High-Skill Immigration, Innovation, and Creative Destruction[*]

Gaurav Khanna[†]

University of California – San Diego

Munseob Lee[‡]

University of California – San Diego

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Abstract

Economists have identified product entry and exit as a key mechanism through which innovation translates into economic growth. In this paper we document how high-skill immigration, under the H-1B visa program, affects product reallocation (entry and exit) at the firm level. We create a new dataset by matching data on H-1B Labor Condition Applications (LCAs) and immigration petitions (I-129s), to the firm-level Nielsen retail scanner data on products and Compustat data on firm characteristics. We first document that H-1B certification is associated with higher product reallocation, which in turn is associated with revenue growth. We then use variation driven by the H-1B lottery to show that winning more lotteries leads to higher product reallocation at the firm level. Our results shed light on new channels of innovation by high-skill immigrants and the ensuing consequences for the US economy.

JEL Classification Numbers: D22, D24, F22

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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 in 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 an important determinant of firm-level innovation and 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, at perhaps a lower cost, allow firms to implement incremental innovations that may lead to newer products on the market. In this paper we fill this gap by studying the impact of H-1B workers, on firm-level product reallocation, defined broadly as the entry of new products and the exit of older products.

We create a novel data set by combining data on H-1B workers and firm production. Our H-1B data consists of publicly-available Labor Condition Applications (LCAs) combined with I-129 petitions that we obtained with the help of a Freedom of Information Act (FOIA) request to the Department of Homeland Security (DHS).[1] Our product level data from the Nielsen Retail Scanner Data is combined

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[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. I-129s are granted by DHS to specific workers; we obtain I-129s data only on those workers that successfully receive an H-1B visa (i.e. lottery winners and cap exempt workers).

with firm characteristics from the Compustat database. Together, a combination of these four datasets at the firm-by-year level between 2006 and 2015 allows us to comprehensively examine the impact of hiring foreign workers on firm production.

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 hired H-1B workers in the first year of our LCA data are more likely to consistently have high product reallocation over the business cycle. Indeed, this association is invariant to a firm's 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 affect the economy widely 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 that firm dynamics 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 number of workers as a fraction of the total firm employment base, is strongly associated with reallocation rates.[3] A one percentage point increase in the share of workers from certified LCAs is associated with a five percentage point increase in the reallocation rate. This association is stronger for software workers than other occupation groups. In a distributed lead and lag set up, we also see that even as future H-1B hiring does not affect current reallocation rates, current H-1B hiring does affect future reallocation rates.

Finally, we use variation generated by the H-1B lottery to study whether winning

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

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

the random lottery in the current period affects future product reallocation rates. The difference between LCAs (which a firm files when they wish to hire an H-1B worker) and I-129s for lottery winners allows us to isolate the impact of winning the H-1B lottery.[4] We have I-129 data for the years 2012-14. In this period approximately 240 thousand LCAs per year are approved (new and continuing), whereas about 60 thousand approved LCAs per year are denied I-129s as they do not win the lottery. Unlike previous work on lotteries (Doran, Gelber and Isen, 2017; Peri, Shih and Sparber, 2015a), we are able to look at these lottery winnings within firms over time, as we have three years of lottery data. We find that converting a higher number of LCAs into I-129s leads to an increase in product 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 polices 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

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[4]If workers are granted an H-1B visa (for e.g, by winning the H-1B lottery) they show up in our I-129 data.

the US economy.

Our paper is organized into five sections. In Section 2 we provide a background on the H-1B program and how that may relate to innovation and product reallocation. In Section 3 we describe the data that we use and how we combine our datasets. Our primary analysis is in Section 4 where we first describe trends over the business cycle, the association between reallocation rates and revenue growth, and then between H-1Bs and product reallocation. The final portion of Section 4 studies the impact of H-1B lotteries, and Section 5 concludes.

2   Background

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.[5] In order to hire a foreigner on an H-1B visa, a firm must first file a Labor Condition Application (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 they have the requisite amount of education and work experience for the posted positions.[6] USCIS then may approve the petition for the H-1B non-immigrant for a period up to three years, which 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 U.S. General Accounting Office 2011

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[5]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.*

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

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 was starting 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 then reverted back to 65,000 thereafter. The 2000 legislation that raised the cap also excluded universities and non-profit research facilities from it, and a 2004 change added an extra 20,000 visas for foreigners who received a masters degree in the US. Renewals of visas up to the six-year limit are not subject to the cap, and neither are employment at an institution of higher education or a non-profit 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 the 2014 fiscal year, USCIS received approximately 124 thousand petitions in the first five days of open applications for 85 thousand visas. A computer generated lottery first determines the visas for petitions of applicants who received a masters degree in the US (a quota of 20 thousand visas), and then the remaining 65 thousand 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 USINS (2000), the number of H-1B visas awarded to computer-related occupations in 1999 was about two-thirds of the visas, and U.S. Department of Commerce (2000) estimated that during the late 1990s, 28% 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 non-IT firms also hire H-1B visas. Such workers may be in-house programmers, but also scientists, mathematicians and engineers.

2.2 The Impact of High Skill Immigrants on the US

Work by economists on the impacts of the H-1B program are 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 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 into 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 do not appear to adversely impact native employment and have a small, statistically insignificant effect on their wages. Indeed, in other research it is evident that changes in the size of the STEM workforce at the city-level may raise wages for US born workers (Peri, Shih and Sparber, 2015b).

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.[7] 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); Kerr, Kerr and Lincoln (2015) are among the first to focus on the firm, and more recently working papers using publicly traded firms (Mayda, Ortega, Peri, Shih and Sparber, 2018) or administrative tax data (Doran, Gelber and Isen, 2017) look at employment outcomes

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[7]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.

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 distributional 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, complements in production, consumers and firm entrepreneurs benefit substantially.

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 highlighted the importance of immigrants in innovation. While patents are a rich measure, they capture a specific type of innovation. While patents may capture larger significant innovations, product reallocation often captures incremental innovation 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 the 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 (like 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 ourselves to filing information and ignore granting-status or citations to avoid issues with truncation.

The propensity to patent and cite innovations also vary widely across types of products and industries. Some patents are heavily cited due to their industry rather

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than "fundamental innovativeness" (Lerner and Seru, 2018). Indeed, a relatively low number of important innovations may ever be patented.[8] 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 transactions, 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 innovation 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.

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

3   Data

We combine data at the firm-by-year level from multiple sources. We first obtain publicly available H-1B data on Labor Condition Applications (LCAs) between 2000 and 2016. With the help of a Freedom of Information Act request to the Department of Homeland Security (DHS) we obtain I-129s for those whose H-1B visas were approved (lottery winners, cap exempt applicants, and extensions) between the years 2012-14. We merge this H-1B data to firm-level data from the Nielsen Retail Scanner Data (2006 to 2015) that 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.

3.1   Data on High-skill Immigration

Data on H-1B visas come from two sources. The first is the publicly available list of 2000-16 Labor Condition Applications (LCAs) which firms file with the US Department of Labor (DOL) when they wish to hire a foreign high-skill worker. Attached to each LCA is 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 this 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), (4) those working in finance or marketing. Together, these categories account for more than 90% of all LCAs in each year of our data.

We augment the LCA dataset with I-129 petitions for workers that are granted H-1Bs (i.e. for cap exempt H-1Bs, and for lottery winners of capped H-1B visas). We

obtained this dataset by filing a Freedom of Information Act (FOIA) request with USCIS. Given the long FOIA processing times, USCIS has currently only provided us with three years (2012-14) of data, and we are still awaiting earlier years. Between 2012-14 approximately 240 thousand applications per year are approved (new and continuing), whereas about 60 thousand LCAs per year are denied I-129s as they do not win the lottery. In addition to all the information in the LCA, the I-129 also contains information on the country of origin for the worker. Since our analysis is only for for-profit firms that produce consumer goods, none of the H-1B visas we eventually match to our products dataset are cap exempt.

With the help of these data we compute a few important variables: (1) we count 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, (4) the number of workers normalized by the total employment in the firm (from Compustat), and (5) the difference between I-129s and number of workers from certified LCAs (as a measure of lottery success at the firm level).

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 is generated by point-of-sale systems and contains approximately 35,000 distinct stores from 90 retail chains across 371 MSAs and 2,500 counties between January 2006 and December 2015. The data is organized into 1,070 detailed product modules, aggregated into 114 product groups that are then grouped into 10 major departments.[9] Table 1 summarizes basic facts on the data.

Our data set combines all sales of products at the national and annual level. As in Broda and Weinstein (2010); Argente and Lee (2016), we use UPC (Universal

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[9]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).

Product Code) 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,b). 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 five- to ten-digit number that identifies firms and their products in over 100 countries where the GS1 is present. In Figure 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 of 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.

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

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 information on employment and R&D expenditure over the sample period from the fundamental annual database of North America. 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 workers, instead of just the number of high-skilled migrant workers. Additionally, data on R&D expenditures allow us to test the importance of H-1B workers on product reallocation relative to R&D investments.

3.4 Merging Datasets

We merge four different data-sets at the firm-by-year level, using a string matching algorithm for names of firms. When there is uncertainty in the name matching, we consult city and/or zipcodes. This procedure may produce some error in matching but we do not expect it to be correlated with our main variables of interest. For our analysis, we create three different merged samples: (i) the LCA-Nielsen sample, (ii) the LCA-Nielsen-Compustat sample and (iii) the I129-LCA-Nielsen-Compustat sample. Table 2 reports descriptive statistics for all three merged samples.

The first sample combines Labor Condition Applications (LCAs) and Nielsen Retail Scanner Data. As Table 2 shows, the LCA-Nielsen sample contains 36,218 distinct firms for 2006 to 2015. This covers both small and big firms, where the average annual number of certified workers from LCAs is 0.79 (many firms file 0 LCAs in certain years) and the average annual revenue in the Nielsen data is 6.25 million dollars.

The second sample adds Compustat to the LCA-Nielsen sample, in order to obtain other firm characteristics. As Table 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 dollars. 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.

The third sample adds I-129 petitions to the LCA-Nielsen-Compustat sample, to incorporate information about the actual number of petitions after the lottery process. As Table 2 shows, we have the same number of distinct firms as the second

sample, but covering only 2012 to 2014. In this period, the average number of certified workers is about five percent smaller than the entire period, and average revenue from the Nielsen data is almost the same in real terms. The gap between the average number of certified workers (23.43) and the average number of I-129 petitions (19.11) approximately represents the average variation in the lottery process for our sample.

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, the number of exiting products, and the total number of products for each firm i over year t, and define the 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, either from the entry or the exit margin.

4 Empirical Analysis

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 result found in Argente, Lee and Moreira (2018b), and theoretically similar to results in Aghion, Akcigit and Howitt (2014). We test for this association in our sample with the following regression specification:

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

where $\Delta Log(Revenue)_{i,t}$ 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 we study this association. Product reallocation has a strong 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.

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 or not they have a propensity to hire H-1B workers. Any firm that filed an LCA that was certified in the first year of our LCA data

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(2000-1) is categorized as a firm that has a propensity to hire H-1B workers. We use the earliest possible year (2000-1) 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.[10] The aim is to capture baseline propensities of the firm that may not be related to differential trends over time in reallocation rates; perhaps, such as the ability of human resources (HR) departments within a firm to be able to file H-1B paperwork, or connections to employers in countries like India.

In Figures 2 we use the LCA-Nielsen sample to look at reallocation rates, product entry and product exit over this period. We split up this analysis between H-1B dependent firms (defined as any firm that hired H-1B workers in 2000-1) and non dependent firms (no new H-1B visas granted in 2000-1). Panel (a) of Figure 2 highlights two important takeaways: (i) H-1B firms have higher product reallocation rates, and (ii) 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 hired H-1B workers started out with a higher reallocation rate, were not as adversely affected as non-H-1B firms, and unlike non-H-1B firms, recovered to their previous reallocation rates by 2015.

In Panels (b) and (c) of Figure 2, 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 firms have marginally higher exit rates. The fall in entry over the recession is not as strong for H-1B dependent firms, and the recovery is mildly stronger – by the end of the business cycle H-1B firms have much higher entry rates than non-H1B 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 is important to understand the interaction between H-1B dependency and R&D expenditures. Our analysis in Table 4 and

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[10]The propensity to hire H-1B workers in 2000-1 is also strongly predictive of the propensity to hire H-1B workers between 2006-15.

Figure 3 investigates this interaction.

Table 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 (2000-1), whereas high H-1B firms did. This division roughly splits the sample in half with somewhat more firms in the low H-1B sample. 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 2000-1). 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% higher than low H-1B firms. Interestingly, enough, within H-1B categories, R&D share is not as strong a determinant of reallocation rates since firms with low and high baseline R&D rates have similar reallocation rates.

In Panel B, we do a somewhat similar exercise, but instead of R&D shares we use baseline revenues from Nielsen. We have a larger sample as we use the LCA-Nielsen sample, and firms that did not apply for an H-1B worker in 2000-1 far outnumber the firms that did apply for an H-1B worker. Once again comparing the means in reallocation rates suggest a meaningful difference between H-1B and non-H1B firms: high H-1B firms have, on average, between 35-38% 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 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 4 and Figure 3 suggest that whether or not a firm has a higher propensity to hire H-1B workers is strongly associated with product reallocation rates. This

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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.

4.3 The Association Between Immigration and Product Reallocation

We first study the association between high-skill immigration and product reallocation graphically in Figure 4. 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:

$$r_{i,t+1} = \alpha + \beta H1B_{i,t} + \mu_i + \tau_t + \epsilon_{i,t+1} \, , \tag{5}$$

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 workers 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 $H1B_{i,t}$ workers take on a few different forms. We look at the: (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 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 year. When we divide certifications into four occupational categories, software matters the most, 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 differently by firm size. We now calculate the share of applications/ certifications by normalizing the number of H-1Bs with the number of employees from Compustat. Table 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 one percentage point increase in the share of certifications is associated with a five percentage point increase in the reallocation rate.[11]

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 workers, which is instead a choice variable for the firm. In the following equation we describe the model:

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[11]The mean share of certifications is 0.047%, so a one percentage point increase in the share of certified workers corresponds to more than double the mean. The reallocation rate in Table 6 ranges from 0 to 200 with a mean of 25.85. A five percentage point increase in reallocation rates corresponds to a 20% increase at the mean. In other words, a 1% increase at the mean share of certified workers is associated with about a 0.2% increase at the mean of reallocation rates.

$$r_{i,t} = \alpha + \beta_1 H1B_{i,t-1} + \beta_2 H1B_{i,t} + \beta_3 H1B_{i,t+1} + \mu_i + \tau_t + \epsilon_{i,t} \ , \tag{6}$$

while we would expect that past H-1B workers $H1B_{i,t-1}$ affects re-allocation rates, we can also test to ensure that the number of future H-1B workers $H1B_{i,t+1}$ is not correlated with current reallocation rates.[12]

In Figure 5 we can see that future H-1B workers do not affect lagged reallocation rates. Furthermore, the main impact on reallocation rates seem to show up with a one-period lag.

4.5 The Impact of H-1B Lotteries on Reallocation, Entry and Exit

Finally, we use information from H-1B lotteries to isolate random variation in receiving an H-1B worker. Here we mostly follow the setup proposed by the two other papers using H-1B lotteries (Peri, Shih and Sparber, 2015a; Doran, Gelber and Isen, 2017). Yet, since we have three years of lottery data instead of one, we can also include firm and year fixed effects in our set up. This allows us to account for firm level characteristics that are stable over time, and also annual shocks to the economy. Since our sample only consists of for-profit firms we do not need to contend with cap exempt workers. Our regression equation is:

$$r_{i,t+1} = \alpha + \beta D_{i,t} + \mu_i + \tau_t + \epsilon_{i,t+1} \ , \tag{7}$$

where $r_{i,t}$ is the product reallocation rate for firm i in year t. Our main independent variable of interest $D_{i,t}$ is the H-1B supply shock: the gap between H-1B applications (LCAs) and actual H-1B hiring. We define $D_{i,t} = I129_{i,t} - LCA_{i,t}$. This difference is primarily driven by a random computer-generated lottery. For values of $D_{i,t}$ close to 0, firms are fortunate enough to be able to hire as many H-1B workers as they desired. For values of $D_{i,t}$ much less than 0, firms were unfortunate and could not

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[12]As we have a limited number of years in our data it is statistically challenging to include more leads and lags.

hire as many foreign workers as they would have liked. We include both firm μ_i and year τ_t fixed effects. We use the I129-LCA-Nielsen-Compustat sample for these last set of regressions.

Table 7 reports the coefficients of regressions using the I129-LCA-Nielsen-Compustat merged sample covering the 2012-14 period. In the first four columns we use all the firms in our data, whereas in columns five through eight we only use the sub-sample of firms that ever filed an LCA in the 2012-14 period. This restriction allows us to compare only firms that participated in the lottery process.

Our first and fifth column first indicate that, unsurprisingly, our measure of the supply shock strongly predicts the likelihood of getting more I-129s at the firm level. In the other columns it is clear that winning more H-1B visas is positively associated with product reallocation rates. One additional H-1B worker is associated with a 0.14 percentage point increase in product reallocation.[13]

Finally, we conduct a placebo test where we estimate whether the likelihood of winning a lottery in the future is associated with current reallocation rates. Table 8 reports the coefficients of a reduced form regression for the placebo test with the I129-LCA-Nielsen-Compustat merged sample. We find that there is no meaningful relationship between current lottery outcomes and past reallocation rates.

5   Conclusion

In this paper we highlight an important fact: H-1B workers 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 product lines. We complement the literature on patenting (which captures larger innovations) and highlight that firm innovativeness may be captured by measures of product reallocation (smaller, incremental innovation).

At the firm-level we merge data on H-1B Labor Condition Applications and I-129 petitions, with Nielsen scanner data on products and Compustat data on firm charac-

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[13]In Table 7 reallocation rates range between 0 and 200 with a mean of 26.12.

teristics. We find that H-1B LCAs are strongly associated with product reallocation, which in turn is associated with firm revenue growth. Using variation generated by a random lottery of who wins the H-1B visa, we find that winning more lotteries is also associated with higher product reallocation, entry and exit.

Our work is consistent with 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). We find it, therefore, 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 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 hire H-1B workers.[14] Such changes affect the welfare of consumers and alter quantitative estimates of the overall impacts of high-skill immigration on the US economy.

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[14]This work is closely related to the findings of Cortes (2008) that finds that low-skill immigration lowers the prices of non-tradable goods and services like housekeeping and gardening. In contrast, we estimate the effects of high-skill migration at the firm level on prices and varieties of tradable products.

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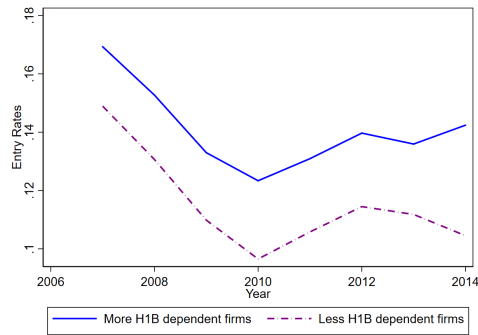
Figure 1: Example of a Company Prefix

Note: This figure shows examples of a 6- and a 9-digit firm prefix. The source is the GS1-US website (http://www.gs1-us.info/company-prefix).

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Figure 2: Product Entry, Exit and Reallocation Over the Business Cycle
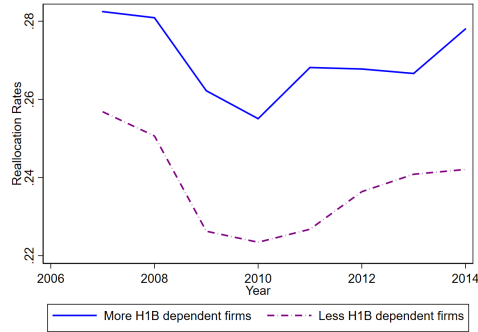
(a) Reallocation Rates
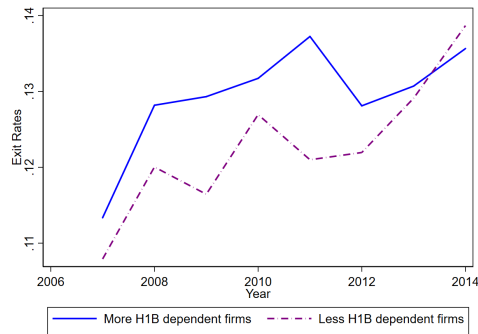
(b) Entry Rates

(c) Exit Rates

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 the 2000-1 (the first year of our LCA data), whereas less H-1B dependent firms have no H-1B worker applications in 2000-1.

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Figure 3: 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 2000-1 (the first year of our H-1B data), whereas less H-1B dependent firms have no H-1B worker applications in 2000-1. Low R&D have below median R&D expenditures as a proportion of sales in 2000-1. High R&D have above median R&D expenditures as a proportion of sales.

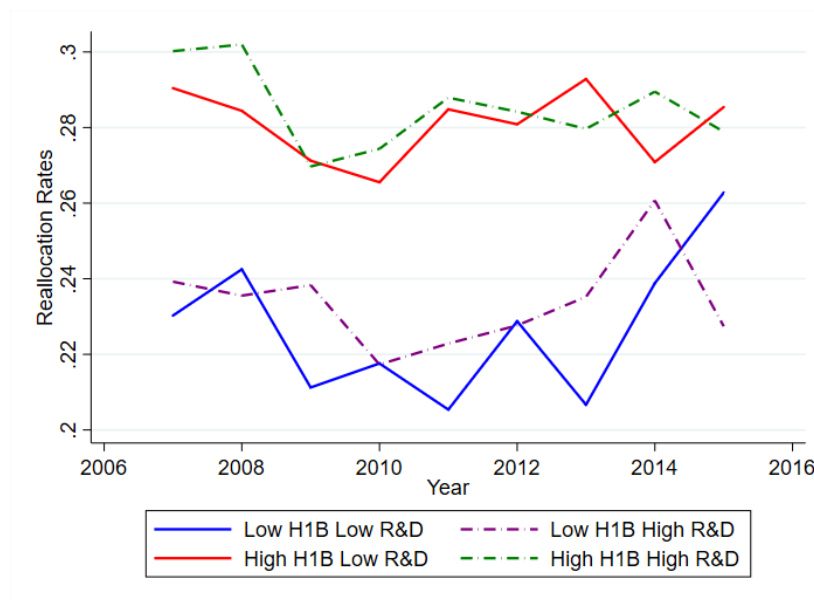Figure 4: Product Entry, Exit and Reallocation v Number of Certified H-1B Workers
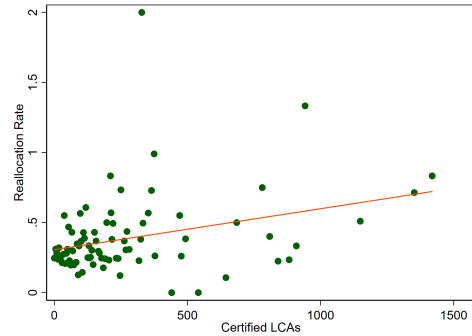
(a) Reallocation Rates
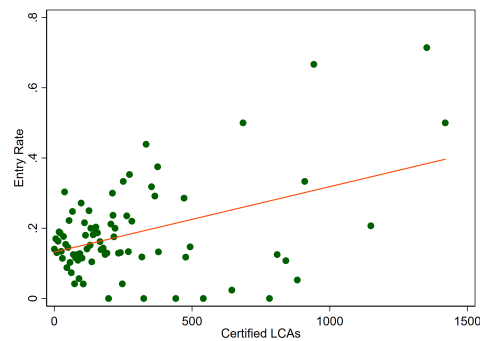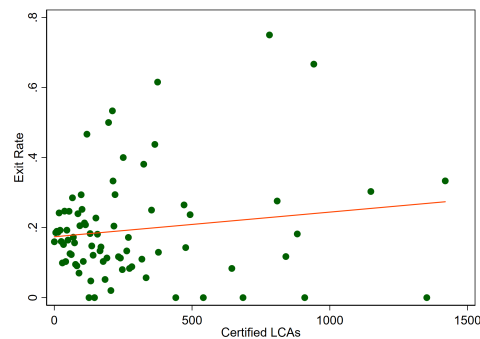
(b) Entry Rates

(c) Exit Rates

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).

Figure 5: Distributed Lead and Lag Model
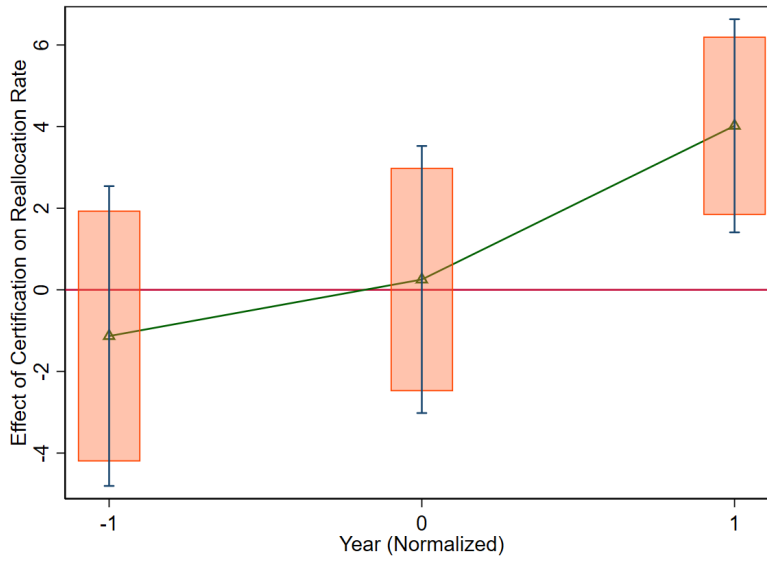
(a) Reallocation Rates
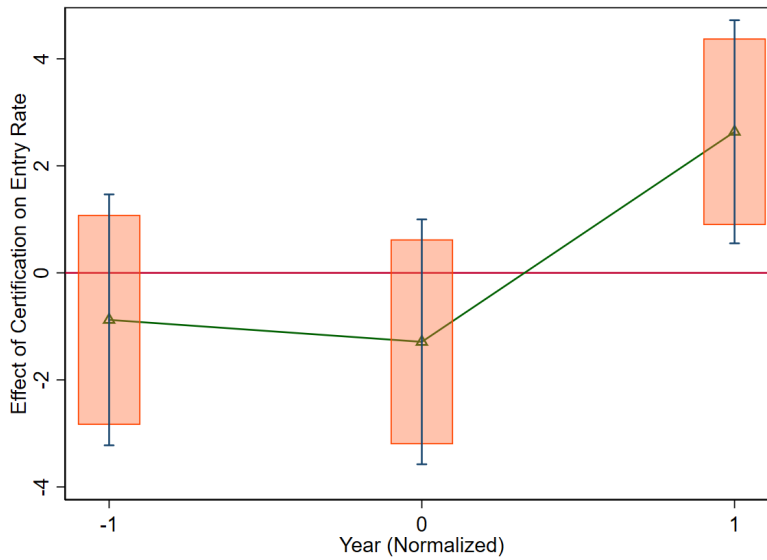
(b) Entry Rates

Note: This figure shows the impact of 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.

Table 1: Facts on Nielsen Retail Scanner Data

The table reports basic facts on the 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 stores
# of states	49
# of counties	2,550
# of products in 2006	724,211
Frequency	Weekly, average
Tag on temporary sales	none

Table 2: Descriptive Statistics for Three Merged Samples

The table reports descriptive statistics for three merged samples: (i) LCA-Nielsen, (ii) LCA-Nielsen-Compustat and (iii) I129-LCA-Nielsen-Compustat.

Merged Samples:	(1) LCA-Nielsen	(2) LCA-Nielsen-Compustat	(3) I129-LCA-Nielsen-Compustat
Number of Firms	36,218	482	482
Years	2006-2015	2006-2015	2012-2014
Variables from LCA/I129			
Average # of Certified Workers	0.79	20.72	23.43
Average # of I129 Workers	-	-	19.11
Variables from Nielsen			
# of Observations	235,522	4,022	1,201
Average Firm Revenue (USD)	6.25 million	154 million	155 million
Average Reallocation Rates (0-2)	0.1944	0.2585	0.2612
Variables from Compustat			
# of Observations	-	4,565	1,373
Average # of Employees	-	43,841	45,158
Average R&D to Sales	-	0.251	0.1715

Table 3: Reallocation Activities and Revenue Growth

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.

Dep. var: $\Delta Log(Revenue)_{i,t+1}$	(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-squared	0.013	0.063	0.009
Number of Firm	27,574	31,626	27,574
Fixed Effects	Year and Firm	Year and Firm	Year and Firm
Cluster	Firm	Firm	Firm

Table 4: Reallocation Rates by Firm H-1B Status and R&D or Revenue

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 2000-1. High H-1B is defined as having at least one H-1B worker application in 2000-1.

Panel A: Reallocation Rates by H-1B and R&D propensity			
	Low R&D	High R&D	Difference
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)	

Panel B: Reallocation Rates by H-1B and Revenue			
	Low Revenue	High Revenue	Difference
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	10442	12170	
Difference	0.069	0.072	
SE	(0.007)	(0.003)	

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Table 5: LCA Application/Certification and Reallocation Activities

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.

Dep. var:	Reallocation Rate in year t			Reallocation Rate in year $t+1$		
	(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 Engineer			0.0300			0.0206
			(0.0446)			(0.0274)
Manager			-0.00273			0.000558
			(0.00976)			(0.0260)
Finance, Analyst and Marketing			0.0359			-0.000832
			(0.0196)*			(0.0228)
Observations	183,554	183,554	183,554	181,451	181,451	181,451
R-squared	0.003	0.003	0.003	0.003	0.003	0.003
Number of firm	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

Table 6: Applying/Certified Immigrant Worker Shares and Reallocation Activities

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.

Dep. var:	Reallocation Rate in year t			Reallocation Rate in year $t+1$		
	(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 Engineer			-0.915			0.203
			(2.140)			(1.402)
Manager			8.953			5.854
			(5.095)*			(4.384)
Finance, Analyst and Marketing			0.771			1.098
			(2.016)			(2.221)
Observations	2,742	2,742	2,742	2,800	2,800	2,800
R-squared	0.015	0.016	0.022	0.022	0.022	0.029
Number of firm	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

Table 7: H-1B Supply Shock and Reallocation Activities

The table reports the coefficients of reduced form regressions with I129-LCA-Nielsen-Compustat merged sample. The dependent variable is the product reallocation rate $r_{i,t}$, entry $n_{i,t}$ and exit rates $x_{i,t}$ next year. Reallocation rates range from 0 to 200, whereas entry and exit rates range from 0 to 100. 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. H-1B supply shock is the number I-129 workers minus LCA certified workers. 'Firms granted at least one certification' include firms that submitted an LCA that was certified in the period 2012-14. Standard errors are clustered at the firm level and presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Samples:	All firms				Granted at least one certification			
Dep. var:	# of I-129s	$r_{i,t+1}$	$n_{i,t+1}$	$x_{i,t+1}$	# of I-129s	$r_{i,t+1}$	$n_{i,t+1}$	$x_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
H-1B supply shock	0.656	0.136	0.0422	0.0960	0.658	0.138	0.0464	0.0955
	(0.0268)***	(0.0753)*	(0.0320)	(0.0386)**	(0.0270)***	(0.0759)*	(0.0318)	(0.0392)**
Observations	1,446	749	777	774	510	272	284	282
R-squared	0.674	0.013	0.033	0.026	0.677	0.046	0.033	0.061
Number of firm	482	392	406	405	220	166	173	172
Fixed Effects		Year and Firm				Year and Firm		
Cluster		Firm				Firm		
Type	First Stage	Reduced Form			First Stage	Reduced Form		

Table 8: Placebo Test for H-1B Supply Shock and Reallocation Activities

The table reports the coefficients of reduced form regressions for the placebo test with I129-LCA-Compustat merged sample. The dependent variable is the product reallocation rate $r_{i,t}$, entry $n_{i,t}$ and exit rates $x_{i,t}$ last year. Reallocation rates range from 0 to 200, whereas entry and exit rates range from 0 to 100. 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. H-1B supply shock is the number I-129 workers minus LCA certified workers. 'Firms granted at least one certification' include firms that submitted an LCA that was certified in the period 2012-14. Standard errors are clustered at the firm level and presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Samples:	All firms			Granted at least one certification		
Dep. var:	$r_{i,t-1}$	$n_{i,t-1}$	$x_{i,t-1}$	$r_{i,t-1}$	$n_{i,t-1}$	$x_{i,t-1}$
	(1)	(2)	(3)	(4)	(5)	(6)
H-1B supply shock	-0.0148	0.00283	-0.0160	-0.0134	0.00335	-0.0153
	(0.0258)	(0.00866)	(0.0195)	(0.0261)	(0.00892)	(0.0196)
Observations	755	780	779	272	283	284
R-squared	0.001	0.015	0.024	0.008	0.007	0.044
Number of firm	389	409	403	165	174	174
Fixed Effects	Year and Firm			Year and Firm		
Cluster	Firm			Firm		
Type	Reduced Form			Reduced Form		