c_s = 0$), and (2) Sunk entry costs (c_e) are reduced by 20%. To motivate (1), policies that ease firm filing of H-1B visas would lower c_s, and we look at the extreme case where application filing can be done with great ease with no lawyer help, eliminating sunk hiring costs to 0. Alternate policies that make it easier for foreign workers to get startup visas are likely to lower sunk entry costs in technology-intensive sectors, and we look at a counterfactual with sightly lower entry costs in (2).[27]

We can see from Table 6 that while lowering either sunk entry cost increases firm entry and average firm productivity, policies that make it easier for entrepreneurs to start new firms have a higher direct impact on new firm entry and average productivity in the economy, without an increase in the stock of foreign skilled workers in the economy. Therefore, a policy that reduces the entry cost for firms can generate productivity gains for high-tech firms, while limiting losses for domestic skilled workers. This policy is comparable to policies that reallocate visas to younger

[27]In practice, such policies could have spillover impacts on q, but we abstract for such interactions.

Table 6. Effect of Skilled Immigration Policy on Aggregate Variables (Relative to the Baseline Case)

	(1) $c_s = 0$	(2) c_e decreases by 20%
Y_1	1.03	0.9998
p_1	0.99	1.0001
p_2	1.01	0.9998
w_s	0.99	1.002
w_u	1.01	0.9998
c_s	0.99	0.9983
c_u	1.01	0.9998
L^f	2.45	0.927
Firm mass	1.06	1.012
New entry	1.17	1.614
Avg. productivity	1.006	1.03

Notes: This table shows the effects of removing c_s or lowering c_e by 20%. All numbers in the table are relative to the values in the baseline case (with all immigration frictions).

firms in Table 5. However, the increase in new firm entry and gains in average productivity are higher relative to the 'reallocation' cases if we directly lower frictions related to firm entry. This suggests that policies that lower entry barriers (like the 'immigration startup' visas) combined with policies that ease immigration barriers for younger firms are likely to have the maximum gains in average firm productivity.

5.3. Policy Implications

The results of the previous two sections suggest that while there is much discussion about reforming H-1B policy and changing the H-1B cap, the design of such reforms is crucial and can significantly affect economic outcomes. Table 5 shows that simply increasing the cap and the hiring probability for all firms may disproportionately help older firms and reduce firm dynamism, whereas a policy that targets young firms, either by increasing the cap for young firms or by reallocating the cap from old firms to young firms, may attract more new entrants, induce old and unproductive firms to exit the market, and increase average firm productivity. Such a comparison suggests that if one of the goals of policy reform is to increase business dynamism and firm productivity, then policies designed specifically to help young firms would be more beneficial.

In terms of welfare, a loosened H-1B cap would increase the number of foreign skilled workers and drive down sector-1 wages. As a result, domestic skilled workers suffer a decline in consumption. In contrast, policies that focus on younger firms lead to smaller increases in foreign skilled workers and, therefore, smaller welfare losses for domestic skilled workers. Of all the cap-altering policies we experiment with, the cap reallocation policy has the smallest impact on domestic welfare, making it potentially more feasible to implement among other cap-altering H-1B reforms if domestic welfare is the primary policy concern.

Lastly, we also experimented with some non-cap-changing policy reforms that are relevant to recent policy discussions. In particular, we found that lowering the barriers for new entrants, which is related to recent discussions on 'immigrant startup' visas, is very effective in increasing firm dynamism by attracting new entrants and inducing old and unproductive firms to exit. As a result, the average firm productivity increases after the entry barrier is lowered. Moreover, such a policy does not increase the H-1B cap and thus has a very small impact on domestic welfare. This result suggests that the combination of cap reallocation policy and the firm entry subsidy is likely to produce the maximum gains in average firm productivity without having large adverse welfare consequences.

6. Conclusion

This paper examines the impact of immigration policy frictions on technology-intensive firms by age cohort. We first use firm-level motivating evidence to show that younger firms are more likely to be impacted by skilled immigration policy frictions imposed by the US H-1B visa cap. We then introduce a general equilibrium macroeconomic model that features endogenous firm entry, exit, and an endogenous choice to hire foreign skilled workers. Importantly, the model features key immigration policy frictions that mimic reality – a sunk cost that reflects the time and effort of filing applications, an idiosyncratic hiring shock that proxies the lottery, and a per-worker hiring cost to reflect the policy-imposed hiring fee for each worker. The model matches key data moments related to firms and workers in the US, including the age distribution of firms.

We use the model to implement a rich set of counterfactual exercises related to proposed changes in US skilled immigration policies. Our main results indicate that even relatively small policy changes that focus on younger firms or reallocate visas to younger firms can spur increased firm entry and competitive forces that lead to the exit of less productive firms. This increase in business dynamism would increase the average productivity of firms in technology-intensive sectors. Such policies may also be more feasible to implement as they lead to fewer welfare costs for domestic skilled workers, the key group that directly competes with foreign skilled workers. All these results highlight the importance of using a general equilibrium model to study the impacts of immigration policy changes on firm dynamics by age cohorts and firm productivity.

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Appendix A. H-1B Program: Institutional Framework and Background

Since the H-1B visa program was implemented in 1990, it has been the main method of entry into the US workforce for foreign college-educated professionals. The H-1B visa is temporary as it is issued for only three years (and can be renewed for another three), but it is a dual intent visa since it can lead to permanent residency if the employer is willing to sponsor the worker for a green card.

The H-1B program has been subject to an annual quota on new visa issuances. The initial visa cap was 65,000, which was subsequently increased to 115,000 in 1999 and 2000 after the cap was met in 1997. The cap was further increased to 195,000 from 2001 to 2003. In 2001, cap exemptions were introduced for employees at higher education, nonprofit, and government research organizations. In 2004, the cap was reduced back to 65,000, but 20,000 additional visas were allocated for workers who had obtained a master's degree or higher from a US institution. The cap applies only to new H-1B visa issuances for for-profit firms.

To obtain an H-1B visa, there are several steps to be followed, and firms are central to this process. The first step requires the firm that wants to hire a foreign worker to file an LCA with the Department of Labor. In the application, the firm specifies the nature of the worker's occupation and attests that it will pay them the greater of the actual compensation paid to other employees in the same job or the prevailing compensation for that occupation. The rationale given for this attestation is to help protect domestic worker wages. The LCA request also certifies that the employer must hire a foreign worker because a US citizen is not qualified, available, or willing to work in that job position.

LCA forms can request one or more foreign workers for a particular occupation, and thus they signal firm vacancies in specific occupations for foreign workers. LCAs are processed relatively quickly, allowing firms to file them either after hiring workers or in anticipation of hiring. However, there are some limitations of using the LCA database. The database contains records for every request submitted, but this is only an intermediate step in the process toward the final visa approval. An LCA is submitted for every H-1B request, whether new or a renewal, and each LCA can contain multiple H-1B workers.

Once the Department of Labor approves the LCA, it is sent to the USCIS along with the I-129 form[28] and the required visa fees. This is the final step, and firms have from April 1 until the beginning of the next fiscal year to file petitions for H-1B visa applications. Crucially, potential employees can only apply for an H-1B visa if they have a job offer from an employer with LCA approval. By law, the employer cannot file more than one I-129 for the same prospective employee. Most of the filing and legal fees are also borne by the employer. If the number of H-1B visa petitions (I-129 forms) that fall within the nonexempt category exceeds the cap, the USCIS randomly selects visas for processing via a lottery system until the 65,000 cap is reached. The total number of petitions filed does not indicate the true demand because the government stops collecting H-1B petitions once it has determined that the cap has been reached for a given year.

In recent years, the Department of Homeland Security has been considering amendments in its regulations regarding the process by which the USCIS selects H-1B petitions for the filing of the H-1B cap-subject petitions. In 2020, the USCIS implemented a preregistration process that begins on March 1 for potential employees who want to file an H-1B petition. If the USCIS receives enough registrations by March 18 (based on historic projections), they will randomly select registrations. An H-1B cap-subject petition may only be filed by a petitioner whose registration was selected (also see Pathak et al., 2022 for an extensive analysis of the H-1B rule changes over the years). In very recent years there have also been increasing cases of fraud and multiple registrations submitted for the same employee. However, such cases are subject to legal actions. The USCIS mentions that "based on evidence from the FY 2023 and FY 2024 H-1B cap seasons, USCIS has already undertaken extensive fraud investigations, denied and revoked petitions accordingly, and continues to make law enforcement referrals for criminal prosecution."[29]

Appendix B. Data Appendix

To compute win rates, we combine data on 'New Approvals' of H-1B visas (from the USCIS H-1B Employer Data Hub) with the indicated demand for foreign workers in fiscal years 2014 and 2015. For the measure of demand, we use LCAs filed between February and April of each calendar year with a start date five to six months away, similar to recent literature, in order to include LCAs

[28] This proves the worker's qualifications.

[29] Source: https://www.uscis.gov/working-in-the-united-states/temporary-workers/h-1b-specialty-occupations-and-fashion-models/h-1b-electronic-registration-process.

that are most likely to have been filed for new H-1B workers.

As a caveat, LCAs do not accurately reflect the number of H-1B petitions each firm submits. We use LCA as a measure of firm demand instead of actual H-1B petitions submitted by firms because the USCIS stops collecting H-1B petitions once it has determined (based on historical projections) that the cap will be reached for a given year. Therefore, the total number of actual H-1B petitions filed gives an incomplete indication of the true demand for foreign workers. LCAs filed with the Department of Labor (DOL) are just the first step for hiring foreign workers via the H-1B program, in which one of the items that they need to specify is the number of foreign workers they would like to hire for a particular occupation. While these LCAs signal vacancies or firm demand for skilled foreign labor, it is not necessary that firms with approved LCAs actually file H-1B petitions for the number of workers indicated in the LCAs. Therefore, we also remove outliers in the LCA data by winsorizing the data.

For matching the H-1B and LCA data, no unique firm identifiers exist in the H-1B data or in the LCA data, and the employer name may not be consistent across H-1B petitions filed (either in the same year or across years). Therefore, we first standardize employer names and use tax ID, zip, city, and state to identify unique firms within the H-1B database. We also use zip, city, and NAICS to identify unique firms in the LCA database. We aggregate LCA petitions made by the same employer in the same year as well as H-1B petitions approved for new workers. We then use probabilistic name matching, location, and manual checks to merge firms in our LCA sample with the H-1B data. Since visas for nonprofit firms like academia and government institutions are not subject to the cap, we exclude these cap-exempt firms in our analysis by filtering out firms with keywords like 'Universities', 'College', 'Federal', and 'Government'. Our baseline win-rate measure for each firm is calculated as

$$\frac{\text{New Approvals in FY2014} + \text{New Approvals in FY2015}}{\text{Winsorized Firm Demand for New Workers in FY2014} + \text{Winsorized Firm Demand for New Workers in FY2015}}$$

We calculate win rates for firms that have potentially submitted H-1B petitions in either fiscal year 2014 or fiscal year 2015, or both. Therefore, our sample includes firms that have submitted applications for foreign workers in either lottery year. An important caveat for our win-rate measure is that among wins, there are both individuals subject to the H-1B masters cap (20,000) and those subject to the general cap (65,000). Those who participate in the master's cap have a second chance in the general cap if they lose the lottery. This may bias win-rate estimates. However, without education-level data for workers hired, we cannot directly control the effects caused by the master's cap.

We then match the firm-level win rates to firm outcomes using the NETS database by probabilistically matching firms by names and location (city) to create a panel data set from 2011 to 2020. The annual NETs data depict business indicators in January of a given year. To measure firm-level variables like survival, employment, and age, we collapse across all establishments at the HQ company level to obtain firm-level variables. We use the "YearStart" and "YearEnd" variables in the NETS database to measure the firm's age and inactive status, and keep only firms that were active in January 2013 and January 2014. By observing changes in the "HQDuns" variables of the headquarter company in years after 2014, we can determine if an acquisition or merger has occurred, according to the NETS data description. We omit firms with missing HQDuns in any years between 2014 and 2020. The data include four-digit NAICS industry codes that help infer technology levels of firms using Heckler (2005) classifications. A firm is coded to be young if its age in 2013 was less than 5 years.

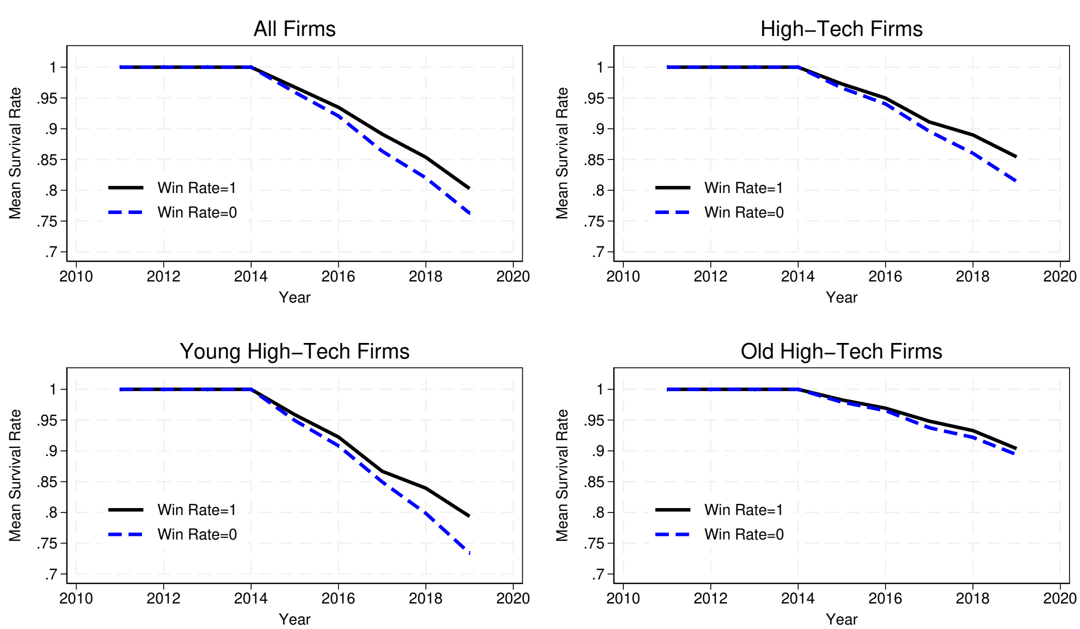
Our final sample includes 15,200 unique firms with win-rate measures matched with the NETS database. Table B.7 displays the summary statistics of key variables used in our main analysis. Figure B.6 plots the average fraction of firms that survived during the post-lottery calendar years 2015–2019 in the raw data. On average, a larger fraction of firms with an H-1B lottery win rate of 1 survived in the post-lottery years compared to firms with a win rate of 0. This difference is noticeable for high-tech firms and young high-tech firms separately but less for older high-tech firms.

Table B.7. Summary Statistics of Firms That Applied for H-1B Workers in Fiscal years 2014 and 2015

	(1) All	(2) High-tech	(3) Young	(4) Young high-tech
Survive	0.93	0.91	0.82	0.87
	(0.328)	(0.286)	(0.382)	(0.335)
Win rate	0.39	0.48	0.39	0.46
	(0.447)	(0.436)	(0.445)	(0.433)
Employment (2013)	33.27	29.37	8.78	11.74
	(180.3)	(146.4)	(50.70)	(43.85)
Age (2013)	10.70	9.91	2.46	2.75
	(17.39)	(12.55)	(1.574)	(1.322)
Total LCAs	2.76	4.22	2.75	4.17
	(3.956)	(5.462)	(3.923)	(5.336)
Observations	76,000	14,780	32,250	6,665

Notes: This table reports mean coefficients with standard deviations in parentheses. Survive refers to the average survival rate of firms during the 2015-2019 calendar years and excludes nonsurvival due to mergers/acquisitions. The table reports the average firm employment and age in the 2013 calendar year. The average total LCAs filed by a firm and the corresponding win rate are for fiscal years 2014 and 2015.

Figure B.6. Raw Data: Average Proportion of Surviving Firms



Notes: Win Rate = 1 includes firms that received 100 percent of their requested skilled foreign workers during fiscal years 2014 and 2015. Win Rate = 0 includes firms that received 0 percent of their skilled foreign workers. We exclude mergers/acquisitions.

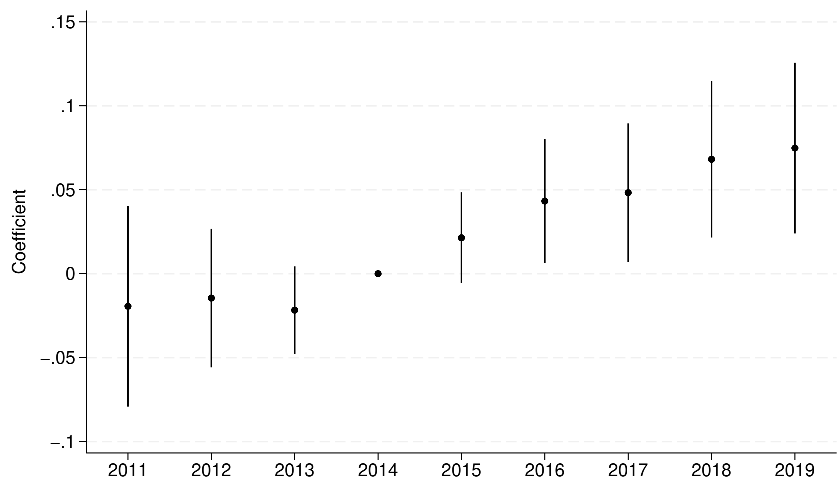
Appendix B.1. Event Study Models for Pre-trends

We use the following model

$$y_{i,t} = \sum_{\tau \neq b} \beta_\tau [WinRate_i \times \mathbb{1}(\tau = t)] + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{B.1}$$

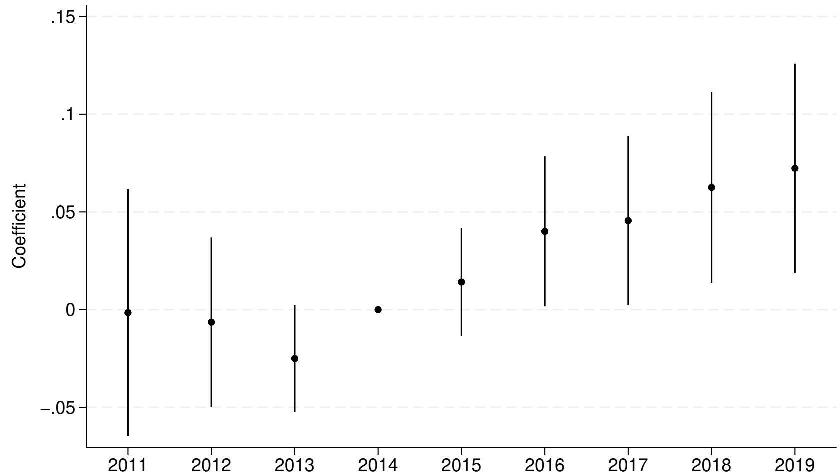
where i denotes the firm and the base year is $b = 2014$. The specification includes firm (γ_i) and year (γ_t) fixed effects. The outcome $y_{i.t}$ include Sales and Employees.

Figure B.7. Employment: Young Firms



Notes: Coefficient estimates and their 95% confidence intervals for WinRate × Year are reported. Includes firm and year fixed effects.

Figure B.8. Sales: Young Firms



Notes: Coefficient estimates and their 95% confidence intervals for WinRate × Year are reported. Includes firm and year fixed effects.

Our event study analysis finds no significant pre-trends for firm sales and employees in the years prior to 2014 for all firms as well as the subsample of young firms.

Appendix B.2. Additional Results by Firm Size and Age

We run the following regression for separate groups of young vs older firms.

$$Survive_{i,t} = \beta_1[WinRate_i \times post_t] + \beta_2[post_t \times small_i] + \beta_3[post_t \times small_i \times Win\_rate_i] + \gamma_i + \gamma_t + \epsilon_{i,t},$$

Table B.8 displays the results for separate samples of young (age less than 5) high-tech firms and older high-tech firms. The results for young high-tech firms indicate that the average impact of the win rate on firm survival is actually greater if a firm had more than 10 employees in 2013. The average impact for a relatively larger young high-tech firm is 10.6 percentage points. Being smaller reduces the average impact of the win rate by 8.6 percentage point, make the net impact of a young and small high-tech firm 2 percentage points.

Appendix B.3. Dynamic Effects on Survival

We use the following model

Table B.8. Impact of Size on Young vs Old HT

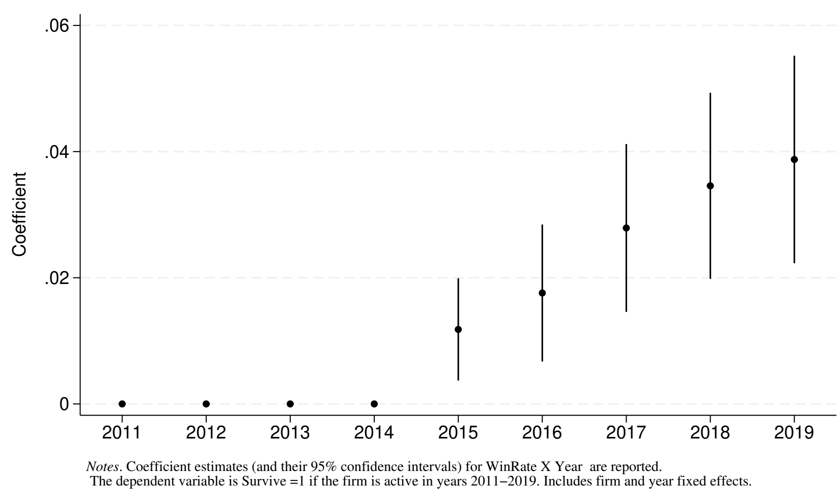
	(1) Young HT	(2) Older HT
post=1 × WinRate	0.106**	-0.016
	(0.042)	(0.014)
post=1 × small=1	0.008	-0.045***
	(0.036)	(0.014)
post=1 × small=1 × WinRate	-0.086*	0.046**
	(0.047)	(0.022)
FE	Yes	Yes
Observations	8068	12070

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$$Survive_{i,t} = \sum_{\tau \neq b} \beta_\tau [WinRate_i \times \mathbb{1}(\tau = t)] + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{B.2}$$

where i denotes the firm and the base year is $b = 2014$. The specification includes firm (γ_i) and year (γ_t) fixed effects.

Figure B.9. Dynamic Effects on Survival: All Firms

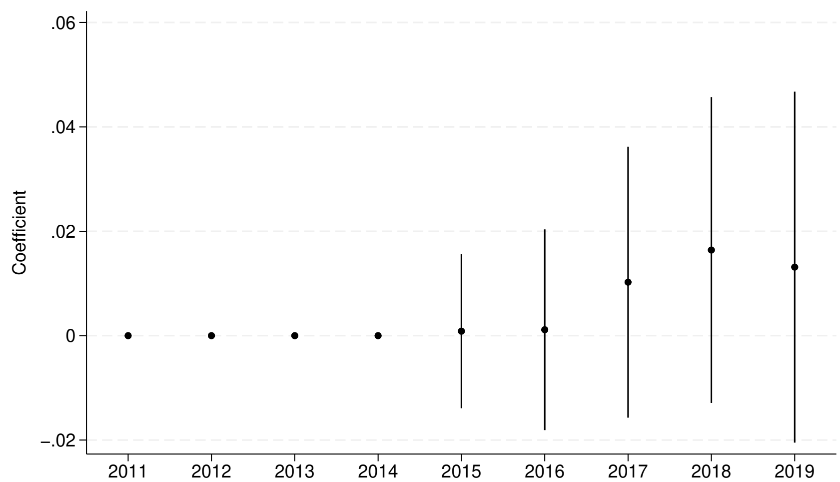


Notes: Coefficient estimates and their 95% confidence intervals for WinRate × Year are reported. Includes firm and year fixed effects.

Figure B.10. Dynamic Effects on Survival: Young High-tech Firms

Notes: Coefficient estimates and their 95% confidence intervals for WinRate $\times$ Year are reported. Includes firm and year fixed effects.

Figure B.11. Dynamic Effects on Survival: Old High-Tech Firms



Notes: Coefficient estimates and their 95% confidence intervals for WinRate $\times$ Year are reported. Includes firm and year fixed effects.

Appendix C. Aggregation

This section discusses how the aggregate variables are calculated using the firm's distributions. The aggregate output of sector 1 is given by

$$
\begin{aligned}
Y_t^1 = &\int \big(1 - \mathbb{1}_{f,exit}(l^f, z)\big) \times \int \Big\{(1-q) \times \Big[\mathcal{Y}_{fu}(l^f, z') - \psi(\mathcal{L}^f_{fu}(l^f, z'), l^f) - c_f\Big] \\
&\qquad + q \times \Big[\mathcal{Y}_{ff}(l^f, z') - \psi(\mathcal{L}^f_{ff}(l^f, z'), l^f) - c_f\Big] \Big\} f(z'|z) dz' d\mu_f(l^f, z) \\
&+ \int \Big\{ \mathbb{1}_{d,switch}(z) \times \int \Big[(1-q) \times \Big[\mathcal{Y}_{fu}(0, z') - \psi(\mathcal{L}^f_{fu}(0, z'), 0) - c_f - c_s\Big] \\
&\qquad + q \times \Big[\mathcal{Y}_{ff}(0, z') - \psi(\mathcal{L}^f_{ff}(0, z'), 0) - c_f - c_s\Big]\Big] f(z'|z) dz' \\
&\qquad + \big(1 - \mathbb{1}_{d,switch}(z)\big) \times \big(1 - \mathbb{1}_{d,exit}(z)\big) \times \int \left[\mathcal{Y}_d(z') - c_f\right] f(z'|z) dz' \Big\} d\mu_d(z) \\
&+ N_e \int \Big\{ \mathbb{1}_{e,switch}(z) \times \int \Big[(1-q) \times \Big[\mathcal{Y}_{fu}(0, z') - \psi(\mathcal{L}^f_{fu}(0, z'), 0) - c_f - c_s\Big] \\
&\qquad + q \times \Big[\mathcal{Y}_{ff}(0, z') - \psi(\mathcal{L}^f_{ff}(0, z'), 0) - c_f - c_s\Big]\Big] f(z'|z) dz' \\
&\qquad + \big(1 - \mathbb{1}_{e,switch}(z)\big) \times \big(1 - \mathbb{1}_{e,exit}(z)\big) \times \int \left[\mathcal{Y}_d(z') - c_f\right] f(z'|z) dz' \Big\} d\mu_e(z), \quad \text{(C.1)}
\end{aligned}
$$

where $\mathcal{Y}_{ff}(l^f, z')$ and $\mathcal{L}^f_{ff}(l^f, z')$ are the production and foreign worker hiring decisions for a type-f firm that (1) just received a positive hiring shock, (2) has number l^f of foreign workers at the beginning of the period, and (3) just drew productivity z' after observing productivity z and making the exit decision. $y_{fu}(l^f, z')$ and $\mathcal{L}^f_{fu}(l^f, z')$ are similarly defined. $\mathcal{Y}_d(z')$ and $\mathcal{L}^f_d(z)$ are the production and foreign worker hiring decisions for a type-d firm that just drew productivity z' after observing productivity z and making the switch/exit decision. $\mathbb{1}_{f,exit}(l^f, z)$, $\mathbb{1}_{d,exit}(z)$, and $\mathbb{1}_{e,exit}(z)$ are the exit decisions for the type-f, type-d, and entering firms. $\mathbb{1}_{d,switch}(z)$ and $\mathbb{1}_{e,switch}(z)$ are the switch decisions made by the type-d firms and entering firms with productivity z. N_e is the mass of new entries, and $f(z'|z)$ is the transition probability of the idiosyncratic productivity shock.

The aggregate skilled domestic worker is given by

$$
\begin{aligned}
L^d_{s,t} =& \int \big(1 - \mathbb{1}_{f,exit}(l^f, z)\big) \times \int \Big\{(1-q) \times \mathcal{L}^d_{fu}(l^f, z') + q \times \mathcal{L}^d_{ff}(l^f, z')\Big\} f(z'|z) dz' d\mu_f(l^f, z) \\
&+ \int \mathbb{1}_{d,switch}(z) \times \int \Big[(1-q) \times \mathcal{L}^d_{fu}(0, z') + q \times \mathcal{L}^d_{ff}(0, z')\Big] f(z'|z) dz' \\
&\quad + \big(1 - \mathbb{1}_{d,switch}(z)\big) \times \big(1 - \mathbb{1}_{d,exit}(z)\big) \times \int \mathcal{L}^d_d(z') f(z'|z) dz' d\mu_d(z) \\
&+ N_e \int \mathbb{1}_{e,switch}(z) \times \int \Big[(1-q) \times \mathcal{L}^d_{fu}(0, z') + q \times \mathcal{L}^d_{ff}(0, z')\Big] f(z'|z) dz' \\
&\quad + \big(1 - \mathbb{1}_{e,switch}(z)\big) \times \big(1 - \mathbb{1}_{e,exit}(z)\big) \times \int \mathcal{L}^d_d(z') f(z'|z) dz' d\mu_e(z), \qquad \text{(C.2)}
\end{aligned}
$$

where $\mathcal{L}^d_{fu}$, $\mathcal{L}^d_{ff}$, and $\mathcal{L}^d_d$ are the hiring decisions for skilled domestic workers made by each type of firm. Similarly, the aggregate skilled foreign worker is given by

$$
\begin{aligned}
L^f_{s,t} =& \int \big(1 - \mathbb{1}_{f,exit}(l^f, z)\big) \times \int \Big\{(1-q) \times \mathcal{L}^f_{fu}(l^f, z') + q \times \mathcal{L}^f_{ff}(l^f, z')\Big\} f(z'|z) dz' d\mu_f(l^f, z) \\
&+ \int \mathbb{1}_{d,switch}(z) \times \int \Big[(1-q) \times \mathcal{L}^f_{fu}(0, z') + q \times \mathcal{L}^f_{ff}(0, z')\Big] f(z'|z) dz' d\mu_d(z) \\
&+ N_e \int \mathbb{1}_{e,switch}(z) \times \int \Big[(1-q) \times \mathcal{L}^f_{fu}(0, z') + q \times \mathcal{L}^f_{ff}(0, z')\Big] f(z'|z) dz' d\mu_e(z). \qquad \text{(C.3)}
\end{aligned}
$$

Appendix D. Additional Results

Appendix D.1. Additional Figures and Tables

Figure D.12. LCAs versus H-1B Cap

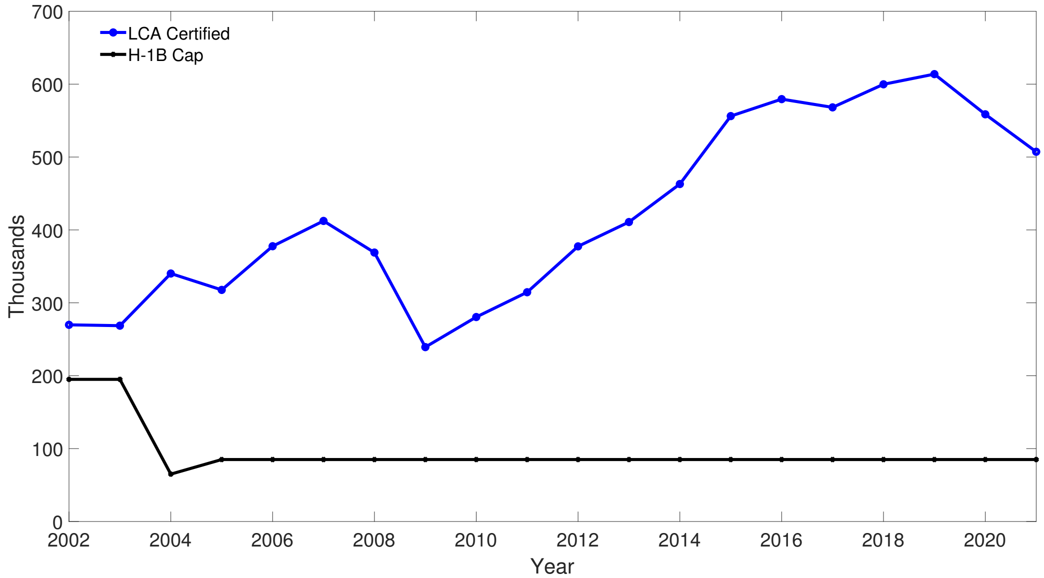
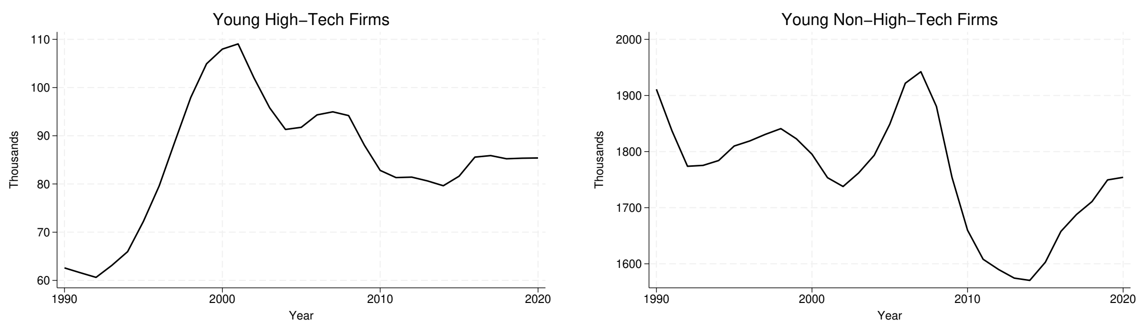
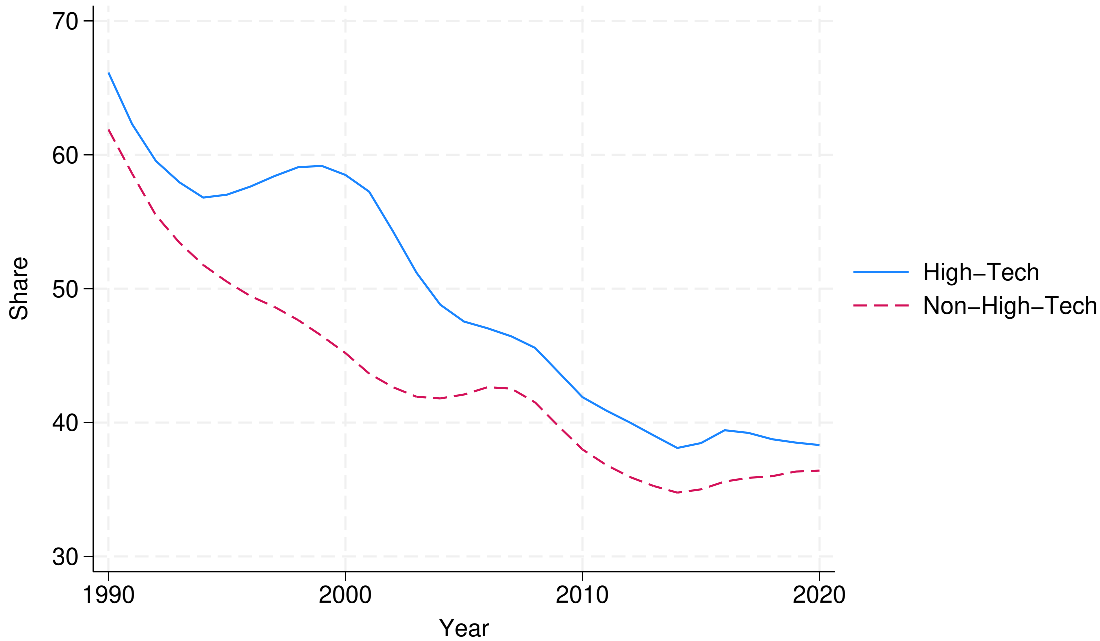


Figure D.13. Number of Young Firms between 1986 and 2020



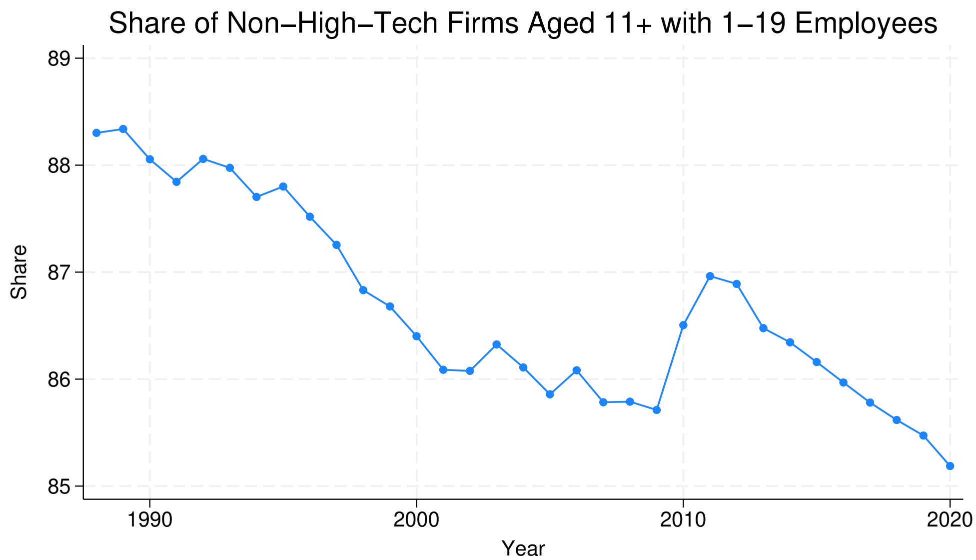
Notes: The figure is compiled using the US Census Bureau's BDS. High-tech firms are computed using four-digit NAICS codes and the BLS classification (Heckler, 2005).

Figure D.14. Share of Young Firms



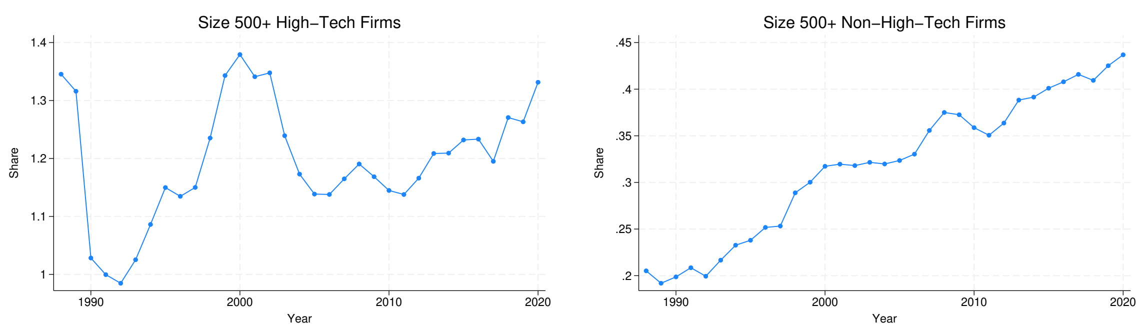
Notes: The figure is compiled using the US Census Bureau's BDS. High-tech firms are computed using four-digit NAICS codes and the BLS classification (Heckler, 2005).

Figure D.15. Share of Smallest Firms in Oldest Age Cohorts



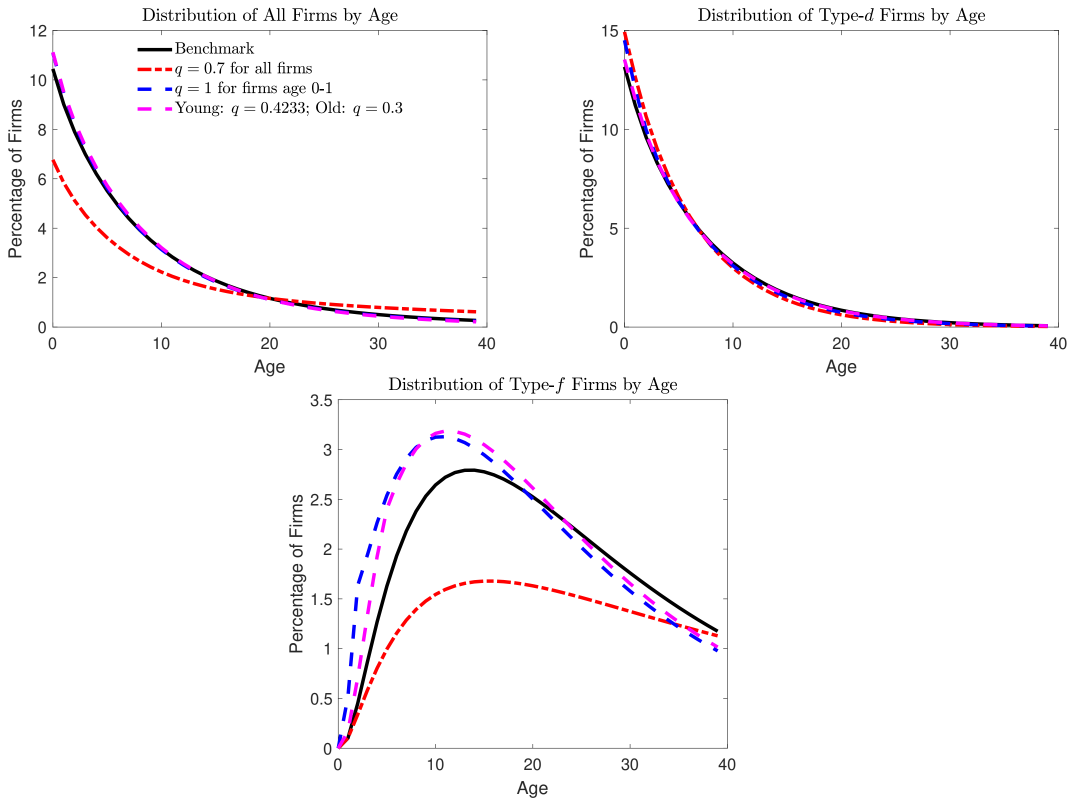
Notes: The figure is compiled using the US Census Bureau's BDS. The upper (lower) panel corresponds to the high-tech sector (non-high-tech sector). High-tech firms are computed using four-digit NAICS codes and the BLS classification (Heckler, 2005).

Figure D.16. Share of Largest Firms (500+ Employees) in Oldest Age (11+) Cohorts



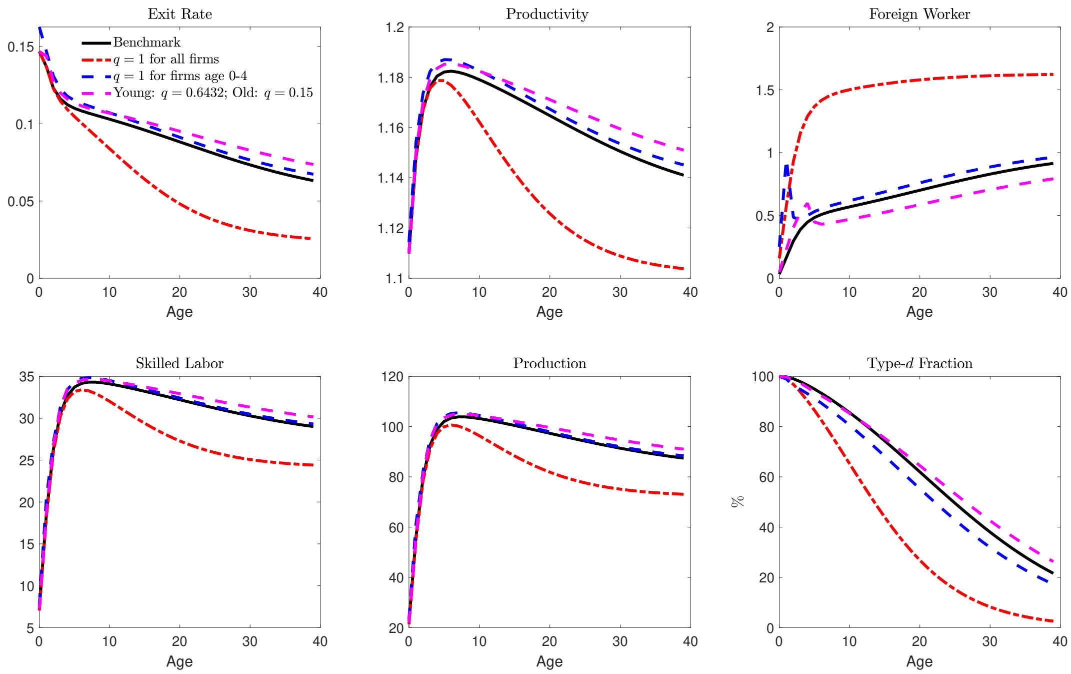
Notes: The figure is compiled using the US Census Bureau's BDS. Left (right) panel corresponds to the high-tech sector (non-high-tech sector). High-tech firms are computed using four-digit NAICS codes and the BLS classification (Heckler, 2005).

Figure D.17. Firm Distributions by Age with Cap Changes



Notes: This figure shows the firms' distributions by age and firm types. We show the distributions for four cases: (1) Benchmark case, (2) increased cap ($q = 0.7$) for all firms, (3) unlimited cap ($q = 1$) for firms with ages 0-1, and (4) the priority is shifted from old firms to young firms so $q = 0.4233$ for firms with age 0-4 and $q = 0.3$ for firms with age 5 or older.

Figure D.18. Average Firm Characteristics by Age with Cap Changes



Notes: This figure shows the firms' average exit rate, productivity, foreign worker, skilled labor, production, and the fraction of type-d firms by age. We show the distributions for four cases: (1) Benchmark case, (2) increased cap ($q = 0.7$) for all firms, (3) unlimited cap ($q = 1$) for firms with ages 0-1, and (4) the priority is shifted from old firms to young firms so $q = 0.4233$ for firms with age 0-4 and $q = 0.3$ for firms with age 5 or older.