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Chapter Author(s): Gaurav Khanna, Munseob Lee

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High-Skill Immigration, Innovation, and Creative Destruction

Gaurav Khanna and Munseob Lee

3.1 Introduction

Recent political and academic discussions have shone a spotlight on issues related to high-skill immigration. This discourse could have far-reaching implications for US policy, the profitability of firms, the welfare of workers, and the potential for innovation in the economy as a whole. Yet the effects of high-skill immigration on receiving countries are theoretically ambiguous. On the one hand, skilled migrants may increase the profitability and innovative capacity of the firm (Kerr and Lincoln 2010) and raise wages of native workers who are complements to production (Peri and Sparber 2009). On the other hand, migrants may crowd out domestic workers (Doran, Gelber, and Isen 2017) and lower the wages of close substitutes (Bound, Braga, Golden, and Khanna 2015).

What has been missing so far from this discourse is a discussion about how migrants may affect the product mix produced by a firm and the innovation involved in creative destruction. The entry and exit of products have long been seen as important determinants of firm-level innovation and

Gaurav Khanna is assistant professor of economics at the University of California, San Diego.

Munseob Lee is assistant professor of economics at the University of California, San Diego.

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Schumpeterian growth (Aghion, Akcigit, and Howitt 2014). Hiring high-skill workers from abroad may have a meaningful impact on such innovation, and this has implications not only for firm profits but also for consumer welfare. For instance, hiring more engineers and programmers from abroad, perhaps at a lower cost, allows firms to implement incremental innovations that may lead to newer products on the market. In this chapter, we fill this gap by studying the impact of H-1B worker applications on firm-level product reallocation, defined broadly as the entry of new products and the exit of outdated products.

We create a new data set by combining data on H-1B worker applications and firm production. Our H-1B data consists of publicly available labor condition applications (LCAs).[1] Our product-level data from the Nielsen Retail Scanner Data are combined with firm characteristics from the Compustat database. Together, a combination of these data sets at the firm-by-year level between 2006 and 2015 allows us to comprehensively examine the impact of wishing to hire foreign workers on firm production and innovation.

Our analysis consists of a few different methods. We first describe the entry and exit of products over the business cycle and across a firm's baseline propensity to hire H-1B workers.[2] We find that product reallocation falls precipitously in times of recession and rises in periods of economic recovery. Moreover, product reallocation is strongly associated with the baseline propensity to hire H-1B workers: firms that applied for H-1B workers in the first year of our LCA data are more likely to consistently have high product reallocation rates over the business cycle. Indeed, this association is invariant to a firm's research and development (R&D) expenditure, size, or revenue share. R&D expenditures and revenues are no longer strong determinants of product entry and exit after accounting for baseline propensities to hire H-1B workers.

We then use panel regressions, where we account for firm-level characteristics that are stable over time and for shocks that widely affect the economy with the help of fixed effects. Our preferred specifications look at outcomes in the following period, as they are less likely to be affected by contemporaneous shocks, and we would expect firm dynamics to change with a lag. We show that an increase in product reallocation is strongly associated with higher firm revenue growth.

We find that the number of LCAs, the number of certified workers, and the number of workers as a fraction of the total firm employment base are strongly associated with reallocation rates.[3] A 1 percentage point increase in the share of workers from certified LCAs is associated with a 5 percent-

1. LCAs are filed with the Department of Labor when a firm wishes to hire H-1B workers, and a single LCA may list many workers.

2. Our baseline propensity is whether or not a firm applied to hire H-1B workers in the first year of our LCA data (2000–2001).

3. A firm can file one LCA for many workers, and this LCA may be either denied, withdrawn, or certified. We define "certified workers" as the number of workers on certified LCAs.

age point increase in the reallocation rate. This association is stronger for software workers than for other occupation groups. In a distributed lead and lag setup, we also see that even as future H-1B certification does not affect current reallocation rates, current H-1B certification does affect future reallocation rates.

Our results speak to the innovative capacity of the firm by focusing on product reallocation, which is found to be highly correlated with firm growth and productivity (Argente, Lee, and Moreira 2018b). Previous work on high-skill immigrants and innovation focus on patenting activity (Kerr and Lincoln 2010; Hunt and Gauthier-Loiselle 2010; Moser, Voena, and Waldinger 2014). The propensity to patent may be affected by rulings of the Federal Court of Appeals, the firm's industry and products, and changes in state policies and taxes (Lerner and Seru 2018). Indeed, many important innovations are never patented (Fontana, Nuvolari, Shimizu, and Vezzulli 2013). While patents may be a good measure of newer production processes and inputs into production, our measure of innovation captures the final products produced by firms. The major advantage of a product reallocation measure is that it captures incremental innovations that are not usually patented. Previous work using patent data might have underestimated the benefits of having additional high-skilled immigrant workers by not being able to capture these incremental innovations.

Such changes affect not just firms but also consumers. Changes in a firm's production portfolio are strongly linked to a firm's revenue generation ability and profitability. In concurrent work, we examine how changes in consumer goods products affect the welfare of US consumers (Khanna and Lee 2018). Together these results have striking implications for the overall consequences of H-1B migration on the US economy.

Our chapter is organized into five sections. In section 3.2, we provide a background on the H-1B program and how that may relate to innovation and product reallocation. In section 3.3, we describe the data that we use and how we combine our data sets. Our primary analysis is in section 3.4, where we first describe trends over the business cycle, the association between reallocation rates and revenue growth, and then the association between H-1Bs and product reallocation. Section 3.5 concludes.

3.2 Background

3.2.1 The H-1B Program

The Immigration Act of 1990 established the H-1B visa program for temporary workers in "specialty occupations" with a college degree.[4] In order to

4. Specialty occupations are defined as requiring *theoretical and practical application of a body of highly specialized knowledge in a field of human endeavor including, but not limited to, architecture, engineering, mathematics, physical sciences, social sciences, medicine and health, education, law, accounting, business specialties, theology, and the arts*.

hire a foreigner on an H-1B visa, a firm must first file a LCA to the Department of Labor (DOL) and pay them the greater of the actual compensation paid to other employees in the same job or the prevailing compensation for that occupation.

After which, the H-1B prospective must demonstrate to the US Citizenship and Immigration Services Bureau (USCIS) in the Department of Homeland Security (DHS) that he or she has the requisite amount of education and work experience for the posted position.[5] USCIS then may approve the petitions up to the annual cap. H-1Bs are approved for a period of up to three years and can be extended up to six years. Once the H-1B expires, employers can sponsor a green card, and each country is eligible for only a specific number of those. The US General Accounting Office 2011 survey estimates the legal and administrative costs associated with each H-1B hire to range from 2.3 to 7.5 thousand dollars. It therefore seems reasonable to assume that employers must expect some cost or productivity advantage when hiring high-skill immigrants.

In the early years, the H-1B cap of 65,000 new visas was never reached, but by the time the IT boom began in the mid-1990s, the cap started binding, and the allocation was filled on a first-come, first-served basis. The cap was raised to 115,000 in 1999 and to 195,000 for 2000–2003 and was then reverted back to 65,000 thereafter. The 2000 legislation that raised the cap also excluded universities and nonprofit research facilities from it, and a 2004 change added an extra 20,000 visas for foreigners who received a master's degree in the US. Renewals of visas up to the six-year limit are not subject to the cap, and neither is employment at an institution of higher education or a nonprofit or governmental research organization.

When the cap is reached, USCIS conducts a lottery to determine who receives an H-1B visa. For instance, in the 2014 fiscal year, USCIS received approximately 124,000 petitions in the first five days of open applications for 85,000 visas. A computer-generated lottery first determines the visas for petitions of applicants who received a master's degree in the US (a quota of 20,000 visas), and then the remaining 65,000 visas are granted. Those not selected in the lottery may file again the next year. Those who are selected will eventually also receive an I-129 form from USCIS.

According to the United States Immigration and Naturalization Service (USINS 2000), the number of H-1B visas awarded to computer-related occupations in 1999 was about two-thirds of the visas, and the US Department of Commerce (2000) estimated that during the late 1990s, 28 percent of programmer jobs in the US went to H-1B visa holders. H-1B visas, therefore, became an important source of labor for the technology sector. Yet many

5. Workers may be educated in the US. The National Survey of College Graduates (NSCG) shows that 55 percent of foreigners working in computer science fields in 2003 arrived in the US on a temporary working (H-1B) or student-type visa (F-1, J-1).

non-IT firms also hire those with H-1B visas. Such workers may be in-house programmers but also scientists, mathematicians, and engineers.

3.2.2 The Impact of High-Skill Immigrants on the US

Work by economists on the impacts of the H-1B program is mostly focused on the wages and employment of native-born workers. Some argue that employers find hiring foreign high-skilled labor an attractive alternative and that such hiring either "crowds out" natives from jobs or puts downward pressure on their wages (Doran, Gelber, and Isen 2017). Given the excess supply of highly qualified foreigners willing to work and given the difficulty in the portability of the H-1B visa, immigrant workers may not be in a position to search for higher wages, allowing firms to undercut and replace US workers (Matloff 2003; Kirkegaard 2005). On the other hand, negative wage effects may be muted as native workers switch to complementary tasks (Peri and Sparber 2009).

Importantly, immigrants may affect the innovative capacity of the firm. Kerr and Lincoln (2010) and Hunt and Gauthier-Loiselle (2010) provide evidence on the link between variation in immigrant flows and innovation measured by patenting, suggesting that the net impact of immigration is positive rather than simply substituting for native employment. Kerr and Lincoln (2010) also show that variation in immigrant flows at the local level related to changes in H-1B flows does not appear to adversely impact native employment and has a small, statistically insignificant effect on their wages. Indeed, in other research, it is evident that changes in the size of the science, technology, engineering, and mathematics (STEM) workforce at the city level may raise wages for US-born workers (Peri, Shih, and Sparber 2015).

Even though much of the theoretical analysis underlying studies of immigration are about firms, a large fraction of the literature focuses on variation across states or metro areas.[6] Yet for high-skilled migrants sponsored by firms in specialty occupations, we may expect that effects on receiving firms will be rather different from the impacts on the larger labor market. Kerr and Lincoln (2010) and Kerr, Kerr, and Lincoln (2015) are among the first to focus on the firm, and more recently working papers using publicly traded firms (Mayda et al. 2018) or administrative tax data (Doran, Gelber, and Isen 2017) look at employment outcomes for native workers and the patenting propensity of the firm.

Yet focusing on either the labor market or innovative capacity may miss overall productivity changes in the US economy. Bound, Khanna, and Morales (2016) and Khanna and Morales (2018) take a different approach and set up a general equilibrium model of the US economy. Doing so allows them to conduct a comprehensive welfare analysis and study the distribu-

6. As Kerr, Kerr, and Lincoln (2015) point out, the word *firm* does not appear in the 51 pages of the seminal Borjas (1994) review of the immigration literature.

tional implications of the H-1B program. Importantly, by modeling the firms' decisions, including the spillovers from technological innovation, they find that even though US computer scientists are hurt by immigration, there are substantial benefits to consumers, entrepreneurs, and workers that are complements to computer scientists.

3.2.3 Innovation and Product Reallocation

Work on high-skill immigrants and innovation often focuses on patenting activity (Kerr and Lincoln 2010; Hunt and Gauthier-Loiselle 2010; Moser, Voena, and Waldinger 2014). Such pioneering work highlights the importance of immigrants in innovation. Although patents are a rich measure, they capture a specific type of innovation. While patents may capture larger significant innovations, product reallocation often captures incremental innovations that are rarely patented.

Certain features of patent data make it important to study alternative measures of innovation as well. First, immigration status is not directly observed in the patenting data, and often ethnicity needs to be inferred by name, and one needs to compare traditionally Indian or Chinese names to more Anglo-Saxon or European names. Second, changes to patenting over time may be a result of changes in intellectual property laws (such as the Computer Software Protection Act of 1980 and the Semiconductor Chip Protection Act of 1984) and rulings of the Court of Appeals for the Federal Circuit rather than actual innovation. Furthermore, there are gaps when a patent is filed and when it is granted, and any contemporary analysis like ours would need to limit itself to filing information and ignore granting status or citations to avoid issues with truncation.

The propensity to patent and cite innovations also varies widely across types of products and industries. Some patents are heavily cited due to their industry rather than "fundamental innovativeness" (Lerner and Seru 2018). Indeed, a relatively low number of important innovations may ever be patented.[7] Lastly, patenting propensities may differ across regions due to changes in state intellectual property policies and taxes or differences in industrial composition across regions, and analyses that use cross-state and -city variation need to account for such changes.

To complement the literature using patenting data, we investigate an alternative measure of innovation. For decades, economists have identified product entry and exit as one of the key mechanisms through which product innovation translates into economic growth (Aghion and Howitt 1992; Grossman and Helpman 1991). In the consumer goods sector, recent developments in point-of-sale systems allow us to investigate barcode-level trans-

7. Fontana, Nuvolari, Shimizu, and Vezzulli (2013) find that 91 percent of R&D award-winning inventions between 1977 and 2004 were never patented. Some inventions, like penicillin, may never be patented, as inventors may never wish to patent them.

actions and therefore product entry and exit. We calculate firm-level product creation and destruction by identifying manufacturers of each barcode-level product and aggregating transactions from about 35,000 stores in the United States. Following the idea of creative destruction, where new and better varieties replace obsolete ones, we define firm-level product reallocation as the sum of firm-level product creation and destruction. Most product reallocation is driven by surviving incumbent firms that add or drop products in their portfolios. The speed of product reallocation is strongly related to the innovation efforts of firms and several innovation outputs, such as revenue growth, improvements in product quality, and productivity growth (Argente, Lee, and Moreira 2018b). The major advantage of product reallocation as a measure of innovation outcomes is that it captures incremental innovations that are not usually patented. Under the presence of incremental innovations, previous work only with patent data might have underestimated the benefits of having additional high-skilled immigrant workers.

3.3 Data

We combine data at the firm-by-year level from multiple sources. We first obtain publicly available H-1B data on LCAs between 2000 and 2016. We merge this H-1B data with firm-level data from the Nielsen Retail Scanner Data (2006 to 2015), which provides us with information on products produced at the firm level, and also Compustat firm-level characteristics for a subset of large publicly listed firms.

3.3.1 Data on High-Skill Immigration

Data on H-1B visas come from the publicly available list of 2000–2001 LCAs, which firms file with the US DOL when they wish to hire a foreign high-skill worker. Attached to each LCA are an employer name, address (including city, zip code, and state), work start date and end date, occupation and job title, and number of workers requested. The LCA database also documents whether the application was denied, withdrawn, or certified. For our analysis, we only use certified applications and count the "certified workers" as the number of workers on certified LCAs. We aggregate the LCA-level data to the firm-by-year level, counting not just the number of LCAs and workers but also the types of workers for broad occupational categories. These categories, in descending order of prevalence, are (1) software workers (including computer programmers, software engineers, and software developers), (2) scientists / mathematicians / statisticians and engineers (including electrical and mechanical engineers), (3) managers (and administrators), and (4) those working in finance or marketing. Together, these categories account for more than 90 percent of all LCAs in each year of our data.

Due to the H-1B caps, not all certified LCAs lead to actual H-1B hires. However, since they are necessary for approved H-1Bs, these LCAs measure

Table 3.1 Facts on Nielsen Retail Scanner Data

	Nielsen Retail Scanner Data
Time period	2006–2015
Coverage	1,071 modules, 114 groups
Observational units	Store
# of stores	35,510
# of states	49
# of counties	2,550
# of products in 2006	724,211
Frequency	Weekly, average
Tag on temporary sales	None

the firms' desire to hire H-1Bs and therefore are likely to be highly correlated with actual H-1Bs. Since our analysis is only for for-profit firms that produce consumer goods, none of the H-1B LCAs we eventually match to our products data set are cap exempt. Importantly, our data set should not be thought of as being representative of H-1B firms. Instead, it is only representative of consumer goods–producing firms. Since about 2011, there has been an increase in outsourcing firms grabbing the majority of H-1B visas and filing a lot of LCAs—yet such firms are not a part of our sample and are not the focus of our analysis.

With the help of these data, we compute a few important variables: we count (1) the number of LCAs filed by a firm each year, (2) the number of workers under certified LCAs, (3) the number of workers in each of the four broad occupational categories mentioned above, and (4) the number of workers normalized by the total employment in the firm (from Compustat).

3.3.2 Data on Products

For data on products, we use the Nielsen Retail Scanner Data provided by the Kilts Center for Marketing at the University of Chicago. Each individual store reports weekly prices and quantities of every UPC (Universal Product Code) that had any sales during that week. The data are generated by point-of-sale systems from approximately 35,000 distinct stores from 90 retail chains across 371 Metropolitan Statistical Areas (MSAs) and 2,500 counties between January 2006 and December 2015. The data are organized into 1,070 detailed product modules aggregated into 114 product groups that are then grouped into 10 major departments.[8] Table 3.1 summarizes basic facts on the data.

8. The ten major departments are Health and Beauty Aids, Dry Grocery (e.g., baby food, canned vegetables), Frozen Foods, Dairy, Deli, Packaged Meat, Fresh Produce, Non-Food Grocery, Alcohol, and General Merchandise.

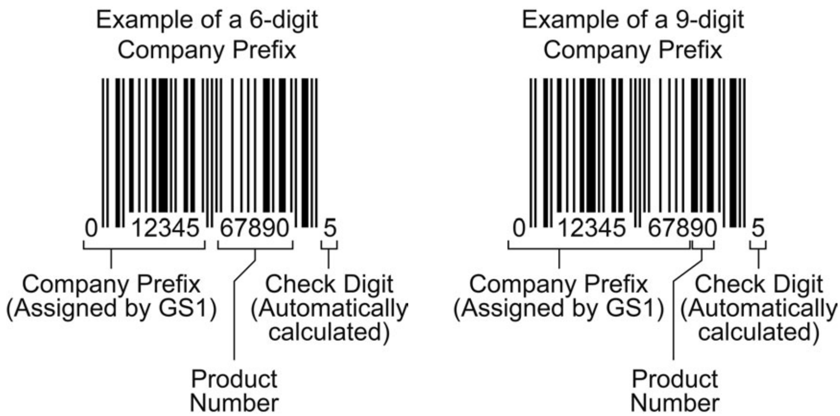

Fig. 3.1 Example of a company prefix

Note: This figure shows examples of a six- and a nine-digit firm prefix. The source is the GS1-US website (http://www.gs1-us.info/company-prefix).

Our data set combines all sales of products at the national and annual levels. As in Broda and Weinstein (2010) and Argente and Lee (2016), we use the UPC as the level of analysis. A critical part of our analysis is the identification of entries and exits, for which we mostly follow Argente, Lee, and Moreira (2018a, 2018b). For each product, we identify the entry and exit periods. We define entry as the first year of sales of a product and exit as the year after we last observe a product being sold.

We link firms and products with information obtained from GS1 US, the single official source of UPCs. In order to obtain a UPC, firms must first obtain a GS1 company prefix. The prefix is a 5- to 10-digit number that identifies firms and their products in more than 100 countries where the GS1 is present. In figure 3.1, we show a few examples of different company prefixes. Although the majority of firms own a single prefix, it is not rare to find that some own several. Small firms, for instance, often obtain a larger prefix first, which is usually cheaper, before expanding and requesting a shorter prefix. Larger firms, on the other hand, usually own several company prefixes due to past mergers and acquisitions. For instance, Procter & Gamble owns the prefixes of firms it acquired, such as Old Spice, Folgers, and Gillette. For consistency, in what follows, we perform the analysis at the parent-company level.

Given that the GS1 US data contains all the company prefixes generated in the US, we combine these prefixes with the UPC codes in the Nielsen Retail Scanner Data. Less than 5 percent of the UPCs belong to prefixes not generated in the US. We were not able to find a firm identifier for those products.

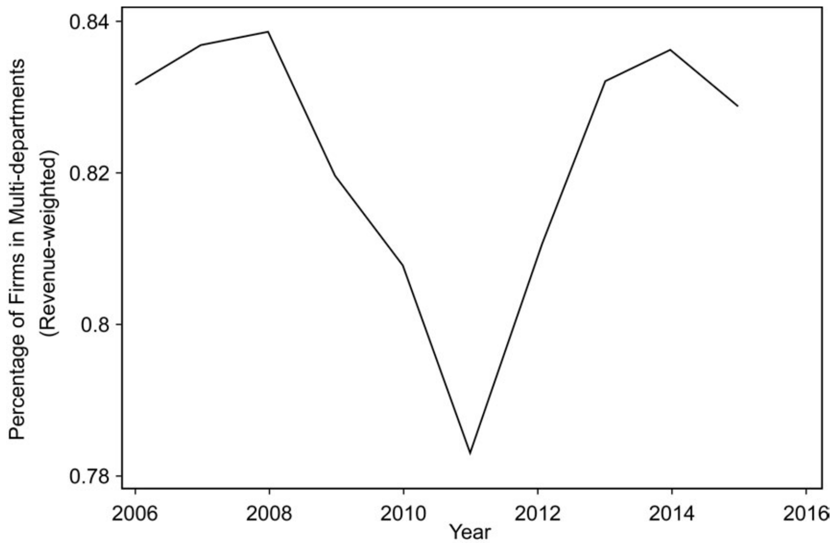

Fig. 3.2 Share of firms in multiple departments

Note: This figure shows the share of firms operating in more than one product department. The share is calculated with real revenue weights. The 10 major departments are Health and Beauty Aids, Dry Grocery (e.g., baby food, canned vegetables), Frozen Foods, Dairy, Deli, Packaged Meat, Fresh Produce, Non-Food Grocery, Alcohol, and General Merchandise.

With this data set on products and firms, we can compute how firm-level product creation and destruction evolve over time.

Note that typical firms in the data produce multiple products in several different categories. Over the sample period, about 82.2 percent of revenue has been generated by firms operating in more than one product department. Figure 3.2 shows that the share of firms in multiple departments has been between 78 and 84 percent from 2006 to 2015, declining a bit during the Great Recession.

3.3.3 Data on Other Firm Characteristics

We obtain other firm-level characteristics from Compustat. The Compustat is a database of financial and market information on global companies throughout the world. For the purpose of this research, we bring in information on employment and R&D expenditures over the sample period from the fundamental annual North American database. This limits the number of firms in analysis but provides much more detailed information on firms. For instance, with information on the number of employees, we can calculate the share of high-skill immigrant worker applications instead of just the number of high-skilled migrant applications. Additionally, data on R&D expenditures allow us to test the importance of H-1B workers to product reallocation relative to R&D investments.

Table 3.2 **Descriptive statistics for two merged samples**

Merged samples	LCA-Nielsen (1)	LCA-Nielsen-Compustat (2)
Number of firms	36,218	482
Years	2006–15	2006–15
Variables from LCA		
Average # of certified workers	0.79	20.72
Variables from Nielsen		
# of observations	235,522	4,022
Average firm revenue (USD)	6.25 million	154 million
Average reallocation rates (0–2)	0.1944	0.2585
Variables from Compustat		
# of observations	—	4,565
Average # of employees	—	43,841
Average R&D to sales	—	0.251

3.3.4 Combining Data Sets

We merge our data sets at the firm-by-year level using a string matching algorithm for firm names. When there is uncertainty in name matching, we consult city and/or zip codes. We do not expect a matching error to be correlated with our main variables of interest. For our analysis, we create two different merged samples: (a) the LCA-Nielsen sample and (b) the LCA-Nielsen-Compustat sample. Table 3.2 reports descriptive statistics for all three merged samples.

The first sample combines LCAs and Nielsen Retail Scanner Data. As table 3.2 shows, the LCA-Nielsen sample contains 36,218 distinct firms for 2006 to 2015. This covers both small and large firms, where the average annual number of certified workers from LCAs is 0.79 (many firms file no LCAs in some years), and the average annual revenue in the Nielsen data is $6.25 million.

The second sample adds Compustat to the LCA-Nielsen sample in order to obtain other firm characteristics. As table 3.2 shows, the LCA-Nielsen-Compustat sample has 482 distinct firms for 2006 to 2015. Due to the limited coverage of the Compustat database, this sample mostly covers large companies, where the average annual number of certified workers from LCAs is 20.7 and the average annual revenue in the Nielsen data is $154 million. From the Compustat database, we additionally know that the average number of employees is 43 and the average R&D expenditure-to-sales ratio is 0.25.

3.3.5 Measurement of Creative Destruction

We start with a description of the measures that we use to identify the degree of creative destruction by firms in the product space.

To capture the importance of product entry and exit, we use information on the number of new products and exiting products and the total number of products for each firm i over year t. We define firm-level entry and exit rates as follows:

$$n_{it} = \frac{N_{it}}{T_{it}} \tag{1}$$

$$x_{it} = \frac{X_{it}}{T_{it-1}}, \tag{2}$$

where N_{it}, X_{it}, and T_{it} are the numbers of entering products, exiting products, and total products, respectively. The entry rate is defined as the number of new products for each firm i in year t as a share of the total number of products in period t. The exit rate is defined as the number of products for each firm i that exited in year t as a share of the total number of products in year $t - 1$.

From the idea of creative destruction at the firm level, the overall change in the portfolio of products available to consumers can be captured by the sum of firm-level entry and exit rates. We refer to this concept as the product reallocation rate:

$$r_{it} = n_{it} + x_{it}. \tag{3}$$

With this measure, we can investigate the extent of changes in the status of a product in our data from either the entry or the exit margin.

3.4 Empirical Analysis

3.4.1 Product Reallocation and Firm Outcomes

To understand the importance of product reallocation, we first study the association between reallocation and firm revenue growth. This is simply a replication of the results found in Argente, Lee, and Moreira (2018b) and is theoretically similar to results in Aghion, Akcigit, and Howitt (2014). We test for this association in our sample with the following regression specification:

$$\Delta \text{Log}(\textit{Revenue})_{i,t+1} = \alpha + \beta r_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t}, \tag{4}$$

where $\Delta \text{Log}(\textit{Revenue})_{i,t}$ is growth in the sum of revenue over all products in firm i's portfolio between years t and $t - 1$. μ_i are firm fixed effects, and τ_t are year fixed effects. With the help of fixed effects, our associations account for firm characteristics that are stable over time and for annual shocks that affect the entire US economy. Our resulting variation is driven by changes over time within firms. Here and elsewhere, we cluster our standard errors at the firm level.

In table 3.3, we study this association. Product reallocation has a strong

Table 3.3 Reallocation activities and revenue growth

DV: Δ $Log(Revenue)_{i,t+1}$	(1)	(2)	(3)
Product reallocation rate	0.432 (0.0235)***		
Product entry rate		1.240 (0.0210)***	
Product exit rate			0.355 (0.0377)***
Observations	147,723	179,502	147,723
R^2	0.013	0.063	0.009
Number of firms	27,574	31,626	27,574
Fixed effects	Year and firm	Year and firm	Year and firm
Cluster	Firm	Firm	Firm

Note: The table reports the coefficients of OLS regressions with the LCA-Nielsen merged sample. The dependent variable is the revenue growth rate in the next year: the change in revenues between year t and $t + 1$. The product reallocation rate is defined as the product entry rate plus the product exit rate at the firm level, as defined in the main text. Reallocation rates range from 0 to 2, whereas entry and exit rates range between 0 and 1. Revenue growth rates are winsorized at the 1% level. Standard errors are clustered at the firm level and presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

positive association with firm revenue growth. When we look at product entry and exit separately, once again it is clear that both entry and exit of new products are strongly associated with firm revenue growth; however, firm entry has a much stronger association than firm exit. While these associations are not causal, they are suggestive as to how product reallocation is important for firm revenue growth.

3.4.2 Reallocation and Immigration over the Business Cycle

Our period of study, 2006 to 2016, encapsulates the Great Recession of 2008–10. This is an ideal setting to understand how the business cycle affects product reallocation and how high-skill migration interacts with this relationship. In much of this subsection, we divide firms by whether they have a propensity to apply for H-1B workers. Any firm that filed an LCA that was certified in the first year of our LCA data (2000–2001) is categorized as a firm that has a propensity to hire H-1B workers. We use the earliest possible year (2000–2001) rather than our sample period (2006–15) for our classification so as to ensure that contemporaneous changes in firm characteristics are not driving much of our analysis.[9] The aim is to capture baseline propensities of the firm that may not be related to differential trends over time in

9. The propensity to hire H-1B workers in 2000–2001 is also strongly predictive of the propensity to hire H-1B workers between 2006 and 2015. However, it is important to note that the propensity to hire may not be actual hiring given the caps.

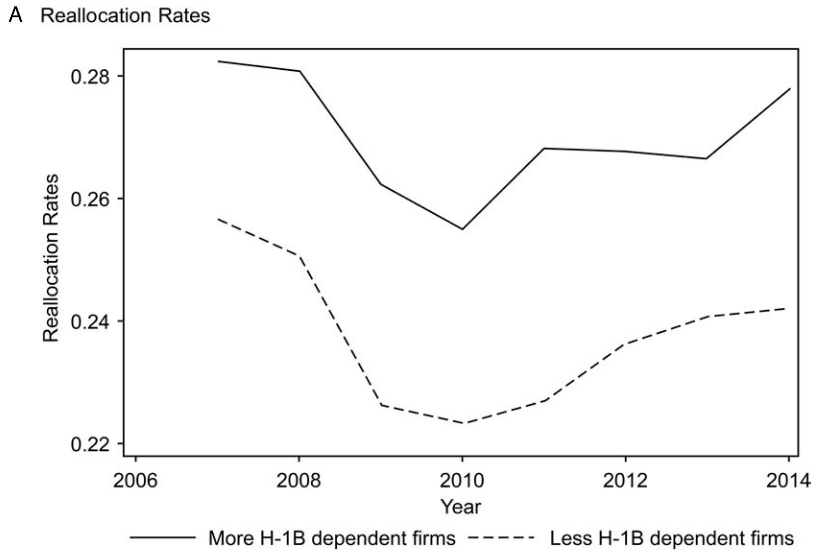

Fig. 3.3 Product entry, exit, and reallocation over the business cycle

Note: This figure shows product reallocation rates, entry rates, and exit rates by type of firm using the LCA-Nielsen sample. Reallocation rates range from 0 to 2, whereas entry and exit rates range between 0 and 1. More H-1B-dependent firms have at least one H-1B worker application in 2000–2001 (the first year of our LCA data), whereas less H-1B-dependent firms have no H-1B worker applications in 2000–2001.

reallocation rates, such as the ability of human resources (HR) departments within a firm to file H-1B paperwork or connections to employers in countries such as India.

In figure 3.3, we use the LCA-Nielsen sample to look at reallocation rates, product entry, and product exit over this period. We split the sample by H-1B dependent firms (defined as any firm that wished to hire H-1B workers in 2000–2001) and nondependent firms (no new H-1B LCAs certified in 2000–2001). Panel (a) of figure 3.3 highlights two important takeaways: (1) H-1B-prone firms have higher product reallocation rates, and (2) the business cycle is strongly correlated with product reallocation. Over the recession, product reallocation fell drastically only to rise again over the recovery. Firms that wished to hire H-1B workers started out with a higher reallocation rate, were not as adversely affected as non-H-1B-prone firms, and unlike non-H-1B-prone firms, recovered to their previous reallocation rates by 2015.

In panels (b) and (c) of figure 3.3, we look at product entry and exit rates. As expected, over the recession, product entry falls and exit rises. H-1B firms have higher entry and exit rates at baseline; however, by the end of the period, non-H-1B-prone firms have marginally higher exit rates. The fall in entries over the recession is not as strong for H-1B-dependent firms, and the

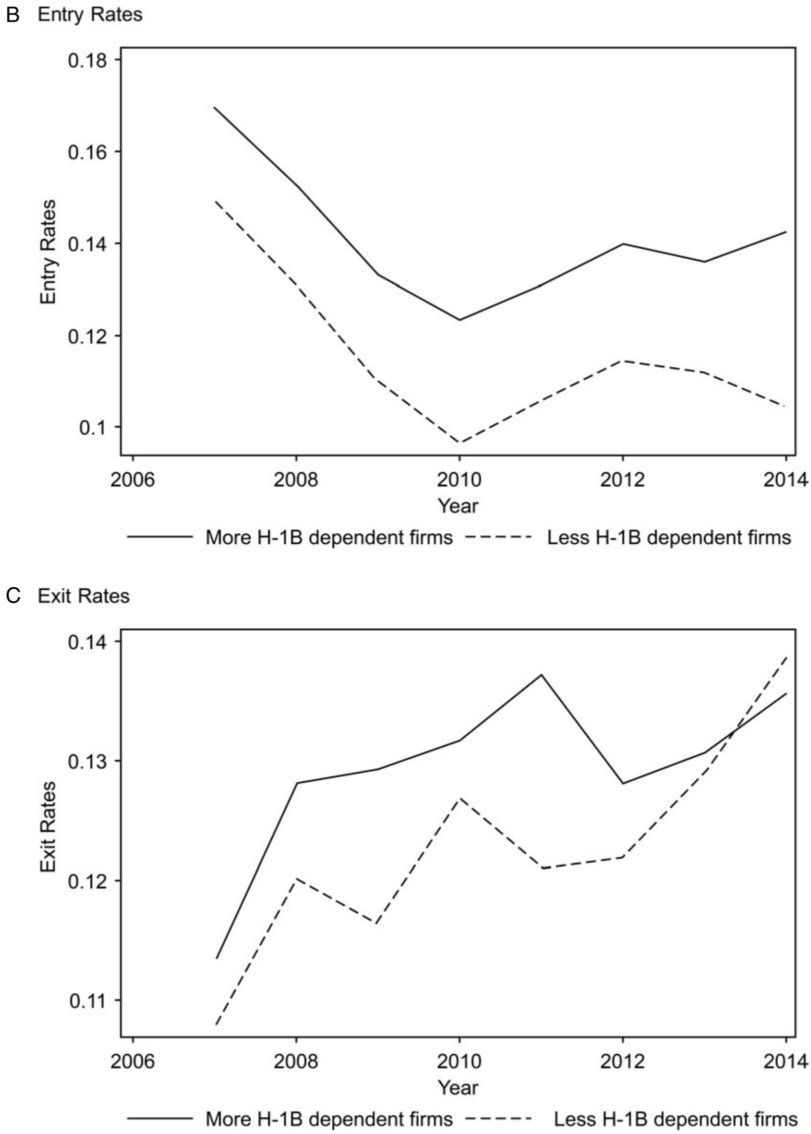

Fig. 3.3 (cont.)

recovery is mildly stronger—by the end of the business cycle, H-1B-prone firms have much higher entry rates than non-H-1B-prone firms.

The stark differences between H-1B and non-H-1B firms in product reallocation may be driven by other factors correlated with H-1B visas. For instance, firms that spend more on R&D, or larger firms in general, may have more H-1B workers and also higher reallocation rates. Additionally, it

Table 3.4 **Reallocation rates by firm H-1B status and R&D or revenue**

	Low R&D	High R&D	Difference
	Panel A: Reallocation rates by H-1B and R&D propensity		
High H-1B	0.289	0.286	–0.002
SE	(0.019)	(0.013)	(0.022)
N	48	62	
Low H-1B	0.247	0.242	–0.006
SE	(0.011)	(0.012)	(0.017)
N	78	63	
Difference	0.041	0.044	
SE	(0.021)	(0.018)	
	Low revenue	High revenue	Difference
	Panel B: Reallocation rates by H-1B and revenue		
High H-1B	0.266	0.260	–0.005
SE	(0.008)	(0.003)	(0.007)
N	305	555	
Low H-1B	0.197	0.189	–0.008
SE	(0.001)	(0.001)	(0.001)
N	10,442	12,170	
Difference	0.069	0.072	
SE	(0.007)	(0.003)	

Note: Panel A compares reallocation rates across H-1B propensity and R&D expenditures (as a fraction of sales) using the LCA-Nielsen-Compustat sample. R&D expenditures as a fraction of sales are divided at the median. Panel B compares reallocation rates across H-1B propensity and firm revenue across all products in their portfolio using the LCA-Nielsen sample. Reallocation rates range from 0 to 2. Revenue is divided at the median. Low H-1B is defined as having no H-1B worker applications in 2000–2001. High H-1B is defined as having at least one H-1B worker application in 2000–2001.

is important to understand the interaction between H-1B dependency and R&D expenditures. Our analysis in table 3.4 and figure 3.4 investigates this interaction.

Table 3.4 is divided into two panels. In Panel A, we use the LCA-Nielsen-Compustat sample and divide firms into four groups by H-1B propensity and R&D expenditures. Low H-1B firms are those that did not apply for a new H-1B worker in the first year of our H-1B data (2000–2001), whereas high H-1B firms did. This division roughly splits the sample in half. We also split the firms by whether or not they are above the median level of R&D expenditures as a proportion of total sales (in 2000–2001). By construction, this division splits the sample in half.

In Panel A, it is clear that high H-1B firms have higher reallocation rates than low H-1B firms. This is true whether or not the firms have a high R&D expenditure share. Regardless of R&D share, high H-1B firms have a reallocation rate that is about 17 percent higher than that of low H-1B firms. Interestingly enough, within H-1B categories, R&D share is not as strong

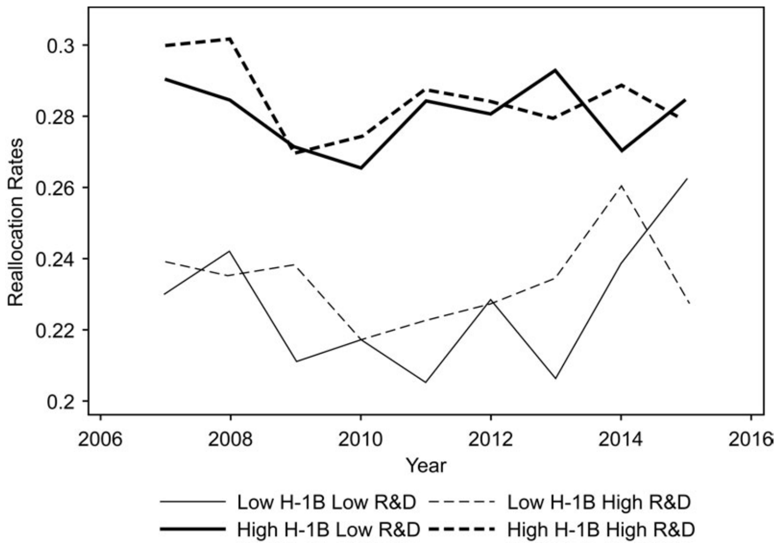

Fig. 3.4 Product reallocation by H-1B dependency and R&D propensity

Note: This figure shows the reallocation rates by type of firm using the LCA-Nielsen-Compustat sample. Reallocation rates range between 0 and 2. More H-1B-dependent firms have at least one H-1B worker application in 2000–2001 (the first year of our H-1B data), whereas less H-1B-dependent firms have no H-1B worker applications in 2000–2001. Low-R&D firms have below-median R&D expenditures as a proportion of sales in 2000–2001. High-R&D firms have above-median R&D expenditures as a proportion of sales.

a determinant of reallocation rates, since firms with low and high baseline R&D rates have similar reallocation rates.

In Panel B, we perform a somewhat similar exercise, but instead of R&D shares, we use baseline revenues from Nielsen. We use the larger LCA-Nielsen sample. Firms that did not apply for an H-1B worker in 2000–2001 far outnumber the firms that did apply for an H-1B worker. Once again comparing the means in reallocation rates suggests a meaningful difference between H-1B and non-H-1B firms: high H-1B firms have, on average, between 35 percent and 38 percent higher reallocation rates than low H-1B firms. On the other hand, baseline firm revenues are not predictive of reallocation rates over the period, as both large and small firms have similar reallocation rates.

Such differences are succinctly captured in figure 3.4, which splits up the sample by H-1B propensity and R&D expenditure share. Consistent with the tables, it shows that there is a substantial difference in reallocation rates between high and low H-1B firms. This difference is unaffected by R&D expenditure share, which in and of itself is less predictive of differences in reallocation rates.

Table 3.4 and figure 3.4 suggest that whether or not a firm has a higher propensity to hire H-1B workers is strongly associated with product real-

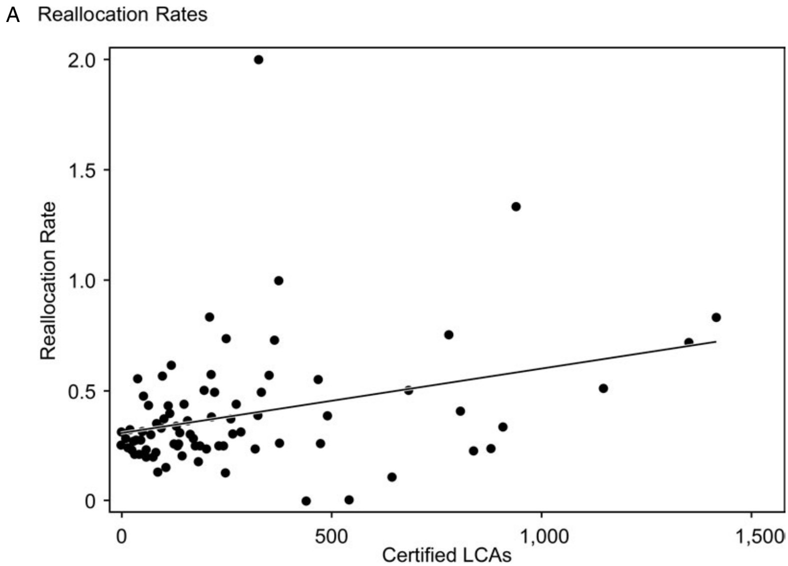

Fig. 3.5 Product entry, exit, and reallocation versus number of certified H-1B workers

Note: This figure shows product reallocation rates, entry rates, and exit rates by the number of certified workers in the LCA data. Reallocation rates range from 0 to 2, whereas entry and exit rates range between 0 and 1. LCAs that are certified (not withdrawn or denied) list the number of workers that a firm wishes to hire. This measure is the number of certified workers. The LCA-Nielsen sample pooled across firms and over 2006–15 is used. Values are binned at each unique point of the *x*-axis (number of certified LCA workers).

location rates. This association is somewhat independent of whether or not the firm has high R&D expenditures or is a large firm with high revenues. Indeed, in comparison to the association between H-1B workers and reallocation rates, it seems like R&D expenditures and firm revenues are less strongly associated with high product reallocation.

3.4.3 The Association between Immigration and Product Reallocation

We first study the association between high-skill immigration and product reallocation graphically in figure 3.5. Here we plot reallocation rates, entry rates, and exit rates across the number of workers on certified LCA applications. Each point is a firm-year observation. There seems to be a mildly positive association between reallocation rates and the number of certified workers. Yet such analyses may be confounded by firm-specific characteristics or annual shocks to the economy. To account for these, we perform a fixed effects regression:

$$r_{i,t+1} = \alpha + \beta \mathrm{H1B}_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t+1}, \tag{5}$$

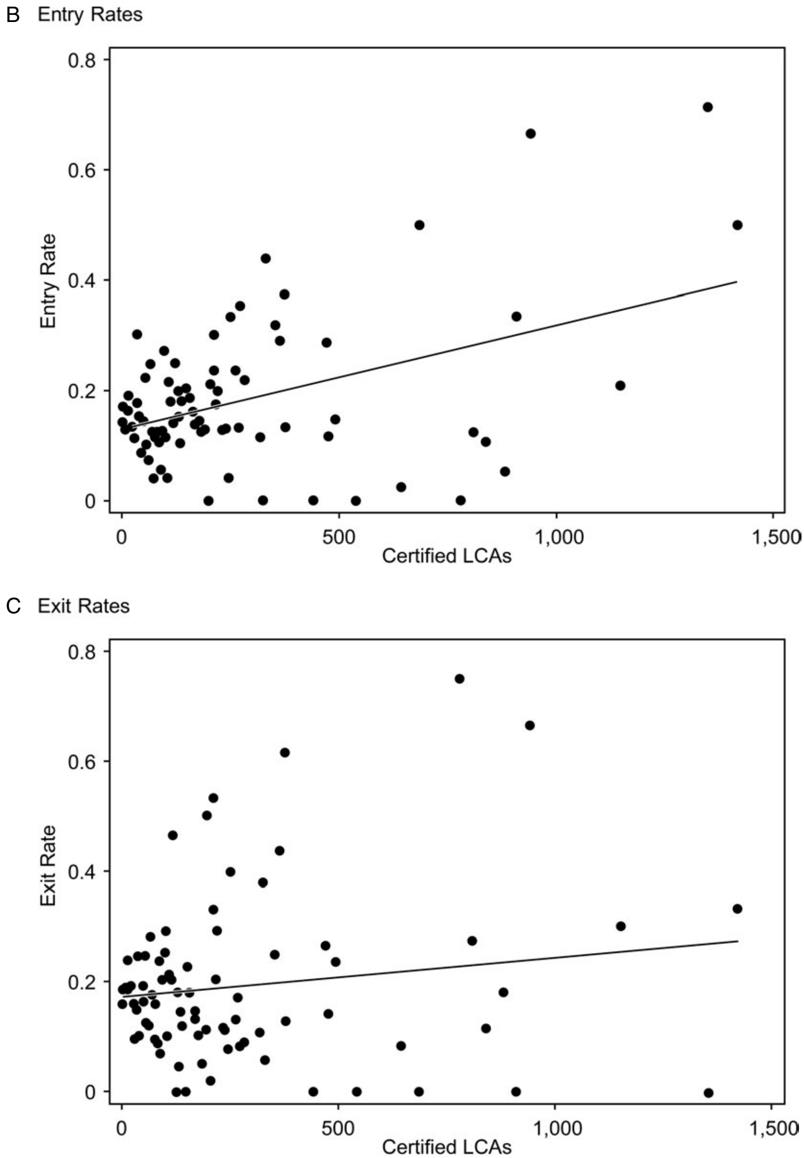

Fig. 3.5 (cont.)

where $r_{i,t}$ is the product reallocation rate for firm i in year t and $H1B_{i,t}$ is a measure of new H-1B worker certifications at firm i in year t. Even as we show results with both contemporaneous and next period's outcomes, our preferred specification looks at future reallocation. As proposed in other similar work (Argente, Lee, and Moreira 2018b), future product reallocation is less likely to be affected by contemporaneous shocks, and we expect that changes in firm dynamics occur with a lag. We include both firm μ_i and year τ_t fixed effects and cluster errors at the firm level.

Our measures of $H1B_{i,t}$ worker certifications take on a few different forms. We look at (1) the number of LCAs filed by a firm each year, (2) the number of workers on certified LCAs each year (called "certified workers"), and (3) the number of workers from certified LCAs in each broad occupational group. We use the LCA-Nielsen sample for such regressions. Additionally, using the LCA-Nielsen-Compustat sample, we can (4) normalize the number of certified workers by total employment in the firm using Compustat measures of employment.

Table 3.5 reports the coefficients of OLS regressions with the LCA-Nielsen merged sample. We find a strong positive association between the number of applications/certifications and reallocation rates in both the current and the following years. When we divide certifications into four occupational categories, science/math and engineering have the largest effect in magnitude, but this is imprecisely estimated. Software more precisely estimates and has a positive effect, which may be consistent with the type of innovations we capture with reallocation rates. Unlike patent data, we mostly capture incremental innovation, where it is possible that lower costs and a better quality of occupations that perform auxiliary functions may matter more.

Next we normalize our measures by the size of firms. The same number of high-skilled immigrants may affect firms differentially by firm size. We now calculate the share of applications/certifications by normalizing them with the number of employees from Compustat. Table 3.6 reports the coefficients of OLS regressions with the LCA-Nielsen-Compustat merged sample. Once again we find a positive association between shares of applications/certifications and reallocation rates. A 1 percentage point increase in the share of certifications is associated with a 5 percentage point increase in the reallocation rate.[10]

In interpreting these results with caution, we acknowledge that even as the number of H-1B visas granted over time is largely driven by changes to policy, the policy itself may respond to the aggregate demand for H-1Bs. Indeed, IT firms often lobby Congress to increase the cap as it often binds. As such, we find it important to compare changes across firms conditional on year fixed effects, which absorb aggregate changes in the cap. Additionally, our final results below test for pretrends in our main outcomes.

10. The mean share of certifications is 0.047 percent, so a 1 percentage point increase in the share of certified workers corresponds to more than double the mean. The reallocation rate in table 3.6 ranges from 0 to 200 with a mean of 25.85. A five percentage point increase in reallocation rates corresponds to a 20 percent increase at the mean. In other words, a 1 percent increase at the mean share of certified workers is associated with about a 0.2 percent increase at the mean of reallocation rates.

Table 3.5 **LCA application/certification and reallocation activities**

	Reallocation rate in year t			Reallocation rate in year $t + 1$		
DV:	(1)	(2)	(3)	(4)	(5)	(6)
Number of applications	0.00217			0.00118		
	(0.000413)***			(0.000615)*		
Number of certifications		0.00291			0.00140	
		(0.000466)***			(0.000767)*	
By occupations:						
Software			0.00217			0.00166
			(0.000471)***			(0.000294)***
Science, math, and engineering			0.0300			0.0206
			(0.0446)			(0.0274)
Manager			–0.00273			0.000558
			(0.00976)			(0.0260)
Finance, analysis, and marketing			0.0359			–0.000832
			(0.0196)*			(0.0228)
Observations	183,554	183,554	183,554	181,451	181,451	181,451
R^2	0.003	0.003	0.003	0.003	0.003	0.003
Number of firms	31,876	31,876	31,876	31,685	31,685	31,685
Fixed effects	Year and firm	Year and firm	Year and firm	Year and firm	Year and firm	Year and firm
Cluster	Firm	Firm	Firm	Firm	Firm	Firm
Type	OLS	OLS	OLS	OLS	OLS	OLS

Note: The table reports the coefficients of OLS regressions with LCA-Nielsen merged sample. The dependent variable is the product reallocation rates this and next year. Reallocation rates range from 0 to 200. The product reallocation rate is defined as the product entry rate plus the product exit rate at the firm level as defined in the main text. The number of applications is the number of LCAs filed by a firm. The number of certifications is the number of workers on LCAs that were certified. The occupation composition is the number of workers in each occupation from LCAs that were certified. Standard errors are clustered at the firm level and presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 3.6 Applying/certified immigrant worker shares and reallocation activities

	Reallocation rate in year t			Reallocation rate in year $t + 1$		
DV:	(1)	(2)	(3)	(4)	(5)	(6)
Share of applications	3.910			5.077		
	(2.693)			(2.040)**		
Share of certifications		4.242			5.593	
		(2.789)			(2.034)***	
By occupations:						
Software			4.839			9.344
			(1.238)***			(0.732)***
Science, math, and engineering			–0.915			0.203
			(2.140)			(1.402)
Management			8.953			5.854
			(5.095)*			(4.384)
Finance, analysis, and marketing			0.771			1.098
			(2.016)			(2.221)
Observations	2,742	2,742	2,742	2,800	2,800	2,800
R^2	0.015	0.016	0.022	0.022	0.022	0.029
Number of firms	416	416	416	429	429	429
Fixed effects	Year and firm	Year and firm	Year and firm	Year and firm	Year and firm	Year and firm
Cluster	Firm	Firm	Firm	Firm	Firm	Firm
Type	OLS	OLS	OLS	OLS	OLS	OLS

Note: The table reports the coefficients of OLS regressions with LCA-Nielsen-Compustat merged sample. The dependent variable is the product reallocation rates this and next year. Reallocation rates range from 0 to 2. The product reallocation rate is defined as the product entry rate plus the product exit rate at the firm level as defined in the main text. The share of applications is the number of LCAs filed by a firm divided by the total employment base in Compustat. The share of certifications is the number of workers on LCAs that were certified divided by the total employment base in Compustat. The occupation composition is the number of workers in each occupation from LCAs that were certified divided by the total employment base in Compustat. Standard errors are clustered at the firm level and presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

3.4.4 The Timing of Effects

To further investigate the timing of effects, we use a distributed lead and lag model. Such a model allows us to check that future H-1B applications do not affect past reallocation rates and to also study whether our outcomes of interest react contemporaneously or with a lag. While informative, however, these results should be interpreted carefully, as we are not necessarily identifying a "shock" in the number of H-1B applications, which is instead a choice variable for the firm. In the following equation, we describe the model:

$$r_{i,t} = \alpha + \beta_1 \mathrm{H1B}_{i,t-1} + \beta_2 \mathrm{H1B}_{i,t} + \beta_3 \mathrm{H1B}_{i,t+1} + \mu_i + \tau_t + \varepsilon_{i,t}. \tag{6}$$

While we would expect that past H-1B certifications $\mathrm{H1B}_{i,t-1}$ would affect reallocation rates, we can also test to ensure that the number of future H-1B certifications $\mathrm{H1B}_{i,t+1}$ is not correlated with current reallocation rates. In figure 3.6, we can see that future H-1B applications do not affect lagged reallocation rates. Furthermore, the main impact on reallocation rates seems to show up with a one-period lag.

3.5 Conclusion

In this chapter, we highlight an important fact: H-1B applications are associated with higher rates of reallocation (entry and exit) of products at firms. Product reallocation is an integral part of Schumpeterian growth, driven by the discarding of older products and the generation of newer products. We complement the literature on patenting (capturing larger innovations) and highlight that smaller, incremental innovations are captured by measures of product reallocation.

At the firm level, we merge data on H-1B LCAs with Nielsen scanner data on products and Compustat data on firm characteristics. We find that H-1B LCAs are strongly associated with product reallocation, which in turn is associated with firm revenue growth.

Our work is consistent with other work showing that high-skill migrants are strongly associated with higher patenting activity (Kerr and Lincoln 2010; Hunt and Gauthier-Loiselle 2010). Measures of firm patenting and new product entry should be thought of as complementary yet capturing different aspects of a firm's innovation ladder. While patenting may be more associated with newer methods of production and newer inputs into final goods, we study the entry and exit of final goods as and when they show up in the consumer market. Yet other work that uses variation generated by the H-1B lottery finds little effect on patenting activity (Doran, Gelber, and Isen 2017). Therefore we find it important to study alternative measures of firm innovativeness to get a comprehensive picture of firm dynamics.

Importantly, as we look at consumer goods, we may expect that such

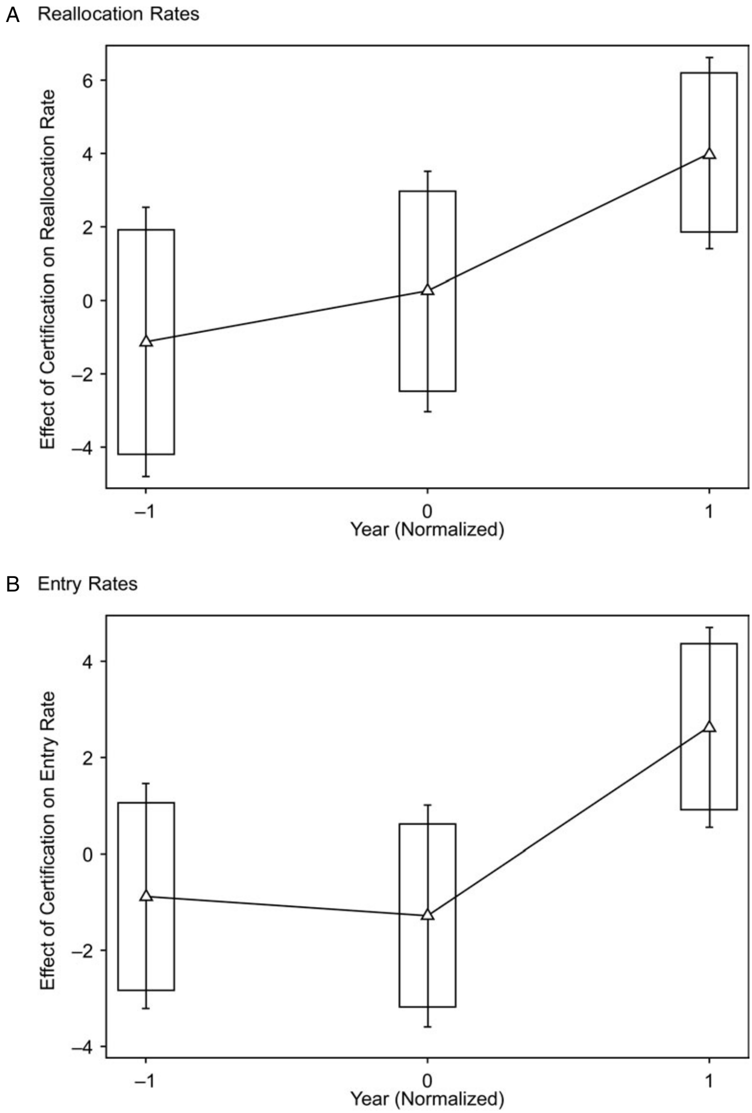

Fig. 3.6 Distributed lead and lag model

Note: This figure shows the impact of the number of certified workers from H-1B LCAs on product reallocation rates and entry rates. Reallocation rates range between 0 and 200, whereas entry rates range between 0 and 100. LCAs that are certified (not withdrawn or denied) list the number of workers that a firm wishes to hire. This measure is the number of certified workers. We use a distributed lead and lag model to estimate the coefficients. The LCA-Nielsen-Compustat sample over 2006–15 is used. Standard errors are clustered at the firm level.

activity affects consumer welfare as well. In Khanna and Lee (2018), we study how prices and the variety of products in the consumer goods market changes as firms introduce newer products and produce older products more efficiently when they wish to hire H-1B workers.[11] Such changes affect the welfare of consumers and alter quantitative estimates of the overall impacts of high-skill immigration on the US economy.

References

Aghion, Philippe, and Peter Howitt. 1992. "A Model of Growth through Creative Destruction." *Econometrica* 60 (2): 323–51.
Aghion, Philippe, Ufuk Akcigit, and Peter Howitt. 2014. "What Do We Learn from Schumpeterian Growth Theory?" In *Handbook of Economic Growth*, vol. 2, edited by Philippe Aghion and Steven N. Durlauf, 515–63. Oxford: North Holland.
Argente, David, and Munseob Lee. 2016. "Cost of Living Inequality during the Great Recession." Kilts Center for Marketing at Chicago Booth—Nielsen Dataset Paper Series 1-032.
Argente, David, Munseob Lee, and Sara Moreira. 2018a. "How Do Firms Grow? The Life Cycle of Products Matters." No. 1174, 2018 Meeting Papers, Society for Economic Dynamics.
Argente, David, Munseob Lee, and Sara Moreira. 2018b. "Innovation and Product Reallocation in the Great Recession." *Journal of Monetary Economics* 93:1–20.
Borjas, George. 1994. "Economics of Immigration." *Journal of Economic Literature* 33:1667–1717.
Bound, John, Breno Braga, Joseph Golden, and Gaurav Khanna. 2015. "Recruitment of Foreigners in the Market for Computer Scientists in the US." *Journal of Labor Economics* 33 (S1): 187–223.
Bound, John, Gaurav Khanna, and Nicolas Morales. 2016. "Understanding the Economic Impact of the H-1B Program on the US." In *High-Skilled Migration to the United States and Its Economic Consequences*, edited by Gordon H. Hanson, William R. Kerr, and Sarah Turner, 177–204. Chicago: University of Chicago Press.
Broda, Christian, and David E. Weinstein. 2010. "Product Creation and Destruction: Evidence and Price Implications." *American Economic Review* 100 (3): 691–723.
Cortes, Patricia. 2008. "The Effect of Low-Skilled Immigration on US Prices: Evidence from CPI Data." *Journal of Political Economy* 116 (3): 381–42.
Doran, Kirk B., Alexander Gelber, and Adam Isen. 2017. "The Effects of High-Skilled Immigration Policy on Firms: Evidence from H-1B Visa Lotteries." NBER Working Paper no. 20668. Cambridge, MA: National Bureau of Economic Research.
Fontana, Roberto, Alessandro Nuvolari, Hiroshi Shimizu, and Andrea Vezzulli. 2013. "Reassessing Patent Propensity: Evidence from a Dataset of R&D Awards 1977–2004." *Research Policy* 42 (10): 1780–92.

11. This work is closely related to the work of Cortes (2008), who finds that low-skill immigration lowers the prices of nontradable goods and services such as housekeeping and gardening. In contrast, we estimate the effects of high-skill migration at the firm level on prices and varieties of tradable products.

Grossman, Gene M., and Elhanan Helpman. 1991. "Quality Ladders in the Theory of Growth." *Review of Economic Studies* 58 (1): 43–61.

Hunt, Jennifer, and Marjolaine Gauthier-Loiselle. 2010. "How Much Does Immigration Boost Innovation?" *American Economic Journal: Macroeconomics* 2 (2): 31–56.

Kerr, Sari Pekkala, William R. Kerr, and William F. Lincoln. 2015. "Skilled Immigration and the Employment Structures of U.S. Firms." *Journal of Labor Economics* 33 (S1): S147–S186.

Kerr, William, and William Lincoln. 2010. "The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention." *Journal of Labor Economics* 28 (3): 473–508.

Khanna, Gaurav, and Munseob Lee. 2018. "High-Skill Immigration and Consumer Welfare." Working Paper.

Khanna, Gaurav, and Nicolas Morales. 2018. "The IT Boom and Other Unintended Consequences of Chasing the American Dream." Working Paper.

Kirkegaard, J. 2005. "Outsourcing and Skill Imports: Foreign High-Skilled Workers on H-1B and L-1 Visas in the United States." Working Paper no. 05-15. Washington, DC: Peterson Institute for International Economics.

Lerner, Josh, and Amit Seru. 2018. "The Use and Misuse of Patent Data: Issues for Corporate Finance and Beyond." Harvard Business School Working Paper no. 18-042.

Matloff, Norman. 2003. "On the Need for Reform of the H-1B Non-immigrant Work Visa in Computer-Related Occupations." *University of Michigan Journal of Law Reform* 36 (4).

Mayda, Anna Maria, Francesc Ortega, Giovanni Peri, Kevin Shih, and Chad Sparber. 2018. "The Effect of H-1B Visas on Publicly Traded Firms." Working Paper.

Moser, Petra, Alessandra Voena, and Fabian Waldinger. 2014. "German Jewish Émigrés and US Invention." *American Economic Review* 104 (10): 3222–55.

Peri, Giovanni, Kevin Shih, and Chad Sparber. 2015. "STEM Workers, H-1B Visas, and Productivity in US Cities." *Journal of Labor Economics* 33 (S1): S225–S255.

Peri, Giovanni, and Chad Sparber. 2009. "Task Specialization, Immigration, and Wages." *American Economic Journal: Applied Economics* 1 (3): 135–69.

US Department of Commerce. 2000. "Digital Economy 2000." Technical Report.

USINS. 2000. "Characteristics of Specialty Occupation Workers (H-1B)." Washington, DC: US Immigration and Naturalization Service.