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 increased entry of younger firms induces greater exit of older, less productive firms, thereby increasing efficiency.

JEL Classification: F22, M13

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

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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 1.[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 older), which could arguably be the byproduct of a less competitive environment. See Figure 2. 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. 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 Figure 3, 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), which coincides with a period of rapid aging of the native population.

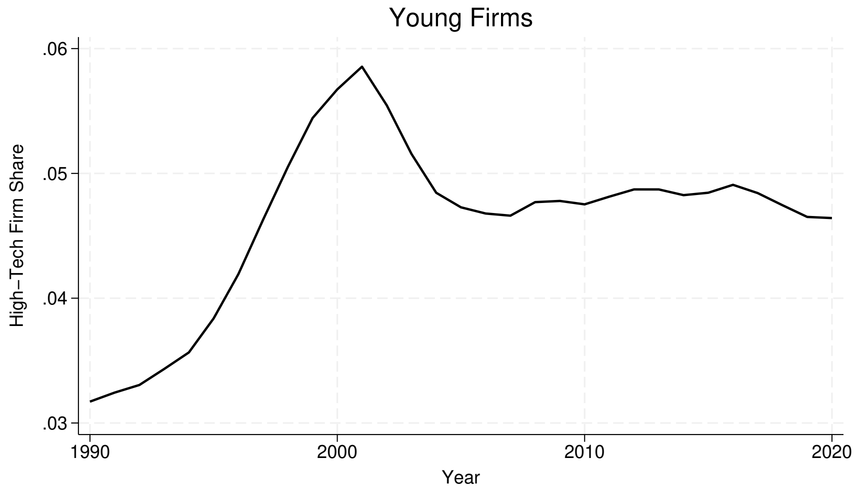
While there is extensive literature on the impact of U.S. skilled immigration policy, to our knowledge, no study has specifically examined the impact of current policy frictions on younger firms and the direct effect of these migration barriers on firm dynamics and their spillovers to the broader economy. This paper aims to

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

Figure 1. Share of High-Tech Young Firms in All Young Firms



Notes: The figure is 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.

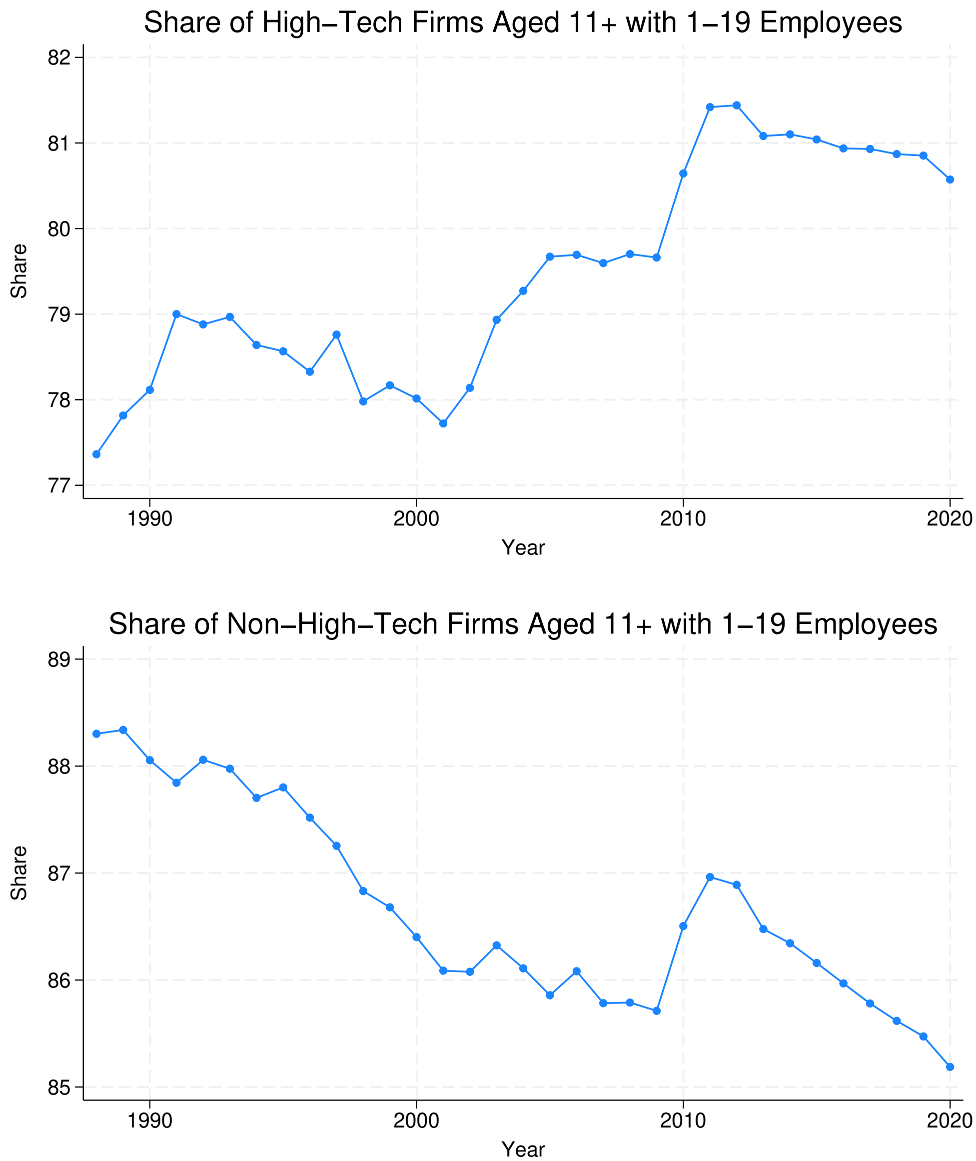
fill this gap by measuring the direct impact of migration frictions with firm-level data, while assessing their general equilibrium implications for different firm-age cohorts through the lens of a quantitative model that is also disciplined by the data.

We first 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 (ages 0–5) 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 & 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 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 and building relationships with law firms that can help with the legal process of hiring foreign workers. 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

[4] We measure H-1B lottery win rates using a similar approach to Dimmock et al. (2021) and recently Brinatti et al. (2023).

Figure 2. Share of Smallest Firms in Oldest Age Cohorts



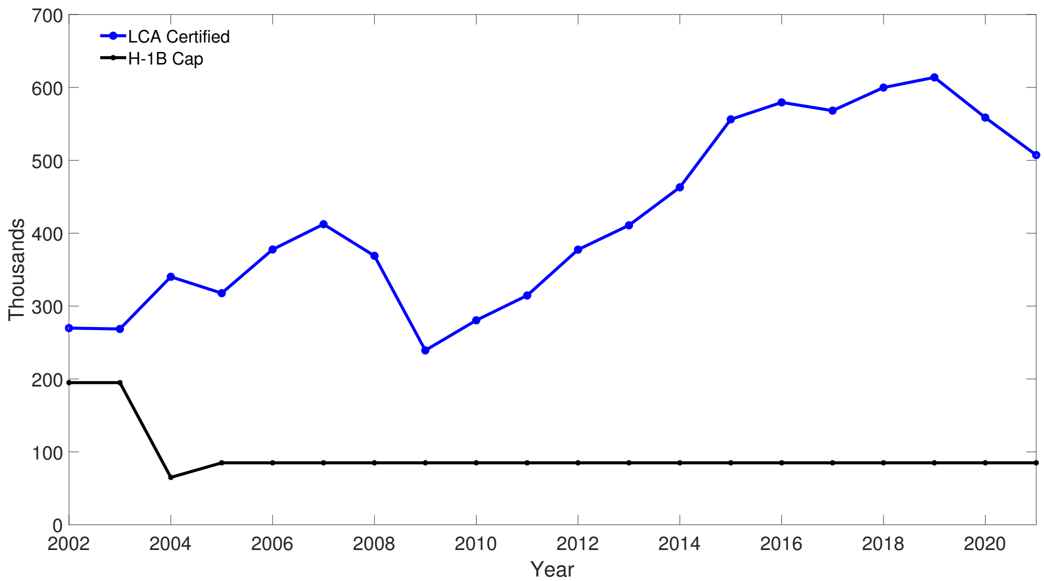
Notes: The figure is compiled using the US Census Bureau's BDS. The upper (lower) panel corresponds to the high-tech sector (non-high-tech sector). High-tech firms are computed using four-digit NAICS codes and the BLS classification (Heckler, 2005).

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 U.S. economy between 2005 and 2020 using data from the Business Dynamics Statistics (BDS), the Current Population Survey (CPS), and the U.S. Citizenship and Immigration Services (USCIS). The distribution of firms in the model by age cohort matches the corresponding

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

Figure 3. LCAs versus H-1B Cap



distribution in the data. Using value function iteration to solve the decentralized equilibrium, our model demonstrates how changes in immigration policy can affect firm dynamics consistent with data trends.

Our counterfactual policy exercises show that easing immigration policy frictions is beneficial due to imperfect substitutability between domestic and foreign workers and additional productivity gains from hiring more productive foreign workers. New entrants have a higher probability of hiring foreign workers immediately upon entry, which increases their survival chances, consistent with our empirical results. The removal of migration barriers leads to a higher mass of entrants, a lower exit rate of younger firms, a larger stock of foreign workers, 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, less productive incumbents are forced out of the market, raising the average productivity of all firms. We also assess the impact of the change in the extensive margin of firms on skilled domestic workers. More than one-third of domestic workers are absorbed by the additional firms that exist due to lower immigration frictions. These additional firms contribute to a 17.9 percent change in the welfare of skilled domestic workers relative to the baseline case with immigration frictions.

Finally, the results of the general equilibrium model are consistent with trends in the data after immigration policy frictions were increased in 2004 (via the H-1B cap reduction), which resulted in a lower average exit rate of older firms, an increase in the average share of older firms, and an increase in the share of the smallest (less productive) firms among the oldest firms in high-tech sectors.

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 U.S. skilled immigration. Notable contributions include, Bound et al. (2015); Waugh (2018); Bound et al. (2017); and Mehra & Shen (2022).[6] 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 & 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 & Şahin (2019). Our results not only show that increased immigration 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 startups. The paper also relates to the literature studying policy distortions and the aggregate impacts of allocative efficiency across heterogeneous firms. Hopenhayn & Rogerson (1993) evaluate the equilibrium effects of tax policies on the labor market. Gabler & Poschke (2013) build a model with endogenous risky experimentation decisions chosen by firms. Bento & 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. Brinatti et al. (2023) find that skilled-intensive firms expand the most after winning the H-1B lottery. Or-

[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 & Kim (2023) study the general equilibrium impacts of the offshoring mechanism.

[7] Mukoyama & Osotimehin (2019) study the effects of firing taxes on reallocation, innovation, and productivity growth. Last, Sedlacek & 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.

renius 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 U.S. 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 (S. P. Kerr et al., 2014; W. R. Kerr & Lincoln, 2010; S. P. Kerr 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 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, Brinatti et al. (2023).[10] Appendix B gives details on the datasets used, construction of key variables, existing omissions in the data and how we address them.[11] Our final sample includes 15,200 unique firms with win-rate measures matched with the NETS database. Appendix Table B.1 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 U.S. Census-based employer universe, NETS mimics administrative employer data with reasonable accuracy. [12]

[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.

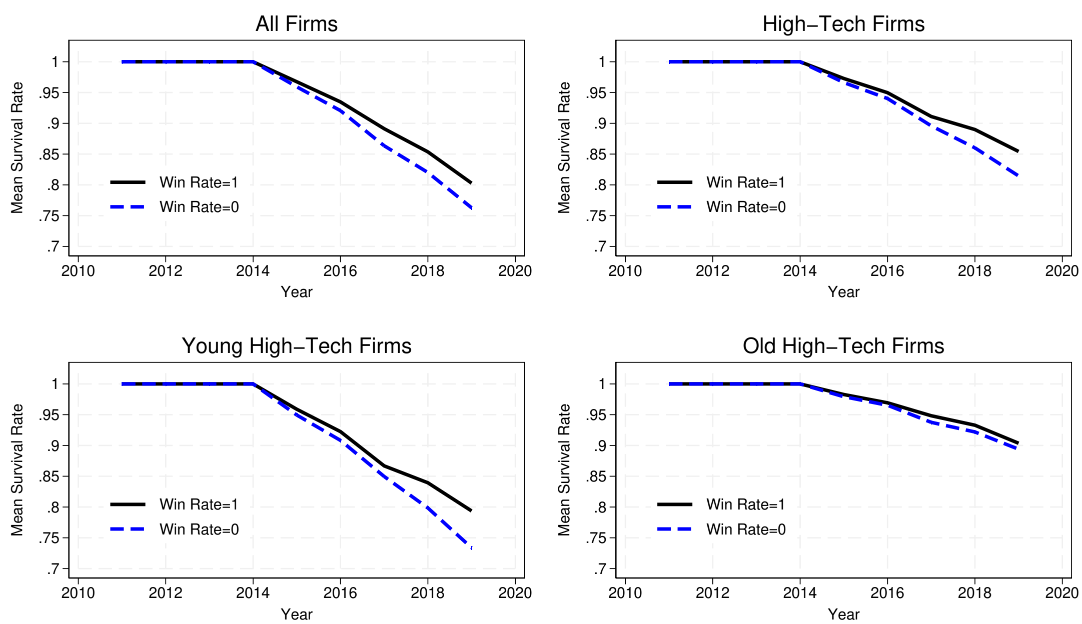
[11] As discussed in Brinatti et al. (2023), LCAs do not accurately reflect the number of H-1B petitions each company files. While LCAs signal vacancies or firm demand for skilled foreign labor, it is not necessary that firms with approved LCAs actually file H-1B petitions for the number of workers indicated in the LCAs. To address this issue, we remove outliers in the LCAs by winsorizing the data. A detailed description of this methodology can be found in the Appendix.

[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.

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.

Figure 4 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.

Figure 4. 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.

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 differences in 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

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

pre-trends in firm sales.

Appendix Figures B.1 and B.2 plot average firm sales of all and young high-tech firms, respectively, excluding firms that were merged/acquired. The sales pre-trends for all firms and young high-tech firms do not indicate that firms with a win rate of 0 experienced different trends in sales in pre-lottery years, that would have differently impacted their survival relative to firms with win rates of 1. The Appendix also shows that changes in firm sales between 2011-12 (pre-lottery years) are uncorrelated with lottery win rates, further supporting our empirical strategy.

3.2 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,

$$Survive_{i,t} = \beta[Win\_rate_i \times post_t] + \Gamma X_i + \gamma_t + \gamma_k + \epsilon_{i,t}, \tag{1}$$

where $post_t = 1$ if calendar year $t = 2015 - 2019$. X_i are firm-level controls, including employment at the beginning of 2013 (size) and total LCA applications submitted in fiscal years 2014-15. γ_t captures time-fixed effects and γ_k industry 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 3.1 percentage points, compared to those that had all their H-1B applications rejected.[14] 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 3.6 percentage points (column 3) compared to a win rate of 0. In contrast, the impact of the win rate on older firms (aged 6+) is not significant (column 4).

Table 1. Effects of Win Rate on Firm Survival in Postlottery Calendar Years (Excluding Mergers)

	(1)	(2)	(3)	(4)
	All firms	High tech (ht)	Age 0-5 (ht)	Age 6+ (ht)
year$\geq$ 2015 $\times$ WinRate	0.031***	0.024**	0.036**	0.009
	(0.006)	(0.010)	(0.018)	(0.011)
Industry and Year FE	Yes	Yes	Yes	Yes
Observations	89,598	23,473	10,615	12,373

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

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.

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.

[14] The results for all firms are similar to that of Brinatti et al. (2023), who find an impact of 2.4 percentage points.

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. 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.

Firms in sector 1 are subject to idiosyncratic productivity shocks and shocks to the hiring of foreign workers. In each period, only a 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 produces 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 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.

In addition, similar to Mehra & Shen (2022), we assume that skilled foreign workers are imperfect substitutes for skilled domestic workers, but both are assumed to earn the same wages.[15] This assumption is consistent with H-1B hiring regulations: 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. Once foreign workers are hired, they remain with the firm until an exogenous separation shock occurs or the firm decides to fire them.

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.

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

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. The issues of these firms are similar to those of the firms described in Sedlacek & Sterk (2019). 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.

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

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

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

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

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

where $\psi(l^f, l^f_{-1})$ is the hiring cost of an additional foreign worker, with $\psi(l^f, l^f_{-1}) > 0$ if $l^f > (1-\delta) l^f_{-1}$ 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.[16]

$a > 1$ represents the additional productivity that foreign workers may bring to production, and this assumption generates additional incentives for hiring skilled immigrant workers. By law, firms must pay a cost for hiring skilled immigrant workers and pay the same prevailing skilled wages to workers as denoted by w_s. 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. Therefore, we assume a positive productivity gain from hiring skilled foreign workers, which is also consistent with the empirical evidence in Peri et al. (2015b).

A type-f firm that decides to stay but receives a favorable hiring shock (i.e., wins the lottery) can hire

[16] 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 the 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.

additional skilled foreign workers and face the following problem:

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

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

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

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

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

where $W^F(l^f_{-1}, z_{-1}) = \mathbb{E}_{z|z_{-1}} \left[q \times W^{ff}(l^f_{-1}, z) + (1-q) \times W^{fu}(l^f_{-1}, z) \right]$ and q is the probability that an incumbent type-f firm receives a favorable hiring shock. We normalize the value of exiting the market to 0.

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 $V^{IF}(l^f_{-1}, z_{-1})$ is increasing in the productivity z_{-1}, there exists a productivity cutoff point $z^{I*}(l^f_{-1})$ for each level of l^f_{-1} such that firms with a productivity $z_{-1} \geq (<) z^{I*}_f(l^f_{-1})$ 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.[17] Then, the new entrant, just like incumbents, can choose to immediately exit or continue operations. Similar to Hopenhayn & Rogerson (1993) and Sedlacek & 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 and compare them with the data.

Since the entering firms face the same problem as the incumbent type-d firms, the continuing entering firm's problem is given by

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

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

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 assume that all households supply labor inelastically. The lifetime utility of unskilled domestic, skilled domestic, and skilled foreign households are

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

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

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

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

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 entrance 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 the 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. Last, 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 (CPS).

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 & Peri 2012). The span of control θ is set to 0.97, which is consistent with the estimates in Basu & Fernald (1997) and more recently Gao & 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 2. Note that the ratio of regulatory cost f_r to skilled wages w_s is computed using data from the 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.[18] 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). Last, w_s/w_u represents the wage skill premium and is measured using the CPS accessed via IPUMs (Ruggles et al., 2003).

[18] 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.

Table 2. 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

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 3 shows that our model generates a firm age distribution that is close to the data.

Table 3. 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).

4.5 Counterfactual Policy Exercises

In this section, we implement the following counterfactual policy exercises and compare the equilibrium distributions to the benchmark economy. We evaluate the impact of the following policy changes on all firms: (1) $q = 1$ (no idiosyncratic hiring frictions), (2) $c_s = 0$ (no sunk costs to switch to type f), (3) $q = 1$ and $c_s = 0$, (4) $f_r = 0$ (no per-worker hiring cost), and (5) no immigration policy frictions ($q = 1$, $c_s = 0$, and $f_r = 0$). In appendix D.1, we also consider counterfactual policy exercises in which new firms are subsidized or are the only ones not to face immigration frictions.

To study the impacts of lower immigration frictions on all firms, Table 4 expresses the stationary equilibrium of the economies under cases (1)–(5) relative to the benchmark economy. Note that a higher q, a lower c_s, or a lower f_r reduces the foreign worker hiring barriers for firms, thus increasing the total number of skilled foreign workers L_s^f in the stationary equilibrium. As expected, the impacts are the largest in the completely frictionless case for all firms, that is, case (5). The higher influx of skilled foreign workers in turn boosts sector 1's output and its consumption Y_1, which is the production net of costs.

The greater output of sector 1 consumption goods pushes down the prices of sector 1 goods (p_1) and boosts the relative price of sector 2 goods (p_2). As a result, skilled-intensive sector wages w_s decrease, and unskilled sector wages w_u rise. Consequently, skilled domestic households experience a reduction in consumption, and unskilled domestic households enjoy a higher consumption from lax skilled immigration policies. Note that the complementarity between skilled and unskilled workers in the model arises through the consumption basket. On the other hand, lower immigration policy frictions encourage more firms to enter the market and enjoy the benefits of hiring foreign workers. In the equilibrium with no immigration policy frictions, the mass of firms is approximately 56 percent higher compared to the baseline economy. The frictionless counterfactual witnesses a more than 14-fold increase in the aggregate skilled foreign labor stock, a 26 percent higher aggregate skilled-intensive output, and a 66 percent higher new firm entry.

Table 4. Effect of Skilled Immigration Policy on Aggregate Variables (Relative to the Baseline Case)

	(1) $q = 1$	(2) $c_s = 0$	(3) $q = 1$ & $c_s = 0$	(4) $f_r = 0$	(5) No frictions
Y_1	1.08	1.03	1.11	1.04	1.26
Y^c	1.04	1.01	1.05	1.02	1.12
p_1	0.96	0.99	0.95	0.98	0.89
p_2	1.04	1.01	1.05	1.02	1.12
w_s	0.96	0.99	0.96	0.98	0.9
w_u	1.04	1.01	1.05	1.02	1.12
c_s	0.97	0.99	0.96	0.98	0.91
w_u	1.04	1.01	1.05	1.02	1.12
L^f	5.16	2.45	6.61	3.31	14.65
Firm mass	1.29	1.06	1.23	1.15	1.56

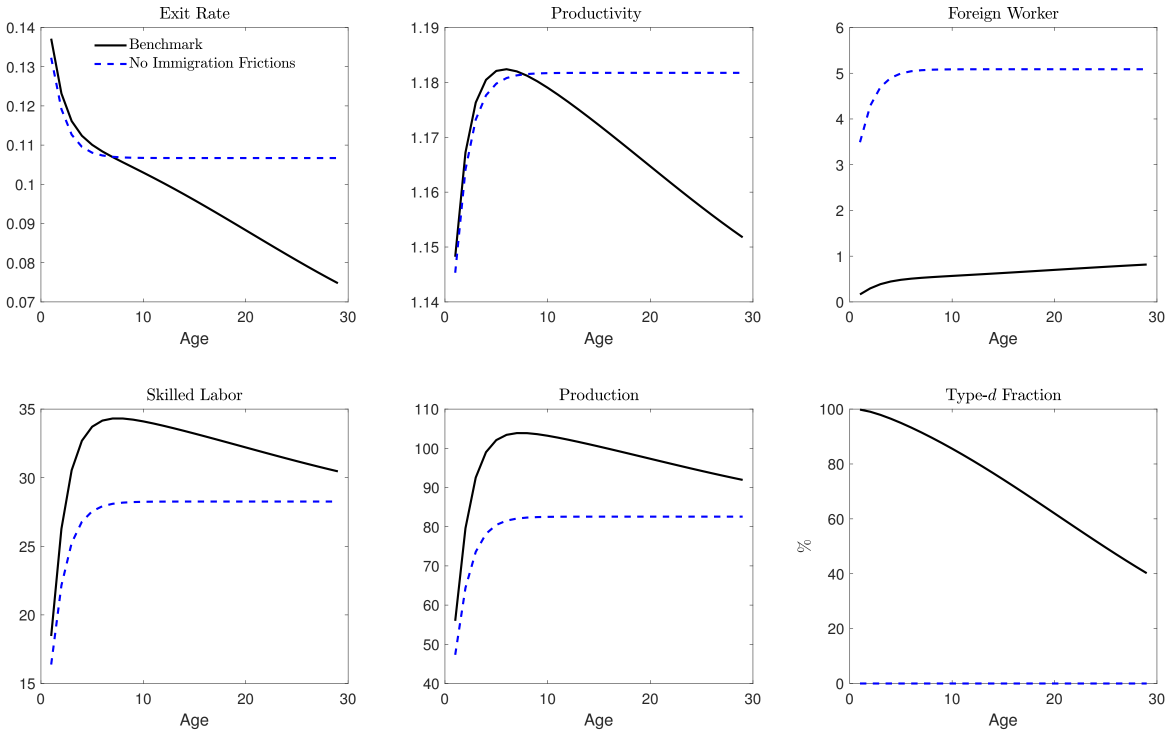
Notes: This table shows the effects of removing immigration frictions. All numbers in the table are relative to the values in the baseline case (with all immigration frictions).

To explore the impacts of our counterfactual policy by firm age cohorts, Figure 5 plots the average sector 1 variables by firm age in the benchmark economy and under the cases with no immigration frictions. Note that Appendix Figure D.5 plots the corresponding averages for the other cases, which are qualitatively similar but have less of a quantitative than the completely frictionless cases.

First, consider the intuition behind the average variables by age in the benchmark case. Firms draw the initial productivity after deciding to enter the market and may choose to exit immediately after observing the draw. Therefore, around 14 percent of the firms exit immediately after entering, and only those with high initial productivity stay. Since the productivity process is persistent, only firms with very unfavorable productivity shocks in the subsequent periods choose to exit, resulting in a lower exit rate in periods after the initial period. As firms become older, only those with greater productivity levels survive, pushing up the average total factor productivity among the surviving firms. It is also intuitive that older firms have higher average skilled workers (skilled foreign or domestic workers), higher average production, and a smaller fraction of type-d firms among older firms.

Reflecting on this, we use Figure 5 to compare the firm averages by age in the benchmark case with the corresponding averages under the case with no immigration frictions ($q = 1$, $c_s = 0$, and $f_r = 0$). Interestingly, eliminating frictions has a similar effect on both the average exit rate and average productivity. Lower immigration policy frictions increase the average exit rate for older firms and increase their average productivity, which pushes up the average productivity of all firms in the economy. The average productivity in the case with no immigration policy frictions is approximately 0.4 percent higher than in the benchmark case. Consistent with our empirical evidence, lower immigration policy frictions also increase the survival

Figure 5. Average Firm Characteristics by Age



of younger firms and decrease their exit rates. Intuitively, a higher new firm entry and young firm survival push out less productive incumbents, leading to higher average exit rates for older firms and higher average productivity. As a result, the higher exit rate is also accompanied by a higher entering mass, leading to a bigger firm mass in equilibrium, as shown in Table 4. This result is also consistent with the fact that the exit rate among older firms declined after immigration policies were tightened in 2005, as we will discuss in the next section.

In addition, lower immigration policy frictions reduce the barrier to acquiring foreign workers and result in more skilled foreign workers for firms of all ages. Moreover, since the mass of firms is higher in the frictionless case, the average production and average skilled labor employed per firm are lower. Therefore, even though the aggregate output of sector 1 increases, the average production of each firm is smaller due to the larger firm mass.

To summarize, lower immigration policy frictions lead to more firms entering, a higher mass of firms, and more foreign workers. The increase in aggregate output for sector 1 leads to a decrease in the sector's overall price p_1 and an increase in the cost of production (w_s/p_1). Therefore, less productive firms are more likely to exit, and the average productivity increases in the economy.

Extensive and intensive margins. In this section, we examine the effects of these immigration policy changes by the extensive versus the intensive margin. Table 4 shows that a relaxed immigration policy reduces the costs of hiring foreign workers, resulting in a higher mass of firms in equilibrium. Therefore, a fraction of the skilled domestic workers can be considered hired by these "additional" firms, which we interpret as the extensive margin. To separate the effects by the intensive and extensive margin, we "ration" the skilled labor so that each worker supplies labor that is smaller than one. Due to the rationed skilled domestic labor market, the wages of skilled workers become higher, reducing the firm value and causing the firm mass to decline. We then search for the fraction of skilled domestic labor that must be rationed to reduce the firm mass back to the baseline case.

Table 5. Effects of Immigration Policies by Extensive versus Intensive Margins (Relative to the Baseline Case)

	No Frictions (Fixed Firm Mass)	No Frictions
L_s^d	0.635	1
Y_1	0.803	1.264
Y^c	0.899	1.120
p_1	1.119	0.886
p_2	0.899	1.120
w_s	1.136	0.900
w_u	0.899	1.120
c_s	0.726	0.905
c_u	0.899	1.120
L^f	9.310	14.646
Firm mass	1	1.573
New entry	1.052	1.656

Notes: This table shows the effects of removing immigration frictions by the extensive and intensive margins. The column with "fixed mass" refers to the case with a rationed skilled domestic labor market, so the total mass of firms is identical to the baseline case (with all immigration frictions). All numbers in the table are relative to the values in the baseline case.

Table 5 shows the effects of removing all immigration frictions and the case with a fixed mass of firms through a rationed labor market, where all numbers are reported relative to the baseline case.[19] As shown in the first row, 36.5 percent of the domestic workers are hired by the additional firms induced by the lower immigration frictions. In the case of rationed skilled domestic labor (thus a fixed firm mass), the consumption of skilled domestic workers is only 72.6 percent of the level in the baseline case, indicating that fully relaxed immigration frictions would reduce the welfare of skilled domestic workers by 27.4 percent by the intensive margin. On the other hand, the total effects (including both the extensive and intensive margins) of relaxed immigration policies reduce the welfare of skilled domestic workers by 9.5 percent, indicating a 17.9 percent increase in the welfare of these workers by the extensive margin relative to the baseline case.

Similarly, a relaxed immigration policy reduces the welfare of domestic unskilled workers by 10.01 percent by the extensive margin. It also increases their welfare by 22.1 percent by the intensive margin, resulting in a total welfare gain of 12 percent for these workers.

[19] We do the same exercises for other cases and report the results in Table D.1.

5 Policy Implications and Conclusion

The results in the previous section show that reducing skilled immigration policy regulations—for instance, by simplifying procedures to lower sunk costs or reducing filing fees and idiosyncratic frictions due to the lottery process—can play an important role in increasing business dynamism in technology-intensive sectors. This is achieved by increasing the mass of younger firms and pushing out older, less productive ones. Eventually, such changes would increase the average productivity of operating firms.

We now highlight two trends observed in high-tech sectors since 2005 that are broadly consistent with our model mechanisms. Note that the period after 2005 can be interpreted as one with higher immigration policy frictions after the H-1B visa cap was reduced in 2004 (Figure 3). First, the period after 2005 was associated with lower average exit rates of older firms in the high-tech sector, compared to the period between 1990 and 2004 (Figure 6).[20] This is consistent with the mechanism of our general equilibrium model (Figure 5)—higher immigration policy frictions would reduce the average exit rate of older firms in the economy. Second, there has been an increase in the share of the smallest firms (least productive firms with 1–19 workers) within the oldest firms (age 11+) in the high-tech sector, as seen in Figure 2.[21] This trend is also consistent with our model mechanism—higher immigration frictions would reduce the mass of entering firms and lead to an increase in the survival of older, less productive firms.

[20] For these trends, we use annual four-digit NAICS-level data from the BDS, disaggregated by firm age and size. Firms are defined at the enterprise level such that all establishments under the operational control of the enterprise are considered part of the firm. To classify firms as high tech, we continue to use the NAICS classification used in (Decker et al., 2016b), which is the same classification as the Bureau of Labor Statistics (BLS) classification (Heckler, 2005) for level 1 high-tech industries. The exit rate in each period is computed as

$$\text{exit rate}_t = \frac{\text{firm deaths in time } t}{\text{average number of firms in } t \text{ and } t-1}. \tag{25}$$

The average exit rate is just the average rate across all years in the relevant period.

[21] This contrasts with the non-high-tech sector, which has witnessed the opposite.

Figure 6. Firm Exit Rate by Firm Age

In summary, our model predictions are not inconsistent with trends observed in the data since 2005 after immigration policies became more restrictive—a lower average exit rate of older firms and an increase in less productive (smaller) firms within the older firms. While there are many other factors that have contributed to these phenomena since the early 2000s, immigration policy restrictions may have played a role in influencing these trends in the high-tech sector, consistent with our model implications. The empirical relationships between immigration policies and firm dynamics by firm age in tech-intensive sectors have been previously overseen and require closer investigation beyond the scope of this paper. However, this paper establishes that skilled immigration policy frictions directly influence the dynamics of young firms in the high-tech sector by impacting firm survival. Additionally, it reveals important general equilibrium impacts of these frictions on firms across age cohorts and on the overall average productivity of firms.

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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[22] 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 regula-

[22]This proves the worker's qualifications.

tions 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."[23]

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 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. Our

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

baseline win-rate measure for each firm is calcuated 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 between 0 to 5.

Our final sample includes 15,200 unique firms with win-rate measures matched with the NETS database. Table B.1 displays the summary statistics of key variables used in our main analysis.

We check pre-trends in key firm outcomes to make sure that the lottery win-rate was exogenous and unrelated to pre-lottery year differences in firm outcomes. By construction, there is no variation in our key dependent variable related to firm survival in pre-lottery years 2011-2013 for all firms (except firms that entered in 2013 or later) since firms in our sample submitted applications in the relevant lottery years and were necessarily active. Therefore, we instead analyze pre-trends in firm sales.

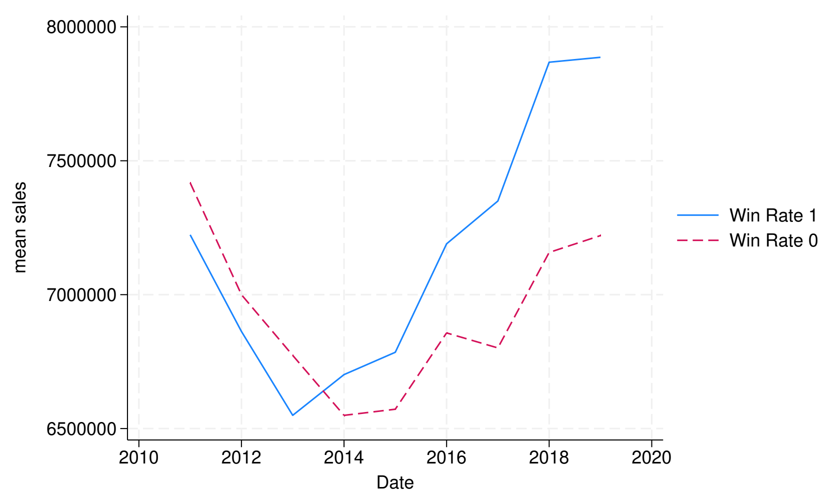
Figures B.1 and B.2 plot average firm sales of all and young firms (aged 0-5), respectively, excluding firms that were merged/acquired. The sales pre-trends for all firms and young high-tech firms do not indicate that firms with a win rate of 0 experienced different trends in sales in pre-lottery years, that would have differently impacted their survival relative to firms with win rates of 1.

Table B.1. 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

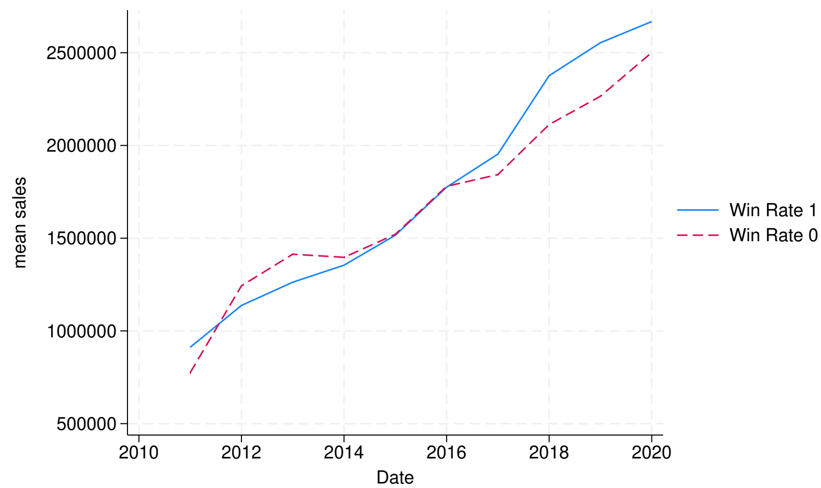
Notes: This table reports mean coefficients with standard deviations in parentheses. Survive refers to the average survival rate of firms during the 2015-2019 calendar years and excludes non survival due to mergers/acquisitions. The table reports the average firm employment and age in the 2013 calendar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

Figure B.1. All Firm Sales by Win rate



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.

Figure B.2. Young High-Tech Firm Sales by Win rate



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. Young firms include ages 0-5. We exclude mergers/acquisitions.

The Table below also shows that changes in log firm sales between 2011-12 (pre-lottery years) are uncorrelated with lottery win rates once we control for firm size and industry fixed effects.

	(1)	(2)	(3)	(4)
	All Firms	High Tech (ht)	Age 0-5 (ht)	Age 6+ (ht)
win_rate	-0.012	-0.025	-0.042	-0.001
	(0.009)	(0.020)	(0.040)	(0.010)
Obs.	9026	2337	733	5448.000

Standard errors in parentheses

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

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

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

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

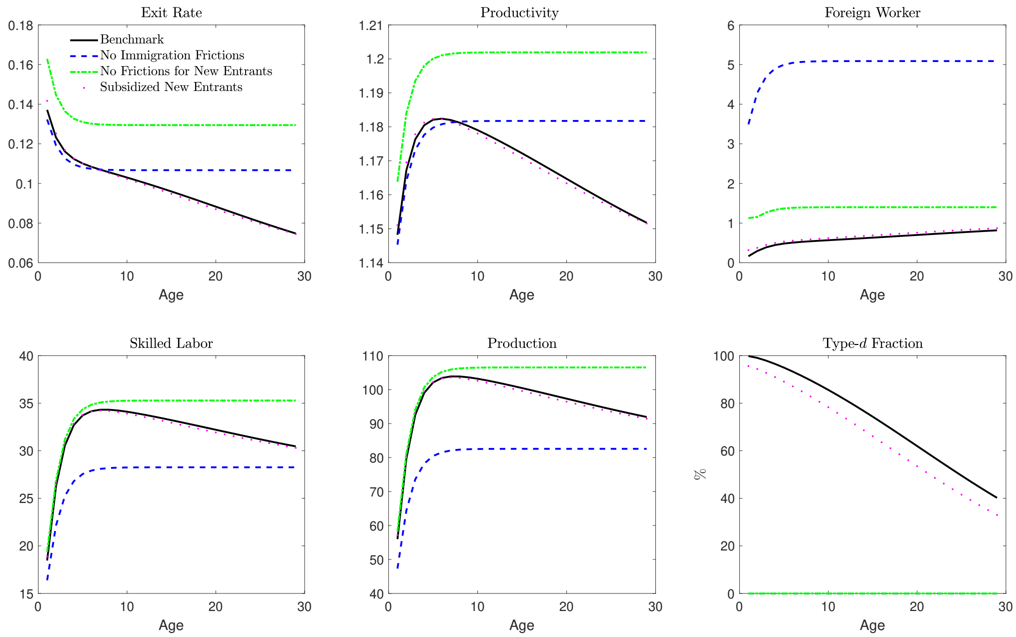
$$\begin{aligned} L^f_{s,t} = &\int \left(1 - \mathbb{1}_{f,exit}(l^f, z)\right) \times \int \left\{(1-q) \times \mathcal{L}^f_{fu}(l^f, z') + q \times \mathcal{L}^f_{ff}(l^f, z')\right\} f(z'|z)dz'd\mu_f(l^f, z) \\ &+ \int \mathbb{1}_{d,switch}(z) \times \int \left[(1-q) \times \mathcal{L}^f_{fu}(0,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

D Additional Results

D.1 Reduced Immigration Frictions for New Firms

In section 4.5, we conducted several counterfactual policy exercises and discussed the effects of policies that reduce immigration policies on all firms. In this section, we show additional results on the effects of immigration policies that target only new firms. Figure D.1 shows the average firm characteristics by age for four cases: (1) the benchmark economy, (2) no immigration fictions for all firms, (3) no immigration frictions for new firms only, and (4) subsidized new firms. In the third case, when all immigration frictions (C_s, f_r, and hiring shock) are removed for new firms, the lower initial costs attract a lot of new firms, which increases the entering mass by 42% compared to the benchmark case. The new entrants take advantage of the zero switching cost and immediately switch to type-f firms upon entry. As a result, type-d fraction immediately becomes 0 for age-1 firms. However, only new firms can enjoy the policy, and they need to face immigration frictions when they turn to age one. Consequently, many of them exit the market as they turn older, and the higher entering mass pushes up the exit rates for firms of all ages by about 2%. Only the very productive firms survive due to the large entering mass and exit rate, and the average productivity becomes higher for firms of all ages.

Figure D.1. Reduced Immigration Policies for New Firms

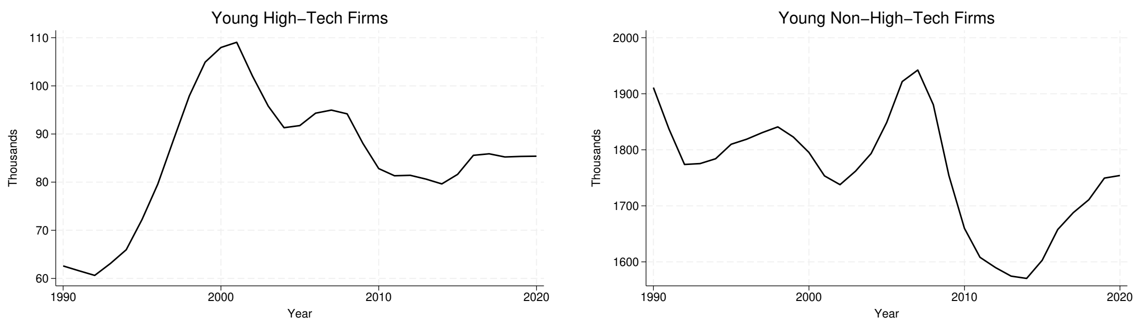


Notes: This figure shows the average firm characteristics by age for four cases: (1) the benchmark economy, (2) no immigration fictions for all firms, (3) no immigration frictions for new firms only, and (4) subsidized new firms. In the fourth case, the switching cost C_s, and hiring cost f_r for new firms are reduced by half. In addition, the probability that new firms cannot hire foreign workers is also reduced by half (i.e., $q = 0.675$).

The previous case assumes that all immigration frictions are removed for new firms. In the fourth case in Figure D.1, we consider a case where the new firms are subsidized and face reduced immigration frictions. Specifically, the switching cost C_s and hiring cost f_r for new firms are reduced by half. In addition, the probability that new firms cannot hire foreign workers is also reduced by half (i.e., $q = 0.675$). Figure D.1 shows that the reduced costs help more firms switch to type-f in their early ages. It also attracts slightly more new entrants to enter the market (0.3% higher than the benchmark case), which leads to a higher exit rate among young firms. However, the overall effects are small due to the small increase in the mass of new entrants.

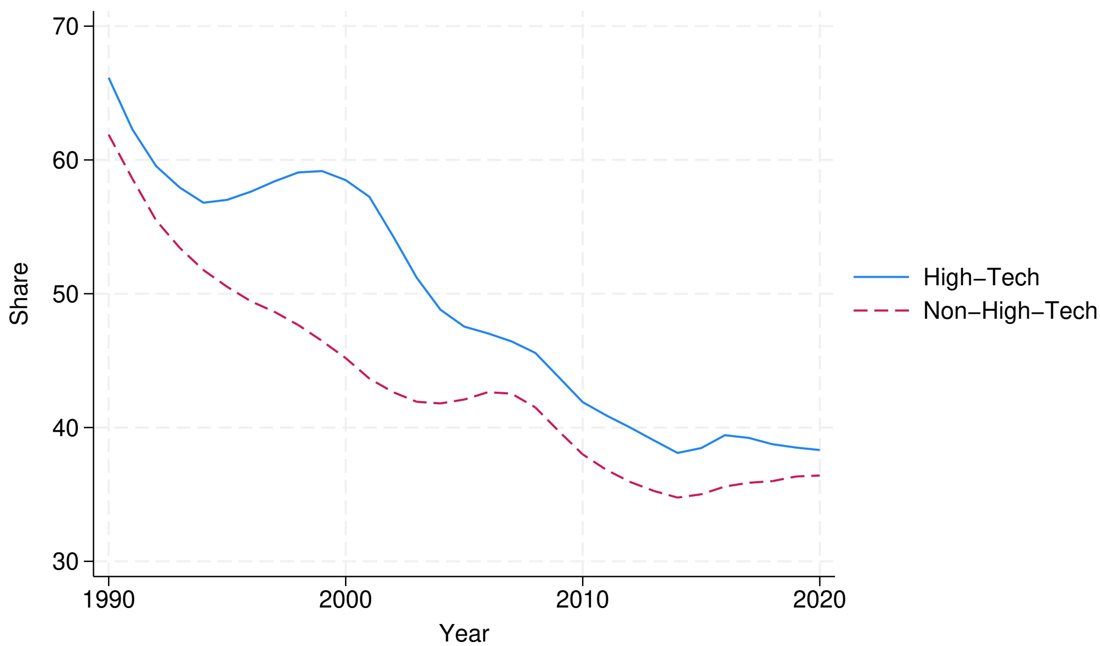
D.2 Additional Figures and Tables

Figure D.2. Number of Young Firms between 1986 and 2020



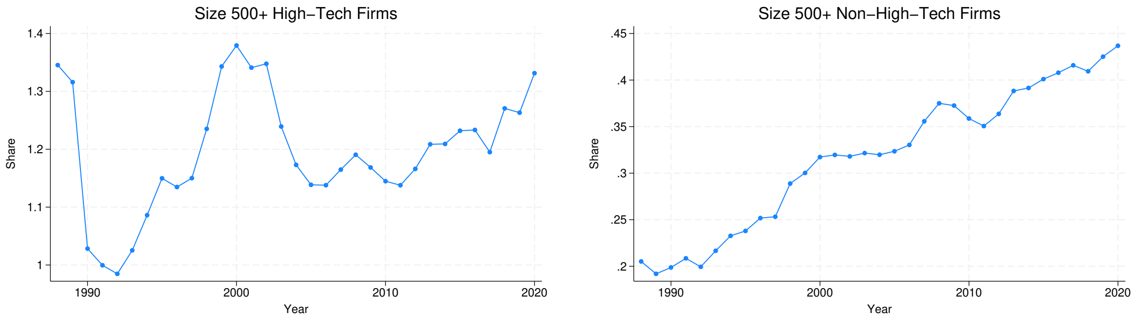
Notes: The figure is compiled using the US Census Bureau's BDS. High-tech firms are computed using four-digit NAICS codes and the BLS classification (Heckler, 2005).

Figure D.3. 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.4. 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.5. Average Firm Characteristics by Age

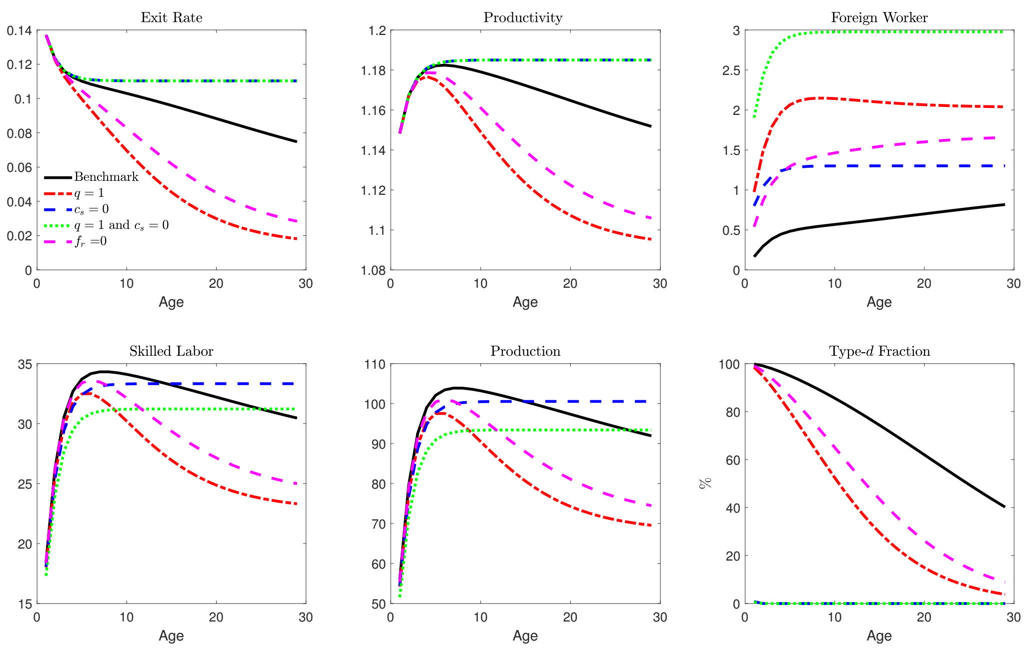


Figure D.6. Firm Distribution by Age

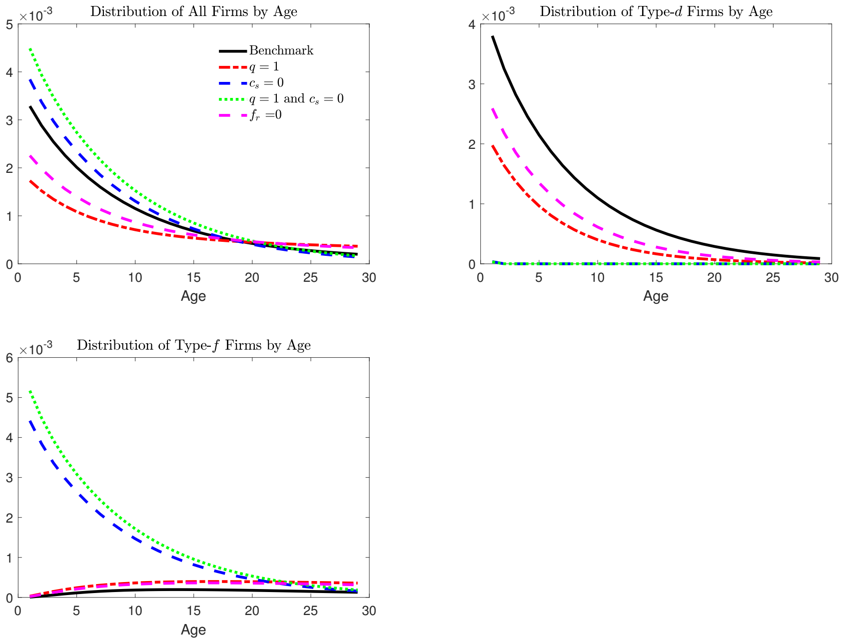


Table D.1. Effects of Immigration Policies by Extensive versus Intensive Margins (All Other Cases)

	$q=1$ (Fixed mass)	$q=1$	$c_s=0$ (Fixed mass)	$c_s=0$	$c_s=0$ & $q=1$ (Fixed mass)	$c_s=0$ & $q=1$	$f_r=0$ (Fixed mass)	$f_r=0$
L_s^d	0.828	1.00	0.969	1.00	0.801	1.00	0.907	1.00
Y_1	0.896	1.081	0.963	1.029	0.890	1.111	0.947	1.044
Y^c	0.948	1.038	0.982	1.014	0.945	1.052	0.974	1.021
p_1	1.057	0.960	1.020	0.985	1.062	0.947	1.028	0.978
p_2	0.948	1.038	0.982	1.014	0.945	1.052	0.974	1.021
w_s	1.061	0.963	1.023	0.988	1.071	0.956	1.030	0.979
w_u	0.948	1.039	0.982	1.014	0.945	1.052	0.974	1.021
c_s	0.884	0.969	0.957	0.989	0.861	0.959	0.936	0.982
c_u	0.948	1.039	0.982	1.014	0.945	1.052	0.974	1.021
L^f	4.277	5.161	2.294	2.452	5.297	6.613	3.006	3.313
Firm mass	1.00	1.207	1.00	1.069	1.00	1.249	1.00	1.103
New entry	0.436	0.527	1.094	1.170	1.094	1.366	0.623	0.686

Notes: This table shows the effects of removing immigration frictions by the extensive and intensive margins. The columns with "fixed mass" refer to the cases with a rationed skilled domestic labor market, so the total mass of firms is identical to the baseline case. All numbers in the table are relative to the values in the baseline case.