Skilled Immigration and the Employment Structures of US Firms

Sari Pekkala Kerr, *Wellesley College*

William R. Kerr, *Harvard University and National Bureau of Economic Research*

William F. Lincoln, *Johns Hopkins University*

We study the impact of skilled immigrants on the employment structures of US firms using matched employer-employee data. Unlike most previous work, we use the firm as the lens of analysis to account for greater heterogeneity and the fact that many skilled immigrant admissions are driven by firms themselves (e.g., the H-1B visa). OLS and IV specifications show rising overall employment of skilled workers with increased skilled immigrant employment by the firm. Employment expansion is greater for young natives than for their older counterparts. The departure rates for older workers relative to younger workers appear highest for those in STEM occupations.

I. Introduction

The immigration of skilled workers is of deep importance to the United States. In 2008, immigrants represented 16% of the US workforce with a

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bachelor's education, and they accounted for 29% of the growth in this workforce during the 1995–2008 period. In occupations closely linked to innovation and technology commercialization, the share of immigrants is even higher at almost 24%. As the US workforce ages and baby boomers retire, the importance of skilled immigration has the potential to increase significantly. Perhaps because of this impact, the appropriate policies and admissions levels for skilled workers remain bitterly debated. Many advocates of higher rates of skilled immigration have recently adopted the phrase "national suicide" to describe the limited admissions of skilled workers compared to low-skilled immigrants to the United States. On the other hand, expansions of admissions are passionately opposed by critics who believe that skilled immigration is already too high.

This study analyzes how the hiring of skilled immigrants affects the employment structures of US firms. Our focus on the firm is both rare and important. From an academic perspective, there is very little tradition for considering firms in analyses of immigration. As one vivid example, the word "firm" does not appear in the 51 pages of the classic survey of Borjas (1994) on the economics of immigration, and more recent surveys also tend to pay little attention to firms. As described in greater detail below, economists instead typically approach immigration through the conceptual framework of shifts in the supply of workers to a labor market. Firms provide some underlying demand for workers, but their role is abstracted from. Much of the debate in the literature is then about what constitutes the appropriate labor market and how its equilibrium is determined.

While this approach is perhaps the correct lens for low-skilled immigration, it seems quite incomplete for skilled migration. First, the structure of many skilled immigration admissions is designed in part to allow companies to select the workers they want to hire rather than migrants being selected by the US government. It thus seems particularly valuable to un-

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derstand the impact of these admissions on the firms themselves. A firm-level analysis also allows us to account for heterogeneity that is not captured with other approaches. This is especially important since firms hold specific assets that are often instrumental in determining employment outcomes and their organizational structures more generally. The development of new employer-employee data offers great promise for expanding our understanding of the immigration process from both empirical and theoretical perspectives. The literature on international trade, for example, has benefited deeply in recent years from greater consideration of the role of the firm.

While our analysis is about skilled immigration more generally, a prime example of the legal role that firms play in skilled immigration is the H-1B visa, which is the largest program for temporary skilled immigration to the United States. The H-1B is a firm-sponsored visa, meaning that a company first identifies the worker it wants to hire and then applies to the US government to obtain the visa. Once the work has started, the immigrant is effectively tied to the firm until obtaining permanent residency or obtaining another visa. This lock-in effect is particularly strong if the firm further sponsors the immigrant for permanent residency. Moreover, most of the arguments in the public debate about the impact of skilled immigration in the United States are also firm-level statements. For example, in the context of the H-1B, Bill Gates has stated in congressional testimony that Microsoft hires four additional employees to support each worker hired on the visa. On the other hand, Matloff (2003) argues that US companies hire skilled immigrants through the H-1B program to displace older citizen workers with high salaries, thereby lowering their cost structures, and he presents case studies about displacement within individual firms. Other examples are National Foundation for American Policy (2008, 2010) and Hira (2010).

Given this context, this article looks at the role of young skilled immigrants within the firm. We focus on the immigration of young workers as they account for a large portion of skilled immigrants; for example, 90% of H-1B workers are under the age of 40. This is likely due to the characteristics of firm demand as well as the preferences of foreign workers to immigrate when they are young. At the center of this project is a confidential database maintained by the US Census Bureau called the Longitudinal Employer-Household Dynamics (LEHD) database. Sourced from required state unemployment insurance reporting, the LEHD provides linked employer-employee records for all private-sector firms in 29 covered states. Among the information included for each employee are the worker's quarterly salary, age, gender, citizenship status, and place of birth. This wealth of information allows us to observe directly the hiring of skilled immigrants and the associated changes in firm employment structures (e.g., the hiring or departures of skilled US-born workers over the age of 40).

From the LEHD data set, we develop an unbalanced panel of 319 firms over the 1995–2008 period. Our selection criteria emphasize top employer firms and top patenting firms in the United States, given that much of the discussion of the effects of skilled immigration focuses on employment outcomes, innovation rates, and the high-tech sector in particular. Given the skewness of the firm size distribution, our sample accounts for 10%–20% of the workforce in covered states (including over 67 million employees in total during the period) and about 34% of US patenting. We construct an annual panel that describes the employment and hiring of skilled immigrants and use the panel to quantify the link between young skilled immigration and firm employment structures.

Ordinary least squares (OLS) estimates show a strong link between expansions in a firm's young skilled immigrant employment, where young workers are defined as those under 40 years old, and expansions in other parts of the firm's skilled workforce. With this framework, we estimate that a 10% increase in a firm's young skilled immigrant employment correlates with a 6% increase in the total skilled workforce of the firm. Expansion is evident and mostly balanced for older and younger native skilled workers. Increases of a similar magnitude are also found for the firm overall, including lower-skilled workers, with the firm experiencing a small increase in the skilled worker share. Similar elasticities are evident on the hiring margin itself, that is, looking at the relationship between changes in the rates at which immigrant and native groups are hired within a year. We quantify effects through a first-differenced framework that removes permanent differences across firms and includes multiple controls in the spirit of other approaches to studying immigration.

OLS estimates are potentially biased by omitted factors, measurement error in immigrant hiring, or measurement error induced by corporate restructurings. We thus turn to instrumental variable (IV) estimates that use national changes in the H-1B visa program's size over the 1995–2008 period interacted with how important H-1B workers are for each firm. While our focus is more broadly on skilled immigration, the H-1B program's substantial size provides useful identifying variation for understanding these impacts. National changes in the H-1B program's size are measured through annual population estimates developed by Lindsey Lowell or through summations of recent H-1B visa caps. Our first instruments measure the dependencies of firms by their Labor Condition Applications (LCAs), a first step toward applying for H-1B visas. We also develop alternative dependency measures through the initial shares of each firm's skilled workforce that come from Chinese and Indian economies or that are employed in science, technology, engineering, and mathematics (STEM) occupations.

We present our IV estimates in two ways. A first set of estimates does not place any structure on the underlying growth process of the firm. With this approach, we have valid instruments only when using the H-1B population trend to model national changes (but not the summation of recent visa caps), and even these estimates are sensitive to specification choice. These limits are not too surprising given that we are attempting to predict annual changes in relative hiring by firms over a 14-year period. As a second approach, we provide greater structure to the underlying growth dynamics of firms by controlling for contemporaneous changes in their medium-skilled workforces, a group of workers mutually exclusive from the skilled workforce and defined precisely below. In these latter estimates, we can no longer examine total firm size as an outcome, but we are able to quantify changes in skilled workforce composition. This second approach offers greater alternatives for instrument design and facilitates many extensions. These IV analyses of the skilled worker composition thus form the centerpiece of this study's findings and where we place our emphasis.

Within these empirical boundaries, the IV estimates deliver several consistent results. First, the IV estimates generally agree with OLS that the overall skilled component of the firm's workforce expands with greater employment of young skilled immigrants. Moreover, the IV estimates consistently show that this expansion comes disproportionately through young skilled native workers and older skilled immigrant workers as opposed to older native workers. While OLS estimates display increases in the immigrant share of the firm and shifts toward younger skilled workers, the IV estimates suggest that OLS underestimates the extent of these changes. The decline in the older worker share is again not solely due to the mechanical effect of employing more young skilled immigrants, as we also find a relative decline for older workers among native employees only.

To summarize, we find evidence that increased employment of young skilled immigrants raises the overall employment of skilled workers in the firm, increases the immigrant share of these workers, and reduces the older worker share of skilled employees. The latter effect is evident even among natives only. As to whether the older worker skilled employment increases or declines in absolute level, the evidence is mixed but suggests that absolute declines are not likely. These estimates suggest that age is an important dimension on which firms make decisions and that there may be lower complementarity between young skilled immigrants and older domestic workers compared to the complementarity between young skilled immigrants and young domestic workers. This finding is consistent with some of the arguments made in the public debate about skilled immigration and suggests that age is an important dimension along which immigration may have heterogeneous impacts. The particular direction of these findings is not obvious ex ante (e.g., one could have imagined the highest complementarity existing between the seasoned experience of older natives and the technical skills of young immigrants). Finally, OLS results consistently find that the overall size of the firm increases with higher employment of young skilled immigrants, but the IV estimates are inconclusive on this dimension.

Building on these results, we consider an extension to our primary estimates by looking at employment effects across occupations. The Current Population Survey (CPS) collects employment data from a random group of workers in the US economy in each year. A bridge has been established between the 1986–97 CPS and the LEHD. While our sample period mostly comes after this link is available, we are able to ascertain the primary occupations of over 25,000 workers in our firm sample at the time of their inclusion in the CPS survey. This platform allows us to evaluate whether workers linked to occupations related to STEM exhibit different responses when skilled immigration increases. As we show below, this might be true because the elasticity of substitution by worker age in these occupations is higher than in other fields. Our evidence is suggestive on this dimension. On the one hand, there is a higher departure rate of older workers in STEM occupations with greater young skilled immigration into the firm. This heightened old-young differential is especially pronounced for workers earning over $75,000 a year. On the other hand, while the coefficients for older workers in STEM occupations are higher than for older workers in non-STEM occupations, the magnitude of the differences between these estimates is not statistically significant or economically large. Breaking down the results across occupations to the extent feasible with our data, relative departure rates for older workers compared to younger workers appear higher in STEM occupations, reflective of the high age elasticity of substitution in these fields.

These results provide a multifaceted view of how young skilled immigration shapes the employment structures of US firms. Interestingly, these results do not align with any single popular account and suggest that greater caution in public discourse is warranted. The next section of this article reviews some of the literature on the impacts of immigration and discusses a conceptual framework that motivates our empirical specification. Section III presents a description of our employment data, and Section IV discusses our OLS employment analyses. Our IV estimates are then presented in Section V. Section VI discusses our occupational results, and Section VII presents conclusions.

II. Literature Review and Conceptual Framework

Firms are mostly absent from the literature on the impact of immigration. Instead, economists have sought to define labor markets and then model immigration as an adjustment in the potential supply of labor to that market. One approach, most closely associated with Card (2001), considers labor markets to be local areas like cities or states (e.g., Hunt and Gauthier-Loiselle 2010; Kerr and Lincoln 2010; Peri, Shih, and Sparber 2015, in this issue). Another approach, most closely associated with Borjas (2003), instead describes a national labor market among workers with similar education and age/experience profiles. This approach has been used more for studying the consequences of lower-skilled immigration than skilled migration. A third approach, which is less common generally but important for the analysis of skilled immigration, considers labor markets to be specialized fields of study or expertise (e.g., Borjas and Doran 2012; Moser, Voena, and Waldinger 2014).

The perspective of the firm is only partially embedded, at best, in each of these approaches. Large companies have distributed spatial footprints and employ workers of many different ages and occupations. Their hiring decisions should optimize over this full corporate structure, internalizing potential complementarities across worker groups and facilities. To this end, the claim by Matloff (2003) that firms use the H-1B program for age-related cost minimization cannot be properly evaluated within existing frameworks since the empirical approaches do not capture the substitution margin advanced. More generally, firms may have internal personnel policies (e.g., wage ladders with tenure) that interact with immigration. Firms and workers may also have implicit contracts or expectations that can be fortified or broken (e.g., Shleifer and Summers 1988).[1]

Outside of the academic literature, much of the discussion in the public debate over skilled immigration revolves around arguments over whether skilled immigrants are complements to or substitutes for citizen workers. In popular accounts, this is frequently expressed as cost minimization versus access to scarce resources/skills. These views are often expressed by employees who claim to be displaced: workers feel they are being dismissed so that the firm can save money, the firm argues that the true issue is that the immigrant has scarce skills that would complement other workers' skills, the displaced worker debates how scarce that skill really is, and so on. For the most part, we do not observe the occupations of workers, and so to an important degree we are not able to analyze these issues as precisely as we would like. Moreover, to the extent that we observe occupations in Section VI, the level of detail is too coarse to settle definitively the claims made in the public debate (e.g., discussions about computer programmer substitution are often about specific computer languages and how quickly one can or cannot learn these languages). Our study instead represents a broader inquiry into the patterns of hiring and employee departures associated with greater

[1] Our working paper (Kerr, Kerr, and Lincoln 2013) reviews these literatures in greater detail and provides extended references. This extended discussion also reviews adjacent literatures on immigration and schooling choices, quality differences over skilled natives and migrants, and evidence accumulated outside of the United States. Recent examples from this issue include Bound et al. (2015), Hunt (2015), and Orrenius and Zavodny (2015). Kerr (2013) also further reviews the high-skilled immigration empirical literature.

employment of skilled immigrants. By separating the dimensions of employee hiring and employee departures, we can shed some light on the activity that lies behind net employment changes for firms. We can ascertain whether some skilled employees are being hired, perhaps because of complementary skills. For example, Peri and Sparber (2011) emphasize how skilled immigrants can specialize in occupations demanding quantitative and analytical skills, while native workers take on occupations requiring interactive and communication skills. Other studies emphasize the benefits of diversity (e.g., Nathan 2015). And we can similarly identify when others are departing, perhaps because of displacement in some form. While interpretation of these margins should be cautious, they provide substantially greater information than previously available.[2]

To gain some simple intuition for our empirical approach, we utilize a conceptual model from Desai, Foley, and Hines (2009). This model was originally applied to cross-border employment in US multinationals, but a similar set of conditions represents one way to motivate our empirical specification. The model considers a firm that makes output using two types of labor—domestic and immigrant—with the concave production function $Q = Q(L_D, L_I)$. Increases in the employment of either group have a diminishing effect on output levels, holding the other fixed ($\partial Q/\partial L_D > 0$, $\partial^2 Q/\partial L_D^2 < 0$, $\partial Q/\partial L_I > 0$, and $\partial^2 Q/\partial L_I^2 < 0$). Our focus is on the cross elasticity $\partial^2 Q/\partial L_D \partial L_I$.

The concave revenue function of the firm is $R(Q, y)$, with y representing economic conditions exogenous to the firm (e.g., price levels). The firm maximizes $R(Q, y) - c_D L_D - c_I L_I$, where c_D is the cost for domestic workers and c_I is the cost for immigrant workers. This leads to the familiar conditions for profit maximization that

$$\frac{\partial R}{\partial Q}\frac{\partial Q}{\partial L_D} = c_D \quad \text{and} \quad \frac{\partial R}{\partial Q}\frac{\partial Q}{\partial L_I} = c_I. \tag{1}$$

In this model, a reduction in the cost of employing an immigrant dc_I increases the employment of immigrants in the firm. This expansion in turn affects the employment of domestic workers through the concavity of the output and revenue functions. This can be seen by totally differentiating the first expression in (1). Denote the change in immigrant employment by

[2] While this focus on the firm is an important step, the hiring of skilled immigrants likely has spillovers outside of the firm's boundaries. One employment-related example is how a firm's hiring decisions and revelations of information about employees enrich future labor pools from which all firms draw (e.g., Tervio 2009; Pallais 2014). The conditions are in fact one reason why tied employment relationships exist with the H-1B program. While spillovers are important, the choice of firms to hire immigrants depends most on their own economics, and so an accurate portrait of these conditions is needed and is the subject of the study.

dL_I and the induced change in domestic employment by dL_D. The total differentiation is

$$\frac{\partial Q}{\partial L_D}\frac{\partial^2 R}{\partial Q^2}\left(\frac{\partial Q}{\partial L_D}dL_D + \frac{\partial Q}{\partial L_I}dL_I\right) + \frac{\partial R}{\partial Q}\left(\frac{\partial^2 Q}{\partial L_D^2}dL_D + \frac{\partial^2 Q}{\partial L_D \partial L_I}dL_I\right) + \frac{\partial Q}{\partial L_D}\frac{\partial^2 R}{\partial Q \partial y}dy = dc_D. \tag{2}$$

We make two important assumptions. First, we assume that $dc_D/dL_I = 0$. This is equivalent to assuming that immigration rates into the firm do not affect the employment costs of domestic employees. This is a fiercely debated topic, but the available empirical evidence suggests that this assumption is plausible. For example, Kerr and Lincoln (2010) do not find any wage effects for domestic workers in a state-level analysis of expansions in the H-1B program. Second, we assume that $dy/dL_I = 0$. The concept behind this assumption is that the firm's revenue function does not change contemporaneously with the change in immigrant employment costs. In our IV application, this represents the important empirical claim that the factors that reduce the immigrant employment cost are not correlated with factors changing the firm's profit function.

With these assumptions, we can rearrange the remaining terms in (2) to be

$$dL_D = \frac{\dfrac{\partial Q}{\partial L_D}\dfrac{\partial Q}{\partial L_I}\dfrac{\partial^2 R}{\partial Q^2} + \dfrac{\partial R}{\partial Q}\dfrac{\partial^2 Q}{\partial L_D \partial L_I}}{-\left[\left(\dfrac{\partial Q}{\partial L_D}\right)^2\dfrac{\partial^2 R}{\partial Q^2} + \dfrac{\partial R}{\partial Q}\dfrac{\partial^2 Q}{\partial L_D^2}\right]}dL_I. \tag{3}$$

The denominator on the right-hand side of expression (3) is positive given the properties of the revenue and production functions $\partial Q/\partial L_D > 0$, $\partial^2 R/\partial Q^2 < 0$, $\partial R/\partial Q > 0$, and $\partial^2 Q/\partial L_D^2 < 0$. The sign of the numerator in expression (3) hinges on the cross-elasticity term $\partial^2 Q/\partial L_D \partial L_I$. The relationship between dL_D and dL_I will be positive only if $\partial^2 Q/\partial L_D \partial L_I > 0$ and is sufficiently large to offset the magnitude of the first term in the summation of the numerator. This makes sense intuitively: if domestic and immigrant worker employment are complementary and sufficiently strong to overcome the concavity of the output revenue functions, then we should see a positive relationship between growth in domestic employment and growth in immigrant employment in the data.

III. Firm-Level Employment Data

In this section we provide a description of the data that we use for our analyses. We first discuss the construction of the LEHD database, how we select the firms in our panel, our definitions of employee hiring and departures, and descriptive statistics on our sample. Our working paper (Kerr et al. 2013) contains a substantially longer and complete description of the data creation process and the traits of the LEHD data set.

A. LEHD Data Description

The LEHD contains linked employer-employee records for all US private-sector firms covered by state unemployment insurance reporting requirements. The 29 states currently participating in the LEHD are indicated by the shaded areas in figure 1. The employment records extend through 2008, but the starting dates differ by state. Our sample uses a balanced panel of 18 states that start by 1995 (indicated by a star in fig. 1), including big (high-immigration) states such as California, Florida, Illinois, and Texas. Our firm sample focuses on large US employers and major US patenting firms. We select these two criteria for choosing the sample since much of skilled immigration is for work in high-tech industries. It is also the case that employment and innovation outcomes are frequently emphasized in debates about skilled immigration to the United States.

We identify major employers using a number of different sources, starting with the Census Bureau's Longitudinal Business Database (LBD), which contains annual employment records for all establishments in the United States. Aggregating to the firm level by summing across establishments, we

FIG. 1.—LEHD state coverage. Stars indicate the primary sample of 18 states whose coverage begins by 1995. The figure indicates with shading the states that are covered by the LEHD. Alaska is not covered. Coverage for all states ends in 2008.

compile the names of the top 100 employers in every year from 1990 to 2008. We also supplement this list with additional firm names that rank in the top 100 US firms for worldwide sales or employment according to Compustat over the full 1990–2008 period. We further include those listed as Fortune 200 companies in 2009. For the major patenting firms, we first extract from filings downloaded from the US Patent and Trademark Office the patent assignee names that account for more than 0.05% of patents applied for during the 2001–4 period. We restrict our analysis to patents with inventors residing in the United States at the time of their Patent Office application.

Our initial list of companies contains 453 firms. This list is reduced to 319 firms as a result of the following exclusions: small employment shares in the core 18 LEHD states, temporary help firms, merged entities, firms not reliably found in the LBD or LEHD, and poor data quality.[3] Consistent with the fact that the firm size distribution is quite skewed, these firms account for a large share of economic activity—10%–20% of all employment spells in the LEHD, depending on the state—and 20%–30% of all workers in the LEHD are employed by these firms at some point during the period of analysis. The sample also accounts for over one-third of US patenting. The sectoral composition of the sample is approximately 30% manufacturing; 25% wholesale and retail trade; 30% finance, insurance, real estate, and services; and 15% other sectors.

For these 319 firms we assemble the list of State Employer Identification Numbers (SEINs) associated with them at any point in time. For each SEIN, the LEHD lists the industry, county location, total annual payroll, and employment of the establishment. We then collect the worker employment histories by SEIN and link in the person-level characteristics such as gender, date of birth, date of death, place of birth, citizenship, and race. The place of birth variable provides information on which country the person was born in, and we utilize this variation extensively below. We also use this variable for identifying immigrants. We can group workers as belonging to one of three categories: US citizens from birth, naturalized US citizens, and noncitizens. Among noncitizens, the data unfortunately do not distinguish temporary visa holders from permanent residents. We use these data to define a worker as an immigrant if he or she is a naturalized citizen or a noncitizen.

Workers are characterized as being "skilled" or "not skilled" on the basis of their long-term earnings. This approach has the benefit of capturing variation in unobservable characteristics that are not necessarily accounted

[3] We account for major corporate restructurings as these events create discontinuous changes in firm employment patterns. We create composite firms that combine the records of both entities before and after the major corporate restructuring.

for with a measure of educational attainment. Our primary wage threshold for describing a skilled worker is that the worker's median annual earnings over the 1995–2008 period exceeds $50,000 in real 2008 dollars, and this threshold is held constant through the course of our analysis. To put the $50,000 figure in perspective, the US Citizenship and Immigration Services (USCIS) has reported that the 25th percentile of proposed H-1B worker salaries on approved petitions in 2005 was $43,000, which represents $47,403 in real 2008 dollars. We consider only workers aged 18–64 in our study.

Our final step takes the assembled worker records and aggregates them to measure the employment composition of the company by year. The construction from the microdata allows us to analyze several dimensions of a firm's workforce simultaneously (e.g., native workers over 40 years old earning $50,000). Our primary empirical approach considers firm-years as the unit of observation.

B. Hiring/Departing Definitions and Descriptive Statistics

As one of our main focuses is the hiring of skilled immigrant workers, it is useful to describe our empirical approach and the nuances imposed by the LEHD's structure in further detail. We define the hiring of a worker as the first time that she is paid a salary by a given firm. We define the departure of an employee as the final time that a person is paid a wage. It is important to emphasize that we do not observe whether a worker's departure was voluntary or whether she was dismissed by the firm. We create these measures over the total employment spell of the worker with the firm. That is, we do not consider an employee not being paid for several quarters by the firm to be a departure and then a rehiring. We cannot distinguish hiring and departures at the sample end points, and so we drop these years from the analysis when appropriate.

The LEHD's structure allows us to observe workers within the firm across the different states in our sample. We do not consider employee migration across states within the same firm to be a worker departure and rehiring. As noted, however, we observe worker-level employment records only for firms in 29 states in the LEHD. Thus, we cannot capture these employment changes if the within-firm migration is to or from a non-LEHD state. This is one rationale for requiring that firms have at least 25% of their employment in the core 18 LEHD states. We obtain similar results when using higher thresholds, and our main reason for a lower cutoff is to have a greater level of identifying variation. Using the available data, we find the rate of cross-state mobility within a firm to be very low at 0.3%.

Table 1 provides descriptive statistics on our main sample. The data contain 319 firms in total and 129 in our subsample of top patenting firms.

Table 1
Descriptive Statistics

	Full Sample		Top Patenting Sample	
	Mean	SD	Mean	SD
Total employment	21,238	29,029	19,631	30,041
Immigrant share	19.8%	11.7%	21.9%	12.9%
Skilled employment share	50.0%	23.8%	64.7%	18.3%
Skilled employment	9,887	15,487	12,921	21,383
Native over-40 share	50.3%	15.6%	47.5%	15.2%
Native under-40 share	31.2%	12.5%	31.5%	9.6%
Immigrant over-40 share	9.0%	6.0%	9.5%	5.4%
Immigrant under-40 share	9.5%	7.8%	11.5%	9.0%
Hiring rate	13.1%	8.3%	12.7%	7.9%
Departure rate	14.4%	7.5%	12.5%	5.9%
Medium-skilled employment	7,928	11,528	5,342	8,037
Initial LCA dependency	.8%	1.7%	1.0%	1.5%
Initial Chinese/Indian share	17.6%	12.2%	19.7%	11.8%
STEM occupation share	12.1%	16.0%	18.2%	16.8%

NOTE.—Descriptive statistics are taken from the LEHD. The sample is an unbalanced panel of 319 firms and their employments in 18 states during the 1995–2008 period. State inclusion is dictated by the LEHD data coverage, and firms must satisfy minimum employment coverage ratios in these states to be included. The sample includes major patenting firms and major US employers as described in the text. Skilled workers are defined as those with median annual earnings over the 1995–2008 period exceeding $50,000 in constant 2008 dollars. Medium-skilled workers are defined as those with median annual earnings over the 1995–2008 period of $25,000–$50,000 in constant 2008 dollars. Younger workers are those less than 40 years old.

These companies average about 22,000 employees in the 18 core LEHD states, with an underlying range of fewer than 200 employees to several hundred thousand. Within these firms, 50% of the workforce is classified as skilled by achieving median annual earnings of $50,000 or more during 1995–2008. The underlying range for this share is less than 10% to greater than 90%. Of the skilled group, older natives account for about 50%, younger natives for 31%, older immigrants for 9%, and younger immigrants for 10%. Annual hiring rates and departure rates of skilled workers are 13% and 14%, respectively.

C. CPS-LEHD Match Occupations

The LEHD generally does not contain worker occupations, which would be a valuable input for our study. We can, however, make some progress with a special match that has been made by the Census Bureau between the 1986–97 CPS and the LEHD. The CPS is a random sample of individuals, and our firms employ 25,765 CPS workers who have median annualized earnings during the 1995–2008 period of $20,000 or more. In total, these employees constitute 132,507 person-year observations during our sample period. While we do not observe time-varying information on these workers, we utilize below the person's primary occupation at the time of the CPS survey response to identify those who were connected to

STEM occupations. In our main employment analyses, we use this STEM variable as one approach to measuring a firm's dependency on skilled immigrants. In a later analysis, we consider differences across occupations in a firm for departure rates. The mean age of these workers at the time of the LEHD observation is 43, and 9.3% of them were connected to STEM occupations when the CPS survey was conducted.

IV. Firm-Level OLS Employment Analysis

This section describes our estimating framework and presents our OLS results. These estimates provide a benchmark for our IV results in Section V.

A. Estimation Framework for Employment Analysis

As our article provides a first empirical depiction of skilled immigration and the employment structures of US firms, we choose a simple estimating equation, outlined below, for the bulk of our analysis. This estimating framework quantifies how expansions in young skilled immigrant employment by a firm are associated with employment changes for other worker groups in the firm. This empirical approach describes the data in a transparent way and is a straightforward extension of the conceptual framework laid out in Section II. Our choice of this framework is also motivated by the many popular discussions and policy questions about the employment effects of these immigrants. As described in the introduction, these statements are often about how many workers are hired or departing as a firm takes on a new immigrant. These estimates are informative for these statements as well.

Our general approach takes the form

$$Y_{f,t} = \beta \cdot \ln(\mathrm{Emp}_{f,t}^{\mathrm{YSI}}) + \nu \cdot X_{f,t} + \phi_f + \eta_{i,t} + \epsilon_{f,t}, \tag{4}$$

where $\ln(\mathrm{Emp}_{f,t}^{\mathrm{YSI}})$ is the log number of young skilled immigrants (denoted with superscript YSI) employed in year t by firm f, $Y_{f,t}$ is the outcome variable of interest, and $X_{f,t}$ is a vector of firm-year controls described shortly. We include a vector of firm fixed effects ϕ_f that control for permanent differences across firms. We also control for sector-year fixed effects $\eta_{i,t}$, where the sector i for each firm is defined as the industry in which the firm employs the most workers in the initial period. We define sectors as manufacturing; wholesale and retail trade; finance, insurance, real estate, and services; and other. As firms span multiple industries, we also include an interaction of linear time trends with the firm's initial share of employment in the first three sector groups as a control variable. We further include an interaction term of a linear time trend with the firm's initial technology intensity measured as patents per skilled worker. When calculating initial values for firms, we use the first 3 years that the firm is observed in the sample.

We first-difference the above equation,

$$\Delta Y_{f,t} = \beta \cdot \Delta \ln(\mathrm{Emp}_{f,t}^{\mathrm{YSI}}) + \nu \cdot \Delta X_{f,t} + \eta_{i,t} + \xi_{f,t}, \tag{5}$$

with the covariates in the $X_{f,t}$ appropriately adjusted, and $\xi_{f,t} = \epsilon_{f,t} - \epsilon_{f,t-1}$.[4] Our baseline regressions contain 3,374 observations, cluster standard errors at the level of the firm, and are weighted by the log of the initial young skilled immigrant employment in the firm. The regression weights in our baseline estimates provide a greater sense of the average treatment effect and emphasize better-measured data. They also implicitly give more weight to firms that have a greater share of their employment in covered LEHD states. They sit conceptually in between unweighted estimates and those that use raw employment counts as weights, and we obtain similar results using alternative weighting approaches.

The vector of controls includes several basic components beyond the sector-year fixed effects noted earlier. Following the influential work of Card (2001) and related papers, we include several measures related to the general employment conditions of the local area in which the company operates. Firms often have multiple facilities, and they may shift activity across locations depending on conditions. We thus calculate these controls through weighted averages using the employment distribution of the initial counties in which the firm is operating at the start of the sample period. These weights are kept constant for each firm over time. Our local area controls include log LEHD employment, the log immigrant share, and the log share of workers who are over the age of 40. This approach forms a set of geographic controls for firm activity.

Second, we include two additional measures related to the supply-push framework developed by Card (2001). We start by calculating each firm's initial skilled immigrant distribution across 12 basic groups based on ethnic and geographic lines. We then calculate each firm's initial skilled immigrant distribution across these different groups. We further calculate the growth in each group relative to 1995 among skilled workers across LEHD states. The supply-push factor then sums across these groups, interacting the initial distributions of workers in the firm with the growth of skilled immigrants at the national level by group. We use an identical procedure to construct a supply-push factor directed at lower-skilled immigration based on the initial composition of the firm's lower-skilled workers and their

[4] The efficiency of this first-differences form vs. the levels specification turns on whether the error term ϵ_{cit} is autoregressive. If autoregressive deviations are substantial, the first-differences form is preferred; a unit-root error is fully corrected. If there is no serial correlation, however, first-differencing introduces a moving-average error component. Estimations of the autoregressive parameter in the levels specification for this study find serial correlations of .75, while .22 is evident in the first-differenced form.

national trends. These measures help control for the well-documented clustering of employees of the same ethnicity and country of origin in the workplace.[5]

Third, following the influential work of Borjas (2003) and related papers, we construct a measure that reflects the potential impact of national immigration trends by workers of different ages and education levels. We use the LEHD's education estimates for this work. We build six age-education cells that consider our young and old age groups along with three education levels (i.e., high school diploma or less, some college, and college degree). We then calculate the firm's initial skilled employment distribution across these six cells. We also calculate for each cell the national growth in skilled immigration compared to 1995 using the public CPS files. Interacting each firm's initial distribution with the national growth by cell, our age-education immigration measure sums over these six groups.

Beyond these baseline controls, we also consider specifications that control for the underlying growth process of the firm by using the employment changes observed for medium-skilled workers. These workers are defined to be those with median salaries of $25,000–$50,000 across the sample period; this group is mutually exclusive from the skilled worker group. When using this control, we naturally sacrifice our ability to study how immigration employment relates to overall firm size, instead shifting attention to effects among skilled worker groups. On the other hand, we gain several benefits. For OLS estimates, the key benefit is having greater robustness to corporate restructuring events or dramatic changes in firm size not linked to immigration. We discuss in the next section even larger benefits for the IV estimates from this control.

B. OLS Employment Estimates

Table 2 provides our baseline OLS results using specification (5), where column headers indicate the outcome variables $Y_{f,t}$ considered by each specification. The title of each panel describes the sample employed and the included controls $X_{f,t}$. Column 1 of row A quantifies the correlation between the change in log employment of older native skilled workers and the change in log employment of young skilled immigrants in the firm without

[5] Six of these groups are within Asia and include Greater China, South Asia (i.e., India, Pakistan, and Bangladesh), Japan, Vietnam, Korea, and other Asian countries. We specifically separate some of these countries because of their importance to US skilled immigration (e.g., the H-1B program draws about 40% of its workers from India). Five groups of broader geographic definition include Europe, the Middle East, countries of the former Soviet Union, Latin America, and Africa. We also have a group of dispersed countries of Anglo-Saxon heritage (e.g., Canada, United Kingdom, Australia) and a residual group. The residual group is not included in the supply-push calculations. For evidence of clustering of employees by ethnicity and country of origin, see, e.g., Mandorff (2007), Andersson et al. (2009, 2012), and Åslund, Hensvik, and Skans (2012).

Table 2
OLS Estimations of Young Skilled Immigrant Employment and Firm Employment Structures

Δ Log Employment of Young Skilled Immigrants	Δ Log Employment of Skilled Worker Group: Older Natives (1)	Young Natives (2)	Older Immigrants (3)	Total (4)	Δ Immigrant Share of Skilled Workers (5)	Δ Older Worker Share of Skilled Workers (6)	Δ Older Worker Share of Native Skilled Workers (7)	Δ Log Overall Firm Size (8)	Δ Skilled Worker Share of Total Firm (9)
A. OLS estimations with no controls	.578	.673	.719	.637	.031	−.031	−.019	.585	.011
	(.022)	(.021)	(.045)	(.020)	(.005)	(.003)	(.003)	(.022)	(.005)
B. OLS estimations with base controls	.564	.656	.709	.626	.032	−.031	−.019	.574	.012
	(.021)	(.020)	(.045)	(.020)	(.005)	(.003)	(.003)	(.022)	(.006)
C. Row B including control for contemporaneous change in medium-skilled workers in firm	.378	.500	.578	.469	.046	−.042	−.025	NA	NA
	(.020)	(.022)	(.050)	(.021)	(.006)	(.003)	(.003)		
D. Row C restricted to top patenting firm sample	.478	.570	.743	.573	.057	−.037	−.021	NA	NA
	(.048)	(.038)	(.043)	(.038)	(.006)	(.007)	(.007)		

Note.—OLS estimations consider the relationship between the change in log employment of young skilled immigrants and the change in log employment of other workers in the firm in the same year. Table 1 describes the firm sample and variable definitions. Outcome variables are indicated by column headers. Row B incorporates a base set of controls that include sector-year effects where the sector is defined to be the dominant sector of the firm; time trends interacted with the firm's initial share of employment in each sector; a time trend interacted with the firm's initial patent per-worker intensity; an age-education immigration factor developed through the firm's initial skilled employment distribution by age and education cells interacted with national immigrant growth in these cells; supply-push immigration factors developed through the firm's initial immigrant distribution by country of origin interacted with national immigrant growth by country in the United States (done separately for skilled and lower-skilled workers); and local area controls for expansion of employment in the firm's counties, the immigrant worker share of the firm's counties, and the share of workers over the age of 40 in the firm's counties. Row C further includes as a control the contemporaneous change in the firm's medium-skilled employees. Regressions contain 3,374 and 1,002 observations in rows A–C and D, respectively. Regressions are weighted by log initial young immigrant skilled employment in the firm and cluster standard errors by firm.

covariates. The β coefficient is well measured and can be interpreted as a 10% increase in skilled immigrant employment for the firm correlating with a 6% increase in the employment of older skilled natives. Column 2 finds a similar expansion of 7% for young skilled native workers. Column 3 displays a slightly larger increase for older skilled immigrant workers, and column 4 finds the overall elasticity of skilled worker employment in the firm to be 0.64.

The next three columns of table 2 document changes in some simple employment traits of the firm's skilled workforce. Across the sample in row A, a 10% increase in young skilled immigrant employment for the firm corresponds to a 0.3% increase in the share of skilled workers who are immigrants. The share of skilled workers in the firm who are over the age of 40 also declines by 0.3%. This older worker share decline is not solely due to the mechanical effect of employing more young skilled immigrants, as column 7 shows a 0.2% decline among native workers only. A similar test shows that a 10% increase in the young skilled immigrant workforce lowers the average age of the firm's skilled workforce by 0.1%.

Columns 8 and 9 analyze the overall US employment of the firm in LEHD states and the skilled immigrant share. A 10% increase in skilled immigrant employment for the firm correlates with a 6% increase in total firm employment. A similar elasticity is evident for lower-skilled workers by themselves. Given the comparability of these elasticities, the final column shows only a slight increase in the skilled worker share of the firm.[6]

Row B then adds the basic controls to the estimation framework, which do not materially influence the estimated elasticities from row A. Row C further adds the log change in the firm's medium-skilled workforce, which has a larger substantive effect on the coefficient estimates. The overall employment elasticity in column 4 declines to 0.47. Thus, a 10% increase in the young skilled immigrant workforce of the firm correlates with a 5% increase in the total skilled workforce of the firm. In columns 1–3, this expansion tends to favor young natives and older immigrants compared to older natives. Accordingly, columns 4–7 show stronger shifts in the

[6] One thing to note with respect to our results in cols. 4–6 and 8–9 is that the employment of young skilled immigrants is naturally a component of the dependent variable in each specification. We report these outcomes since their magnitudes are informative and nonobvious. For example, the expanding employment of young skilled immigrants clearly plays a direct role in the positive increase in the immigrant share of skilled workers in col. 5. This share is nevertheless an important summary statistic, and the overall response could even have been negative if the expanding employment of young skilled immigrants is associated with large increases in native employment (e.g., the claims made about hiring alongside the H-1B program noted in the introduction). The econometric issues with having the young skilled immigrants as a component of the dependent variable should be kept in mind when viewing these results.

immigrant and older worker shares of the firm. Finally, row D finds similar effects when looking at the subsample of top patenting firms.

C. OLS Hiring and Departing Estimates

Tables 3 and 4 next consider the hiring and departing of various worker groups contemporaneous with the hiring of young skilled immigrants. We continue to use specification (5), with the key regressor being $\Delta\ln(\text{Hiring}^{\text{YSI}}_{f,t})$. Thus, we are quantifying how changes in the rate at which firms hire young skilled immigrants are associated with changes in the hiring or departing rates of other groups. The hiring of skilled immigrants in this analysis is not restricted to new arrivals but includes any immigrants regardless of how long they have been working in United States. Rows A–D are defined as in table 2.

Columns 1–4 of table 3 consider as outcomes the log hiring of different groups. Elasticities on this margin are similar to those measured for the total change in the workforce in table 2. In row C, a 10% increase in young skilled immigrant hiring is associated with a 5%–6% increase in older and younger native hiring. We generally find similar results when including additional controls or restricting the sample to the top patenting firms. Columns 5–8 consider as outcomes the log departing rates of groups. Rows A and B find no material changes in leaving rates associated with increased young skilled immigrant hiring. Rows C and D incorporate the medium-skilled worker control and find a decline in departing rates for skilled workers when young skilled immigration hiring increases.

Table 4 then relates these hiring changes to shifts in the overall composition of the firm's skilled workforce, similar to table 2. The coefficient estimates are substantially lower here than in table 2 because of our focus just on changes in the hiring dimension rather than net changes in overall employment. The specification in row C suggests that a 10% increase in the hiring of young skilled immigrants increases the total skilled workforce of the firm by about 0.5%. Growth is strongest in the immigrant worker group documented in column 4, but it is also present for other groups of workers as well. Growth is again weakest among older natives.[7]

We have repeated this analysis without the log transformation of variables. While the nonlog approach introduces scale effects, it is useful to consider them given that the claims of advocacy groups are often expressed in raw counts. The hiring of one young skilled immigrant worker is associated with a total employment expansion of 4.5 workers. This includes about 1.4 older native workers, 1.7 younger native workers, and 0.4 older immigrant workers. It also includes the net addition of fewer than one young skilled immigrant worker after accounting for departures. More importantly,

[7] These patterns look very similar when also considering "new arrival" immigrant hiring as the explanatory variable, where new arrival is defined to be the first time the immigrant is observed in the LEHD data set.

Table 3
OLS Estimations of Worker Hiring and Departing Margins

	Δ Log Hires of Skilled Worker Group				Δ Log Departures of Skilled Worker Group			
Δ Log Hiring of Young Skilled Immigrants	Older Natives (1)	Young Natives (2)	Older Immigrants (3)	Young Immigrants (4)	Older Natives (5)	Young Natives (6)	Older Immigrants (7)	Young Immigrants (8)
A. OLS estimations with no controls	.579	.591	.672	NA	−.008	.027	−.001	.085
	(.026)	(.024)	(.030)		(.020)	(.020)	(.027)	(.026)
B. OLS estimations with base controls	.577	.584	.670	NA	−.021	.012	−.013	.069
	(.027)	(.024)	(.030)		(.020)	(.020)	(.027)	(.027)
C. Row B including control for contemporaneous change in medium-skilled workers in firm	.527	.535	.642	NA	−.122	−.083	−.114	−.023
	(.028)	(.025)	(.032)		(.021)	(.021)	(.028)	(.027)
D. Row C restricted to top patenting firm sample	.590	.603	.746	NA	−.199	−.161	−.236	−.110
	(.056)	(.042)	(.051)		(.043)	(.038)	(.054)	(.041)

NOTE.—See the note to table 2. OLS estimations consider the relationship between log changes in young skilled immigrant hiring and log changes in the hiring/departures of other skilled workers in the firm in the same year.

Table 4
OLS Estimations of Worker Hiring and Departing Margins

Δ Log Hiring of Young Skilled Immigrants	Δ Log Employment of Older Native Skilled Workers (1)	Δ Log Employment of Young Native Skilled Workers (2)	Δ Log Employment of Older Skilled Immigrant Workers (3)	Δ Log Employment of Young Skilled Immigrant Workers (4)	Δ Log Total Employment of Skilled Workers (5)
A. OLS estimations with no controls	.100	.122	.125	.194	.115
	(.009)	(.009)	(.011)	(.011)	(.009)
B. OLS estimations with base controls	.095	.115	.120	.190	.110
	(.009)	(.008)	(.010)	(.011)	(.009)
C. Row B including control for contemporaneous change in medium-skilled workers in firm	.038	.058	.062	.137	.054
	(.006)	(.005)	(.007)	(.009)	(.005)
D. Row C restricted to top patenting firm sample	.043	.062	.058	.122	.061
	(.014)	(.011)	(.010)	(.010)	(.011)

Note.—See the note to table 3.

the overall depiction of the results is quite similar to the approach using logs. The lower elasticity of older natives in the log format in part reflects the larger base of older natives in the workforce.

D. OLS Robustness Analysis

The OLS results overall speak to increased hiring and employment of natives when the young skilled immigrant workforce of a firm expands. These results are robust to a number of different approaches. To mention a few important ones, we first find similar results using a firm-state approach that allows us to include all 29 states. We also find similar results when raising the inclusion threshold to 66% employment in LEHD states, when splitting the sample by the long-term growth rates of the firms, when setting minimum employment thresholds for companies, when using different weighting strategies, and when using the alternative definitions of skilled workers noted in the previous section.

V. Firm-Level IV Employment Analysis

The OLS patterns documented in Section IV are striking and novel to observe. There are, however, two clear concerns. The first is that the hiring of young skilled immigrants is likely to be influenced by other factors affecting the firm. The resulting biases could be upward or downward in direction. For example, an upward bias might result from the firm having a new product that it wants to launch, with the firm hiring both natives and young skilled immigrants to pursue the opportunity. Likewise, large-scale employment declines for a shrinking firm can hit all groups at once and induce a correlation. On the other hand, a downward bias could emerge to the extent that young skilled immigrants are being recruited to provide staffing in difficult hiring situations. This latter scenario, in fact, is one of the original intentions of the H-1B visa program, and multiple studies have documented the role of immigrants in these situations (e.g., Borjas 2001; Kerr 2010; Ruiz, Wilson, and Choudhury 2012).

The second concern is more mundane but also important. While building from the microdata, our right-hand-side variables are measured with error. First, we will have some degree of classical measurement error as a result of inaccurate reporting (e.g., an individual's place of birth is inaccurately transcribed). This measurement error biases coefficient estimates downward toward zero. Second, there are corporate mergers and acquisitions that we have not been able to account for with our composite firms. This type of issue will bias our estimates upward to a degree that depends on how similar the employment distribution of the joining firm is to the base firm. Our working paper describes factors that suggest that this bias overall would be in the neighborhood of unit elasticity. This section develops and presents IV estimates to address these concerns.

A. IV Design

Before describing the specifics of our IV design, it is helpful to start with a discussion of what using the instruments is attempting to accomplish. We begin by considering our control variable, the supply-push immigration factor for skilled workers. Recall that this measure interacts the initial place of birth distribution of a firm's skilled workers with aggregate changes in skilled immigration from various countries across LEHD states. This factor is a strong predictor of increased young skilled immigrant employment in the firm, and one potential approach would have been to use this supply-push factor as an instrument. In doing so, we would encounter two potential concerns to address. The first would be whether the initial distribution of country groups for skilled immigrants used in the interaction is correlated with something else that affects the measured outcomes. The second concern for this type of instrument is whether the national trends used for immigration groups are endogenous to the needs or opportunities of the firms that employed them. For example, immigration flows from Japan to the United States might increase when firms that rely heavily on skilled Japanese workers have better opportunities. Thus, even though we would instrument for the direct hiring of the firm, the instrument's reliance on the national trends might not be a complete solution.

A stronger IV approach would instead consider mandated rates of immigration to the United States by country. US immigration policy does not generally contain such country-specific controls on immigration, but it does provide some empirical footholds through the H-1B program. We next describe the H-1B program in greater detail and the instruments that we have developed on the basis of changes in this program. The construction of our instruments is conceptually similar to the supply-push framework just discussed. We will seek, however, to use the program's legal structure to deal with some of the concerns that would have existed for a traditional supply-push framework (which still serves as a control variable).

The H-1B is a temporary immigration visa that allows US employers to seek short-term help from skilled foreigners in "specialty occupations." These occupations are defined as those requiring theoretical and practical application of specialized knowledge such as engineering or accounting; virtually all successful H-1B applicants have a bachelor's education or higher. The visa is used especially for STEM occupations, which account for roughly 60% of successful applications. The worker can come from anywhere in the world, and the application specifies the local area in which the employee will work in the United States. Approximately 40% and 10% of H-1B recipients over 2000–2005 came from India and China, respectively. Shares for other individual countries are less than 5%.

Since the Immigration Act of 1990, there has been an annual cap on the number of H-1B visas that can be issued. The cap governs new H-1B visa issuances only; renewals for the second 3-year term are exempt, and so the maximum length of stay on an H-1B is effectively 6 years. While most aspects of the program have remained constant since its inception, the cap has fluctuated significantly. Figure 2 uses fiscal year data from the USCIS to plot the evolution of the numerical cap. The 65,000 cap was not binding in the early 1990s but became so by the middle of the decade. Legislation in 1998 and 2000 sharply increased this limit over the next 5 years to 195,000 visas. These short-term increases were then allowed to expire in 2004, when visa demand fell short of the cap. The numerical limit returned to the 65,000 level and became binding again, despite being subsequently raised by 20,000 through an "advanced degree" exemption.

While the level of the cap is published by the USCIS, H-1B entry rates and population stocks are not definitively known. Lowell (2000) builds a demographic model for this purpose that factors in new admissions and depletions of the existing H-1B pool by transitions to permanent residency, emigration, or death. While H-1B inflows are reasonably well measured, constructing the latter outflow estimates requires combining available statistics with modeling assumptions. In Lowell's model, emigration and adjustment to permanent residency are roughly comparable in magnitude, with the time spent from entry to either event being estimated through typical H-1B experiences. Figure 2 shows updated estimates provided to us by Lowell. The H-1B population grew rapidly in the late 1990s before leveling off after 2000. The lack of growth immediately after this point can be traced to weak US employment opportunities during this period. When demand returned, however, the reduced supply of H-1B visas restricted further growth.

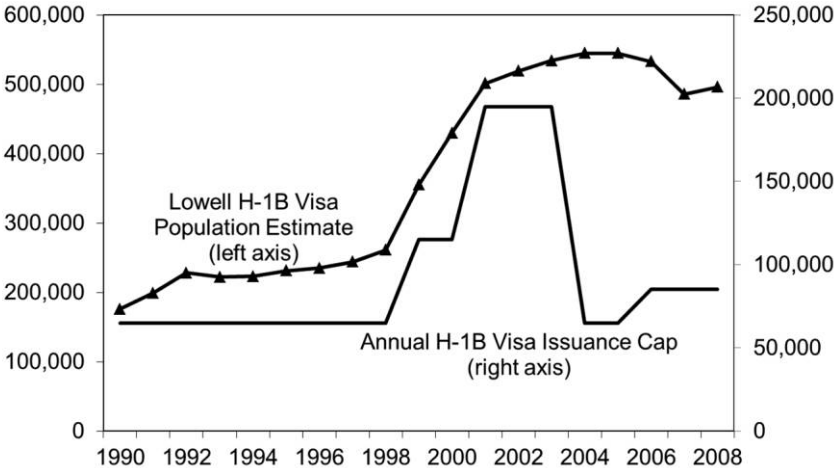

FIG. 2.—H-1B population estimates and numerical caps by USCIS fiscal year. Population estimates are on the left-hand axis; numerical caps are on the right-hand axis.

These shifts in the size of the H-1B program, driven in large part by legislative changes, provide an attractive alternative to using national immigration trends by country. We thus construct instruments that are similar in spirit to the supply-push approach but that are more exogenous. The basic approach for the construction of each of these instruments is to first measure a fixed dependency for the firm on the H-1B program. We then interact this dependency with the log change in the program's size to define an instrument for the log change in young skilled immigrant employment in the firm.

We measure the fixed dependency of the firm in three ways. Our first measure is the log ratio of the firm's LCAs to its skilled employment in 2001. To obtain an H-1B visa, an employer must first file an LCA with the US Department of Labor (DOL). The primary purpose of the LCA is to demonstrate that the worker in question will be employed in accordance with US law. The second step in the application process after the LCA is approved is to file a petition with the USCIS, which makes the ultimate determination about the visa application. The DOL releases micro records on all applications that it receives, numbering 1.8 million for 2001–6. These records include firm names and proposed work locations. We use these records to describe firm dependencies (in the 18 core LEHD states) from the earliest year that is available (2001). It is important to note that this measure does not indicate granted visas but instead the demand that firms have for the visas. One drawback of this measure, however, is that it is measured in the middle of our sample period.

We complement this LCA-based measure with two other indicators of a firm's sensitivity to changes in the H-1B visa program. Given the program's heavy reliance on Chinese and Indian immigrants, our second measure uses the LEHD records to define the firm's initial share of skilled immigrant workers that were born in these countries. Likewise, as the program is particularly important for STEM occupations, we define our third measure as the share of the firm's workforce in STEM occupations using the LEHD-CPS match. We measure this in the first 3 years in which matched employees are observed, which may be later than the typical initial period. Given the limited LEHD-CPS match counts for some firms, this metric has higher measurement error than the other two approaches. These raw measures are quite skewed, and so we winsorize these shares at their 5% and 95% values. The pairwise correlation of the three measures is .59 between the LCA-based measure and the initial Chinese and Indian share, .45 between the LCA-based measure and the initial STEM share, and .59 between the initial Chinese and Indian share and the initial STEM share.

We then interact these three measures, in turn, with a measure of the H-1B program's size. Our primary measure of program size is Lowell's set of H-1B population estimates, expressed in logs. The Lowell estimates have the advantage that they reflect the population's true development and experienced growth that was predominantly governed by a mandated cap. They have the disadvantage that they may retain some endogeneity given the slow growth in the program's size during the high-tech recession when demand fell well short of the cap. As a result, in robustness checks we consider a second measure of the log of the summation of the previous 6 years' numerical visa caps. The time frame is chosen because the H-1B visa is effectively of a length of 6 years, inclusive of visa renewal. The advantage of this measure is that it is more exogenous. There is a key period in the early 2000s, however, when H-1B demand declined substantially at the same time that the cap was still high, and thus the 6-year summation is not as reflective of the program's size. We describe further below the limitations of using cap summations.

The exogeneity of the instruments requires that the initial shares used in their construction be uncorrelated with the error term. The natural worry would be that a measure like the initial Chinese and Indian share is associated with some other firm trait besides H-1B usage that affects employment outcomes during the period of study. The most plausible candidates would include a firm's innovation intensity or its economic sector, and so we must assert that the existing covariates are sufficient in this regard. Likewise, we rely on our "supply push" controls to account for ethnic hiring networks outside of the visa changes. We will further test below including an interaction of the initial traits with time trends, in order to require that the identification comes off the nonlinear movements of the H-1B trend. This will help provide comfort against slow-moving, linear omitted factors that could be correlated with the initial shares.

Finally, it is worth noting that our sample contains a large proportion of the United States' H-1B workers and that these workers also represent a large portion of the young skilled immigrant group within these firms. We do not know either of these shares precisely, but we can make some rough calculations. Within the 18 LEHD states, our final sample contains about 16,400 LCAs in 2001, out of a raw sample of 127,000. After removing non-US companies, universities and public-sector institutions, and similar users of H-1B visas, we estimate that about 15%–20% of LCAs are included in our firm group, representing a substantial share of the program. In 2001, the vast majority (86%) of firms in our sample filed for an LCA, and the average number of applications for those firms found in the LCA data was 97. For the second figure, the 0.8% LCA dependency average in table 1 represents 1 year of applications made by our firms. We multiply this share by five to represent the 6-year nature of the program but also the fact that 2001 was a high year for H-1B visas. Dividing this figure by the 9.5% average share for young skilled immigrants in table 1 suggests that about 42% of the young skilled immigrant workers in these firms are H-1B holders. A broader calculation of 35% is derived by comparing Lowell's estimate of 501,000 H-1B workers in 2001 to the CPS estimate of 1.4 million noncitizen immigrants with bachelor's educations in the same year. These estimates do not count past H-1B holders who have transitioned to permanent residency.

B. IV Estimates

Tables 5–7 report our IV results. Standard errors are clustered by firm across our different specifications. Table 5 begins with IV estimates that do not contain the medium-skilled workforce control. The order of columns in table 5 mirrors that in table 2. Panel A presents results that use the LCA-based dependency measure, panel B considers estimates that use the initial Chinese/Indian share of skilled workers, and panel C presents results that use the initial STEM worker shares. Each of these dependencies is interacted with the Lowell population estimate for the national size of the program. The fit of the first-stage estimates, indicated beneath each panel, passes standard criteria in panels A and B. The first stage in panel C is weak. Generally, across our IV estimates, the first stages tend to be weaker for the occupation-based measure, which is not surprising given measurement error from the CPS sample noted above.

The second-stage estimates resemble and differ from the OLS estimates in meaningful ways. The first four columns again consider changes in employment levels of skilled groups. The IV estimates generally suggest in column 4 that the skilled workforce of the firms grows with expansions in immigrant employment, although panel A finds no response. On the other hand, in columns 1–3, IV estimates agree that young native employment expands with the hiring of young skilled immigrants. The ambiguity for the total workforce comes from differences across the IV estimates in whether the older skilled native workforce expands. In panel A, a decline is evident, while in panels B and C, increases are evident. Even in the latter two cases, coefficient estimates tend to be significantly smaller for older skilled natives than for younger skilled natives.

With this background, it is not surprising that the strongest points of similarity are on the ratios provided in columns 5–7 of table 5. IV estimates consistently show that the immigrant share rises and the older worker share falls with expansions in skilled immigrant employment in the firm. On this dimension, the IV estimates are larger in magnitude than the OLS specifications. Thus, the IV specifications suggest that OLS estimates understate the extent to which the employment structure of the firm shifts to favor immigrants and younger workers when the young skilled immigrant group expands. In the last two columns, we consider firm size and skilled worker shares. Table 5's IV estimates do not confirm the growth in total

Table 5
IV Estimations without Medium-Skilled Workforce Control

	Δ Log Employment of Skilled Worker Group				Δ Immigrant Share of Skilled Workers	Δ Older Worker Share of Skilled Workers	Δ Older Worker Share of Native Skilled Workers	Δ Log Overall Firm Size	Δ Skilled Worker Share of Total Firm
	Older Natives (1)	Young Natives (2)	Older Immigrants (3)	Total (4)	(5)	(6)	(7)	(8)	(9)
	A. IV Using Log LCA Dependency in 2001 Interacted with Log Annual H-1B Populations (First Stage: t-Statistic 3.93; F-Statistic 10.36)								
Δ Log employment of young skilled immigrants	−.189	.333	.119	.123	.105	−.180	−.148	−.174	.053
	(.302)	(.183)	(.275)	(.223)	(.029)	(.054)	(.048)	(.280)	(.034)
Exogeneity test p-value	.000	.004	.001	.000	.000	.000	.000	.000	.181
	B. IV Using Initial Chinese/Indian Skilled Shares Interacted with Log Annual H-1B Populations (First Stage: t-Statistic 6.77; F-Statistic 32.38)								
Δ Log employment of young skilled immigrants	.449	.740	.597	.632	.051	−.110	−.090	.381	.096
	(.115)	(.083)	(.104)	(.081)	(.014)	(.022)	(.022)	(.108)	(.026)
Exogeneity test p-value	.137	.220	.215	.926	.035	.000	.000	.005	.000
	C. IV Using Initial STEM Occupation Shares Interacted with Log Annual H-1B Populations (First Stage: t-Statistic 2.82; F-Statistic 5.36)								
Δ Log employment of young skilled immigrants	.330	.630	.360	.583	.060	−.140	−.104	.115	.143
	(.261)	(.170)	(.297)	(.167)	(.028)	(.057)	(.049)	(.291)	(.063)
Exogeneity test p-value	.116	.841	.047	.714	.121	.000	.001	.001	.001

NOTE.—See the note to table 2. Instruments utilizing H-1B fluctuations interact a fixed dependency on the program for each firm with a measure of the national size of the H-1B program. The instrument for the change in young skilled immigrant employment for the firm is the change in this factor. The fixed dependency in panel A is a measure of H-1B dependency developed in 2001 through the firm's filings of Labor Condition Applications, a first step in the H-1B application process. The fixed dependency in panel B is the firm's initial share of skilled immigrant employment that is of Chinese and Indian ethnicity. The fixed dependency in panel C is the firm's share of workers in STEM occupations in the initial years for which this variable can be measured using the CPS-LEHD match. Instruments use Lowell's H-1B population estimate for the second part of the interaction. Regressions include the full set of controls similar to row B of table 2. The null hypothesis in Wu-Hausman exogeneity tests is that the instrumented regressors are exogenous.

Table 6
IV Estimations with Medium-Skilled Workforce Control

	Δ Log Employment of Skilled Worker Group				Δ Immigrant Share of Skilled Workers	Δ Older Worker Share of Skilled Workers	Δ Older Worker Share of Native Skilled Workers
	Older Natives (1)	Young Natives (2)	Older Immigrants (3)	Total (4)	(5)	(6)	(7)
	A. IV Using Log LCA Dependency in 2001 Interacted with Log Annual H-1B Populations (First Stage: t-Statistic 4.84; F-Statistic 23.36)						
Δ Log employment of young skilled immigrants	−.051	.410	.223	.224	.093	−.159	−.131
	(.161)	(.111)	(.180)	(.123)	(.017)	(.034)	(.033)
Exogeneity test p-value	.000	.328	.004	.001	.000	.000	.000
	B. IV Using Initial Chinese/Indian Skilled Shares Interacted with Log Annual H-1B Populations (First Stage: t-Statistic 7.02; F-Statistic 49.10)						
Δ Log employment of young skilled immigrants	.442	.736	.591	.627	.052	−.112	−.092
	(.098)	(.077)	(.098)	(.071)	(.013)	(.018)	(.020)
Exogeneity test p-value	.514	.003	.909	.035	.025	.000	.001
	C. IV Using Initial STEM Occupation Shares Interacted with Log Annual H-1B Populations (First Stage: t-Statistic 3.49; F-Statistic 12.14)						
Δ Log employment of young skilled immigrants	.414	.676	.446	.632	.052	−.122	−.090
	(.173)	(.125)	(.197)	(.118)	(.021)	(.036)	(.034)
Exogeneity test p-value	.838	.211	.481	.225	.773	.008	.039

NOTE.—See the note to table 5. Estimations include a control for contemporaneous change in medium-skilled workers in the firm.

Table 7
Table 6's IV Analysis Using H-1B Cap Summations

	Δ Log Employment of Skilled Worker Group				Δ Immigrant Share of Skilled Workers	Δ Older Worker Share of Skilled Workers	Δ Older Worker Share of Native Skilled Workers
	Older Natives (1)	Young Natives (2)	Older Immigrants (3)	Total (4)	(5)	(6)	(7)
	A. IV Using Log LCA Dependency in 2001 Interacted with Log Annual H-1B Cap Summations (First Stage: t-Statistic 4.77; F-Statistic 22.71)						
Δ Log employment of young skilled immigrants	.121	.537	.349	.400	.075	−.149	−.129
	(.114)	(.092)	(.148)	(.085)	(.015)	(.030)	(.032)
Exogeneity test p-value	.018	.635	.109	.457	.031	.000	.000
	B. IV Using Initial Chinese/Indian Skilled Shares Interacted with Log Annual H-1B Cap Summations (First Stage: t-Statistic 5.37; F-Statistic 28.78)						
Δ Log employment of young skilled immigrants	.423	.785	.619	.654	.051	−.130	−.116
	(.109)	(.091)	(.135)	(.078)	(.016)	(.024)	(.026)
Exogeneity test p-value	.678	.001	.761	.023	.716	.000	.000
	C. IV Using Initial STEM Occupation Shares Interacted with Log Annual H-1B Cap Summations (First Stage: t-Statistic 3.26; F-Statistic 10.59)						
Δ Log employment of young skilled immigrants	.391	.741	.583	.649	.052	−.131	−.124
	(.168)	(.134)	(.172)	(.116)	(.024)	(.035)	(.040)
Exogeneity test p-value	.941	.083	.976	.149	.781	.002	.002

NOTE.—See the note to table 6. Instruments use the summation of the previous 6 years' H-1B caps as a second version of the program's national size.

firm size observed in OLS, but the increase in the skilled worker share is again observed. The qualifications noted earlier for specifications in which the employment of young skilled immigrants is a component of the dependent variable hold in these IV results.

Unfortunately, we are unable to make further progress with this unstructured approach. We are not able, for example, to substitute in the cap summation for the Lowell population trend as doing so delivers an insufficient first-stage fit. Moreover, these estimates are sensitive to various reasonable adjustments like removing sample weights. The underlying challenge is straightforward. We are attempting with the IV to predict the year-by-year changes in young skilled immigrant hiring for firms across the 1995–2008 period. With such a long time period, there are many other forces that affect these firms, weakening our first-stage fit. The cap summation approach is also very difficult here given the behavior of the H-1B cap during the high-tech recession.

To gain further traction, we introduce additional structure on the firm growth process in table 6 by controlling for the contemporaneous changes in medium-skilled worker employment in the firm. By doing so, we sacrifice the ability to estimate changes in total firm size, but we are able to consider changes among skilled workers. Table 6 generally agrees with table 5. It continues to be true that expansions in young skilled employment in firms connect to a higher immigrant share of skilled workers and a younger age structure. With this framework, we find more substantial agreement across the IV estimates that the total skilled workforce size grows.

This empirical specification in table 6 provides substantially more traction, and table 7 considers an alternative instrument that uses the log of the summation of the previous 6 years' numerical visa caps as a measure of H-1B program size. As mentioned above, this measure has the benefit that it is likely more exogenous but has the liability that it is not as reflective of the program's true size. Results here are generally similar to those in the preceding two tables but tend to be somewhat sharper in terms of statistical significance. In particular, we find consistent evidence of larger responses among young natives to young skilled immigrant employment expansions relative to older natives. We also find significant increases in the total skilled workforce in response to greater employment of young skilled immigrants. We consider instruments separately as joint estimation fails overidentification tests in the first stage.

Our working paper (Kerr et al. 2013) provides further robustness checks on tables 6 and 7. We show similar results using the sample of major patenting firms only and with unweighted specifications. We test including an additional control for the fixed LCA-based dependency in the first-differenced regression, equivalent to a linear time trend interacted with the dependency in a levels regression. The same patterns are again evident with this control, with the results even more accentuated. This robustness holds true when alternatively considering our other interaction measures. We find similar results using a balanced panel of firms present across the full sample period, when dropping major mergers and acquisitions firms or when dropping firms that lobby about immigration issues (Kerr, Lincoln, and Mishra 2014). We also discuss the comparable results obtained in estimations that split the sample into firms primarily engaged in manufacturing, trade, or services/other.

On the other hand, it is important to note two limitations of these IV analyses. We have tested various approaches that adjust the dates of the major H-1B changes by a couple of years forward or back from the true reforms. When doing so, the patterns are mixed. We often find contemporaneous effects to be the most important, but the patterns are unfortunately too sensitive to draw conclusions. Likewise, while our results are robust to dropping a few years at the beginning or end of the sample period, they are not robust to major changes in sample duration (e.g., dropping years prior to 2002) because of the much smaller sample size and reduced variation in the H-1B population changes.

VI. Occupation-Level Estimates

This section considers how employment effects might differ across workers by occupation within a firm. In particular, we focus on whether older workers in STEM occupations are more vulnerable to displacement effects from young skilled immigration. We first undertake some calculations on the age elasticities of substitution for skilled workers by occupation to provide a more systematic foundation for understanding why this might be the case. We then study departure patterns by occupation in our data using the CPS-LEHD matched sample.

A. Occupation-Level Elasticities of Substitution by Age

Starting with Borjas (2003), a number of studies within the immigration literature consider estimating elasticities of substitution using a constant elasticity of substitution production function. Skipping some of the theoretical background that is provided, for example, by Borjas, Grogger, and Hanson (2012), we similarly focus on estimating the elasticity of substitution between worker groups along a specified dimension. For our purposes this estimation takes the form

$$\ln(\text{Wage}_{a,t}) = \gamma \cdot \ln(\text{Emp}_{a,t}) + \phi_a + \eta_t + \epsilon_{a,t}, \quad (6)$$

where a indicates worker age groups and t indicates time. This estimation is intuitively a panel analysis of how the employment of an age group correlates with the earnings of workers in that age group. If there is very little substitution across age groups, the increase in employment of workers in one age category relative to the other groups should depress the wages of the workers in that group (a negative γ coefficient). On the other hand, if substitution across the groups is very easy, then the increased employment of one group should not influence that group's relative wage significantly (a γ coefficient of zero). This measure can also be expressed as the elasticity of substitution $-1/\gamma$, with larger elasticities indicating greater levels of substitution.

The specification is estimated at the occupational level using workers with bachelor's degrees or higher in the CPS from 1995 to 2008. We consider workers aged 20–59 and define our four age categories as 20–29, 30–39, 40–49, and 50–59. We further group the CPS's base occupations into larger groups to provide a sufficient level of identifying variance and more meaningful comparisons. The elasticities with respect to age are substantially higher in the STEM-related fields than among other workers. STEM fields account for three of the four highest elasticities that we estimate (elasticity and standard error): computer-related occupations at 27.4 (19.7), engineers at 14.6 (8.3), social workers at 8.6 (4.8), and scientists at 7.4 (3.5). Management-related occupations are next at 7.0 (1.6), and many occupations have elasticities between 5 and 7, including lawyers, accountants, administrators, and doctors. Some occupations such as teachers have elasticities of substitution close to zero.

Higher elasticities of substitution by age for STEM occupations give one indication as to why older natives may experience displacement from young skilled immigration. In terms of the recent nested models emphasized by Ottaviano and Peri (2012), the argument surrounding STEM substitution can be essentially thought of as a four-level system with the order of education, occupation, age, and then immigration status. We are focusing on workers with at least a bachelor's education, and we allow for different elasticities over ages by occupation. Finding a very high elasticity of substitution by age in an occupation suggests that immigrants in one age group of the occupation can substitute equally as well for natives in other age groups as they can for natives in their own age group.

Some visual evidence for this effect can be seen in a descriptive exercise using the CPS. Figure 3 plots immigration and age profiles in computer occupations in the top five H-1B-dependent states relative to the rest of the United States. We focus on computer occupations given the high elasticities just identified. We plot three series: (1) the relative rate of immigration employment in computer-related occupations in the top five H-1B states to other states, (2) the relative rate of older worker employment in computer-related occupations in the top five H-1B states to other states, and (3) the relative rate of older worker employment in all occupations in the top five H-1B states to other states. As can be seen in the figure, the second series varies inversely with the first series, while the third series is relatively flat. This is true both with respect to the expansion of the H-1B visa program

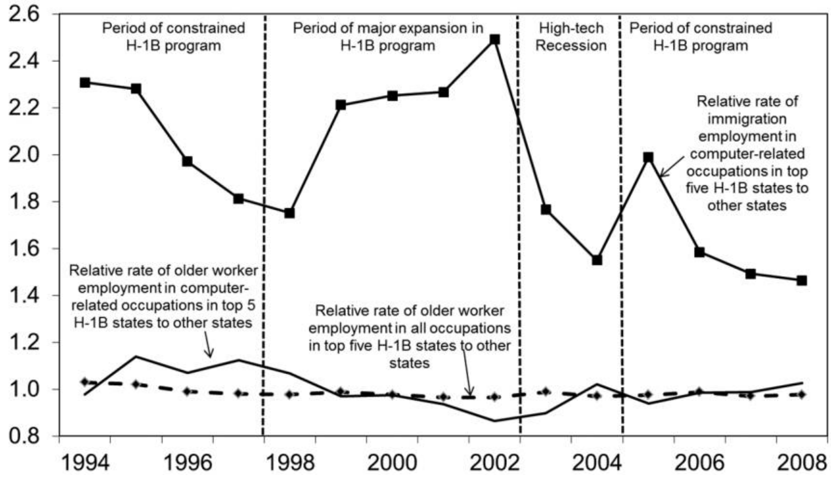

FIG. 3.—Immigration and age profiles in computer occupations. National trends from the CPS comparing top five H-1B states to the rest of the country. Relative rates for older workers are calculated by comparing the share of workers aged 40–65 in the top five H-1B states (CA, DC, MA, NJ, NY) to the share in the other 45 states. Relative immigration rates are similarly defined. Data are from the Current Population Survey. Caution should be exercised on the levels between 2002 and 2003 as the CPS was redesigned during this period.

and when the legislation behind this expansion expired and the program reverted to its original size in 2004.[8]

B. Departure Rates by Occupation

With this background, table 8 provides some simple estimates of departure rates by occupation within our firms and how they correlate with the hiring of young skilled immigrants. It is worth stressing again that an employee's occupation is observed once during the 1986–97 period, and we are applying that past trait forward to the 1995–2008 period. Our sample includes US-born workers aged 20–65 in the observation year of the LEHD. Included workers have median annualized earnings during the 1995–2008 period of $20,000, and our final data set comprises 132,507 person-year observations with 25,765 workers.

To study substitution across different types of workers, we consider a linear probability model in which the outcome variable is an indicator variable for an individual departing from his or her firm. Our analysis here uses OLS and thus should be considered descriptive. The key explanatory

[8] Caution should be exercised in considering levels changes between 2002 and 2003 since the CPS was redesigned during this period. See also Wadhwa (2010) and Brown and Linden (2011).

Table 8
Departure Rates by Occupation, Age, and Salary Level

	(0, 1) Worker Departs from the Firm				Column 4 with Dependent Variable of (0, 1) Worker Hired in Year
	Estimation Including Age and Year Fixed Effects (1)	Estimation Including Age and Firm-Year Fixed Effects (2)	Estimation Including Age and Firm-Year Fixed Effects (3)	Estimation Including Age-Occupation and Firm-Year Fixed Effects (4)	(5)
Δ Log hiring of young skilled immigrants in the firm	−.072		(Reference category: young, non-STEM occupations)		
	(.025)				
× Older worker in STEM occupations	.073	.056			
	(.038)	(.032)			
× higher wage			.119	.102	−.005
			(.041)	(.039)	(.036)
× lower wage			−.076	−.089	−.020
			(.074)	(.079)	(.059)
× Younger worker in STEM occupations	.056	.025			
	(.045)	(.041)			
× higher wage			.015	.013	−.043
			(.044)	(.039)	(.057)
× lower wage			.060	.033	.075
			(.092)	(.096)	(.088)
× Older worker in non-STEM occupations	.021	.011			
	(.020)	(.018)			
× higher wage			.086	.086	−.004
			(.026)	(.027)	(.033)
× lower wage			−.024	−.023	−.061
			(.023)	(.023)	(.027)

Note.—OLS estimations consider departure rates and hiring rates by occupation for workers matched from the CPS to the LEHD firm sample. The CPS sample is a random sample taken during the 1986–97 period; occupation is held fixed at that indicated to be the worker's primary occupation at the time of the CPS survey response. The sample considers native workers aged 20–65 in the observation year of the LEHD, comprising 132,507 person-year observations from 25,765 workers. Included workers have median annualized earnings during the 1995–2008 period of at least $20,000. STEM occupations are designated as those related to computers, science and engineering, and mathematics. Salary splits are in real 2008 dollars on an annualized basis. Age fixed effects group workers into 20–29, 30–39, 40–49, 50–59, and 60+ years old. Regressions are unweighted and cluster standard errors by firm. In cols. 1 and 2, differences across groups are not statistically significant. In cols. 3 and 4, differences across salary levels for older workers are statistically significant at a 10% level for STEM and non-STEM occupations; differences between older STEM and non-STEM workers are not statistically significant.

variable is the growth in young skilled immigrant employment in the firm by year. To study occupational and age differences in an intuitive way, we interact this immigration regressor with three indicator variables for older workers in STEM occupations, young workers in STEM occupations, and older workers in non-STEM occupations. With this approach, the reference category is young workers in non-STEM occupations. We include in all regressions a vector of fixed effects for current worker ages using the bins 20–29, 30–39, 40–49, 50–59, and 60+ years old. Regressions are unweighted and cluster standard errors by firm.

Column 1 of table 8 reports the base results that include year fixed effects. The first row finds that higher growth of young skilled immigration to the firm is associated with lower departure rates for young natives in non-STEM occupations. These baseline estimates are consistent with the idea that firms on a positive growth trajectory may better retain employees and also recruit new ones. There are, however, substantial differences across worker types. There is no reduction in departure rates for older workers in STEM fields at the time of increased young skilled immigration into the firm, and the departure rate for young natives in STEM fields is only modestly affected. Column 2 finds similar results with an alternative approach in which we include firm-year fixed effects. With these fixed effects, we no longer estimate the main effect of young skilled immigrants into the firm, and the coefficients still provide age-occupation comparisons to the omitted category of young native workers in non-STEM occupations. Young skilled immigration is most closely associated with departures of older STEM workers in the firm, although the differences by age across STEM occupations are not statistically significant.

Columns 3 and 4 take a second step of splitting workers on the basis of salary levels, which are estimated using the LEHD and are allowed to be time varying. We define high-wage workers to be those earning more than $75,000 in real 2008 dollars on an annualized basis. This added dimension uncovers several interesting comparison points. Among older STEM workers, the higher departure rates are exclusively in the higher wage group, with the differences by salary levels statistically significant. There is not a comparable pattern for young STEM workers. On the other hand, one observes in the non-STEM occupations directionally similar patterns. The results in column 4 show that this finding is robust to including age-occupation fixed effects. In this specification, the differences across salary levels for older STEM and non-STEM workers are 0.192 (0.093) and 0.110 (0.032), respectively. While the former is larger in magnitude, the base effects for higher earners are not significantly different from each other at 0.102 (0.039) and 0.086 (0.027), respectively.

We have extended this analysis in several ways. First, column 5 examines firm-level hiring of these matched workers and does not find this pattern, indicating that this is not due to greater churn in the labor market. We find similar results that are sometimes even sharper when using the estimated age elasticities by occupation from the CPS calculated in Section VI.A. We adopt table 8's indicator variable approach for reported results given its intuitive nature. Finally, because the CPS-LEHD match predates our sample period, we cannot use it to describe the immigrants in the firms. We can, however, obtain a glimpse using the occupations listed on the LCA applications the firm makes in 2001. Using the elasticities calculated in Section VI.A, we identify the weighted elasticity of substitution by age across the applications that the firm makes. The differentials estimated across salary levels are almost three times higher for firms whose LCA applications display an average elasticity above the sample median compared to firms below the median. These tests provide some additional verification that the age elasticity of substitution for occupations can have an important moderating effect for how firm employment structures are influenced by young skilled immigration.

VII. Conclusions

In summary, the results of this study provide a multifaceted view of the impact of young skilled immigrants on the employment structures of US firms. We find consistent evidence linking the hiring of young skilled immigrants to greater employment of skilled workers by the firm, a greater share of the firm's workforce being skilled, a higher share of skilled workers being immigrants, and a lower share of skilled workers being over the age of 40. Results on whether total firm size increases or not are mixed. There is also consistent evidence in our IV specifications that older native employment expands very little, which is different from the other employment groups. In contrast to this lack of growth, however, there is limited evidence connecting actual departures of workers to the hiring of young skilled immigrants. The closest connection is a relative statement across occupations within a firm that suggests that departure rates for older workers relative to younger workers appear highest for those in STEM occupations.

Beyond this specific application, our study makes the larger point that the firm needs to take a much bigger role in immigration work going forward. This approach accounts for a greater level of heterogeneity and makes sense intuitively given that substantial portions of the US immigration framework have been designed to allow US firms to choose the immigrants that they want to hire. Some of the most prominent features of this analysis would have been obscured with standard approaches to immigration's effects. Our results have important implications for the competitiveness of US firms, the job opportunities of natives and immigrants employed by the firms, the capacity of the United States for innovative activity, and much beyond. This study is a first step toward this characterization, and in current research we are linking these employment changes to changes in patenting levels for firms. We hope that future work continues in this vein.

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