Skilled Immigration and the Employment Structures and Innovation Rates of U.S. Firms

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Abstract

We study the impact of skilled immigrants on the employment structures and innovation outcomes of U.S. firms using matched employer-employee data. We use the firm as the lens of analysis given that many skilled immigrant admissions are driven by firms subject to regulations and mandated caps (e.g., H-1B visa). OLS and IV specifications find rising overall employment with increased skilled immigrant employment by the firm; employment expansion is greater for younger natives than older natives. Departure rates for older workers appear higher for workers in STEM occupations. Skilled immigration expands firm innovation with little impact on the traits of patents filed.

JEL Classification: F15, F22, J44, J61, O31.

Key Words: Employment, Age, Innovation, Research and Development, Patents, Scientists, Engineers, Inventors, H-1B, Immigration, Ethnicity.

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1 Introduction

The immigration of skilled workers to the United States is of deep importance to our economy. In 2008, immigrants represented 16% of the U.S. workforce with a bachelor's education, and they accounted for 29% of the growth in this workforce during the 1995-2008 period. Moreover, in occupations closely linked to innovation and technology commercialization, the share of immigrants is higher at almost 24%. As the U.S. workforce ages and baby boomers retire, the importance of skilled immigration has the potential to increase significantly. Despite this impact, the appropriate policies and admissions levels for skilled workers into the U.S. economy remain bitterly debated. Many advocates of higher rates of skilled immigration have recently adopted the phrase "national suicide" to describe the United States' low admissions of skilled workers compared to low-skilled immigrants. On the other hand, expansions of admissions are passionately opposed by critics of the H-1B visa program who believe that skilled immigration is already too high.

This paper analyzes how the hiring of skilled immigrants affects the employment structures and innovation rates of U.S. firms. At the center of this project is a confidential database maintained by the U.S. Census called the Longitudinal Employer-Household Dynamics (LEHD) database. Sourced from state unemployment insurance reporting requirements, the LEHD provides linked employer-employee records for all private sector firms in 29 covered states. Among the information included for each employee is 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 by firms and changes in the employment structures associated with the hired immigrants (e.g., the hiring or departures of skilled native workers over the age of 40). Moreover, as we link in patenting data for these firms to the LEHD's structure, we can quantify how skilled immigration affects the associated pace and traits of innovation within these 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; 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 *prima facie* incomplete for skilled migration given the United States' framework described next. To add to this, analyzing the impacts of immigration at the firm level allows us to account for heterogeneity that is not captured with other approaches. The literature on international trade, in contrast, has benefitted deeply in recent years from greater consideration of the role of the firm.

The H-1B visa program is the largest program for temporary skilled immigration into the United States and a prime example of the firm's role in the skilled immigration process. To begin, the H-1B is a firm-sponsored visa, meaning that a firm first identifies the worker it wants to hire. The firm then applies to the U.S. government to obtain the visa and pays the associated fees. In addition to the firm being the prime actor, the labor market for the H-1B visa is difficult to define. The identified worker may currently be a U.S. student, an employee of a firm in Bangalore, or anywhere in between. The application procedure does require some labor market conditions with respect to the local area in which the worker will locate in the United States, but these conditions are primarily non-equilibrium in nature (i.e., the firm is struggling to find a suitable local worker). The visa has a regulated supply that lacks a pricing mechanism and is sometimes allocated by lottery. Finally, once the skilled immigrant has arrived in the United States, the immigrant is effectively tied to the firm until obtaining permanent residency or obtaining another temporary visa. The firm can potentially sponsor the employee for a green card, a process that takes six years or longer for some nationalities, during which time the employee is even more closely tied to the firm.

Throughout this H-1B visa description, it is clear that the firm plays an important role that warrants greater inquiry. Indeed, the structure of this program is designed in part to allow firms to select the workers they want to hire, rather than having the U.S. government select workers. Thus, the motivations of the firm are essential to understand, especially as many aspects of the program are governed by factors beyond market forces. In addition, many of the arguments in the public debate about the impact of skilled immigrants for the United States are firm-level statements. For example, Bill Gates has estimated in congressional testimony that Microsoft hires four additional workers to support each H-1B worker hired. Policy briefs like National Foundation for American Policy (2008, 2010) suggest even higher levels of complementarity. On the other hand, Matloff (2004), a critic of the H-1B program, argues that the principal use of the program by high-tech firms is to minimize their internal labor costs. Matloff argues that firms use skilled immigration to displace older natives with high salaries, thereby lowering their cost structures, and presents case studies about displacement within individual firms. Hira (2010) decries cases where American workers are tasked with training the H-1B workers who will be taking over their own job.

Given this background, this paper looks at the role of young skilled immigrants within the firm. Young workers are defined as those less than 40 years old. 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 the top patenting firms in the United States, given that much of the discussion of skilled immigration's effects focuses on employment outcomes or innovation rates. Given the skewness of the firm size distribution (Gabaix, 2011), 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 U.S. patenting. We construct an annual panel that describes the employment and hiring of skilled immigrants and use the panel to quantify the link of young skilled immigration to firm employment and innovation outcomes.

Ordinary least squares (OLS) estimations find a strong link between young skilled immigration and the expansion of the skilled workforce of the firm. Our data allow us to analyze this connection at three levels: overall young skilled immigrant employment by firm and its net changes over time, the hiring of young skilled immigrants by firm, and the hiring by the firm of immigrants who appear to be arriving in the United States for work for the first time. As we discuss later, our data do not perfectly discern the third case. We quantify effects through a first-differenced framework that removes permanent differences across firms, includes multiple controls that account for other approaches to studying immigration, and controls for contemporaneous changes in overall firm size (results are also shown without this control).

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 without conditioning on total firm size growth. Expansion is evident and mostly balanced for older and younger native skilled workers. Expansions of 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. Once controlling for aggregate firm size growth, we identify that a 10% increase in a firm's young skilled immigrant employment correlates with a 2% increase in the total skilled workforce of the firm. In contrast to the balanced growth noted for the unconditional estimations, this employment growth is substantially weaker among older native skilled workers than among younger natives or older immigrants.

Similar elasticities are evident on the hiring margin itself—that is, looking at changes in the rates at which native groups are hired within a year as hiring rates of skilled immigrants increase in that same year. On the leaving margin, which our data do not distinguish as forced or voluntary, the increased hiring of skilled immigrants is associated with lower leaving rates for natives. Combining the hiring and leaving margins, we again observe balanced employment growth of different skill groups when not conditioning on total firm size changes. Once conditioning on firm size changes, we continue to observe employment growth of young workers but not of older workers. This set of patterns is also evident in the hiring of new-arrival immigrants and in a subsample of top patenting firms.

OLS estimations are potentially biased by omitted factors and/or measurement error in immigrant hiring. Even with employee-level records, measurement error can be substantial in our data given incomplete state coverage and corporate restructuring issues discussed in Section 2. We thus turn to instrumental variable (IV) estimations that focus on the overall employment effects. We develop a set of six instruments 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. Our primary instruments measure this dependency through the log ratio of the firm's Labor

Condition Applications (LCAs) to the firm's skilled workforce size in 2001. As we describe later, LCAs are a first step to obtaining an H-1B visa, and microdata on LCAs are released by the Department of Labor that identify sponsoring firms. We also develop two additional measures from earlier in the sample period that indicate dependency on the program. These include the share of the firm's skilled workforce that comes from Chinese and Indian economies and the approximate share of the firm's skilled workforce in Science, Technology, Engineering, and Mathematics (STEM) occupations. The second part of the instrument construction then interacts these fixed dependencies with two measures of changes in the H-1B visa program's size over the 1995-2008 period, to give six instruments in total. Our first measure is an estimate of the national H-1B population by year developed by Lindsey Lowell, and our second measure is a summation of numerical caps that are placed on program admissions. Each of these IVs has advantages and liabilities discussed further below.

IV estimations deliver several consistent results. When conditioning on aggregate firm size, IV estimations agree with OLS that the skilled component of the firm's workforce expands with greater employment of young skilled immigrants. This expansion comes almost exclusively, however, through young skilled natives and older skilled immigrant workers. There is no employment expansion for older natives. These forces lead OLS to underestimate how much the immigrant share of the skilled workforce increases and how much the age structure of the firm tilts. These effects have the same pattern but are somewhat weaker within the subsample of top patenting firms, with some of the strength coming off of the comparison of the top patenting firms to the rest of the sample. Finally, when removing the firm size control, we observe that OLS estimates are upwardly biased with respect to the total firm expansion itself. These latter estimations generally point to increases in both skilled worker employment and overall firm employment but lack the statistical precision of some of our other results. They do, however, highlight consistent increases in immigrant shares of employment, reductions in older worker shares of employment, growth of skilled worker shares, and other relationships.

Building on these results, we consider two extensions that provide a richer context to the observed employment structure changes. The Current Population Survey (CPS) collects employment data from a random group of workers in the economy in each year. A link has been established between the 1986-1997 CPS and the LEHD. While our sample period mostly comes after this link, we are able to ascertain the primary occupations of over 25,000 workers in our firm sample at the time of their CPS survey. This platform allows us to evaluate whether workers linked to occupations related to STEM show greater future departure rates from firms when young 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 fields like accounting and law. Our evidence is suggestive on this dimension. On one hand, there is a higher departure rate of older workers in STEM occupations with young skilled immigration into the firm. This heightened old-young differential is especially pronounced for workers earning over $75,000 per 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 differences between these are not statistically significant or economically large.

Our second exercise turns to the innovation outcomes of firms given the special role that skilled immigrants play for the United States' science and engineering labor force. Indeed, beyond employment outcomes, innovation may be the most highly discussed outcome for skilled immigrants' role in the U.S. economy. To analyze this feature, we link individual records of all patents made by the firms from the United States Patent and Trademark Office (USPTO) database into the LEHD data set. We focus this exercise on 129 top patenting firms that are included in our firm panel. Every patent includes the name of at least one inventor, and one can identify the probable ethnicities of inventors from their names (e.g., inventors with the surnames Gupta or Desai are more likely to be Indian). Using ethnic-name matching procedures developed by Kerr (2008) and Kerr and Lincoln (2010), we use these data on patents to characterize the ethnic composition of the firm's inventor workforce to provide a deeper assessment. We also calculate a variety of additional traits about patents (e.g., citation counts, age of technologies used, how much the patent relates to the firm's prior work).

OLS estimations find that a 10% increase in the skilled immigrant employment by firms is associated with a 1%-2% increase in the patenting of the firms. This positive response is statistically significant in the base estimates, but not so when controlling for aggregate firm size changes. There is clear evidence for growth in patenting by inventors of non-Anglo-Saxon ethnic origin as young skilled immigration into the firm increases. There is some evidence of greater collaboration between Anglo-Saxon inventors and non-Anglo-Saxon inventors with greater skilled immigration, but there is no evidence for greater Anglo-Saxon invention by itself once firm size is controlled for. These results are suggestive of higher levels of innovative activity and an overall expansion of the inventor workforce of the firm with greater skilled immigration. Across the many traits measured for patents, we find very little evidence that the patents filed by the non-Anglo-Saxon inventors are different than Anglo-Saxon inventors. Innovation gains from these immigrants thus appear to come mostly through quantity rather than quality dimensions.

These results provide a multi-faceted view of how young skilled immigration shapes the employment structures of U.S. firms that does not align with any single popular account. To summarize, we find consistent evidence of rising overall skilled employment in the firm, with gains in total firm size being suggestive but not conclusive. While we generally do not observe evidence of heightened departures from the firm, with the one exception being a relative comparison across occupations within firms, the employment expansion is substantially higher for younger natives than older natives. The latter group either expands little or not at all. As such, the skilled worker share of the firm grows, the immigrant share of skilled workers in the firm grows, and older worker share of the firm declines. Breaking down occupations to the extent feasible with our data, relative departure rates for older workers appear higher in STEM occupations, reflective of the high age elasticity of substitution in this field. Skilled immigration expands firm innovation with little impact on the traits of patents filed.

The next section of this paper reviews some of the literature in this field and discusses some important conceptual notes. Section 3 presents our employment data, and Section 4 presents our OLS employment analyses. Section 5 discusses the construction of our instruments and undertakes the IV analyses. Section 6 presents our occupational results, and Section 7 presents our patenting data and analyses. The final section concludes.

2 Literature Review and Conceptual Framework

This section provides greater background to our study. We start with a brief literature review about academic approaches to analyzing immigration, and we discuss ways in which the firm's perspective is captured or not. We then outline two alternative perspectives from industry accounts of skilled immigration within firms. We postpone discussion of age elasticity of substitution until Section 6.

2.1 Definitions of the Labor Market and the Role of the Firm

Firms are mostly or entirely 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. A natural consequence of this approach has been a debate about what constitutes the appropriate labor market. Even more debate and research has followed about related questions like: Do natives move out from the labor markets (and thereby dampen the supply increase)? How quickly do other factors of production like capital or technology respond to labor inflows (and thereby alter relative price effects)? What are the non-employment effects of immigration? These and similar questions have typically been directed toward general immigration, and so are not reviewed here.[1] We instead focus on the initial question as to what the appropriate labor market is, identify skilled immigration studies that follow that perspective, and describe how the perspective of a firm may be captured or not.

A first approach defines labor markets as local areas like cities or states and is most closely associated with Card (2001). With this lens, immigrants to Boston are thought to most directly impact the opportunities of natives currently living in Boston, with less emphasis on other attributes like the relative ages of workers. Hunt and Gauthier-Loiselle (2010) and Kerr and Lincoln (2010) are two examples of this approach with respect to skilled immigration and innovation.[2] To the extent that a firm that makes employee choices within a single local area,

[1]General surveys of the immigration literature include Borjas (1994), Friedberg and Hunt (1995), Freeman (2006), Dustmann et al. (2008), and Kerr and Kerr (2011). An incomplete list of some of the most recent work includes Lewis (2011), Cortes (2008), Lach (2007), and Lubotsky (2007).

[2]Examples of studies using this approach for broader immigration patterns include Card (1990), Hunt (1992), Friedberg (2001), and Peri (2011, 2012). Longhi et al. (2005, 2006) provide meta-reviews.

either because the firm is small or because local units have high autonomy, then the behavior of the city at large may be reflective of the underlying firms. Possible limits with respect to the firms we study and their immigrant hiring include the fact that our firms typically extend across multiple geographic areas and labor markets. Moreover, the stated intent of some skilled immigration programs is to alleviate local labor shortages, and firms can cast a worldwide net when recruiting these employees.

Another approach, most closely associated with Borjas (2003), instead describes a national labor market among workers with similar education and age/experience profiles. With this lens, the 25-year-old immigrant with a bachelor's education in San Francisco may affect the opportunities of the 25-year-old native graduating from college in Boston more than older natives of similar education who also live in San Francisco. While there are reasons to suspect the skilled labor market may be national in scope, this approach has not been used for analyzing skilled immigration. This is in large part because the highest education group in these frameworks is typically bachelor's education and greater—a level which is usually taken as the starting point for defining skilled immigration.

The age-education framework also does not capture elements of the firm hiring decision given that the firms are optimizing over a full wage bill, internalizing potential complementaries across worker groups, and other relationships. And while the displacement effects identified by Borjas (2003) are frequently cited by critics of the H-1B program, some of their strongest claims rest on substitution margins that the basic framework does not allow.[3] One particularly powerful example is the argument made by Matloff (2003) that the H-1B program is all about age. Matloff proposes that the H-1B program offers firms two types of potential savings. One type of savings centers on the fact that a 25-year-old Indian H-1B programmer might be paid less than a 25-year-old American programmer.[4] Matloff argues that this emphasis is entirely misplaced, and that the real savings to the firm come from instead displacing a 50-year-old American programmer whose salary has grown with time. More generally, firms may have internal personnel policies (e.g., wage ladders with tenure) that interact with immigration in unique ways.

A third approach, which is less common generally but important for skilled immigration analysis, considers the labor market to be specialized fields of study or expertise. Examples of this work with respect to skilled immigration include Borjas and Doran's (2012) study of the migration of Russian mathematicians following the Soviet Union's collapse and Moser et al.'s (2012) study of Jewish scientist expellees from Nazi Germany.[5] This work again partially captures the firm's economics and partially does not. For example, the Borjas and Doran (2012) study is set

[3]Recent work builds more nesting into these models. Examples include Ottaviano and Peri (2012) and Borjas et al. (2012).

[4]Lowell and Christian (2000) and Kerr and Lincoln (2010) provide broad introductions to the H-1B program; Mithas and Lucas (2011) is a recent example of a study of H-1B wage effects and includes further references.

[5]In related work, Borjas (2005, 2006) and Chellaraj et al. (2008) examine the impact of immigrant graduate students on natives. Stephan and Levin (2001), Hunt (2011, 2012), Hayes and Lofstrom (2012), and Gaule and Piacentini (2012) assess quality differences between immigrants and natives with respect to innovation.

in an institutional environment with limited room for overall growth and mostly lacking complementary inputs. Firms, which are often engaged in a global competition, frequently suggest that the skilled immigrants they seek are necessary to grow the firm. In contrast to the substitution argument, this view suggests that skilled immigrants possess complementarities with domestic workers that can unlock greater opportunities. Moreover, firms tend to have greater flexibility than other institutions in the speed with which they can adjust their scale and composition, suggesting that their responses may differ from those measured across university departments.[6]

2.2 Substitution vs. Complementarity

In terms of the public debate over firms' role in skilled immigration, much of the discussion revolves around arguments over whether skilled immigrants are complements 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: the 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 existing workers' skills, the displaced worker debates how scarce that resource really is, and so on.

For the most part, this study does 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 we observe occupations in Section 6, the level of detail is too coarse to settle definitively the claims (e.g., the debates about computer programmer substitution are often about specific computer languages and how quickly one can or cannot learn these languages). Our study represents instead a broader inquiry into the patterns of hiring and employment departures associated with the hiring of skilled immigrants. By separating the dimensions of employee hiring and employee departures, we shed some light on the activity that lies behind net employment changes for the firm. Thus, we can ascertain whether some skilled employees are being hired (perhaps due to complementary skills)[7] and some others are departing (perhaps due to displacement in some form). While interpretation of these margins should be cautious, they provide substantially greater information than previously available.

Moreover, our characterization of the total change in the firm's skilled employment and innovations are very informative for the aggregate impact as the complementarity argument is more closely associated with unlocking growth. One conceptual note here is important. A frequent remark is that any evidence of firm growth or higher innovation is sufficient for concluding that the substitution perspective does not hold. This intuition is generally incorrect as access to a

[6]Firm-level studies on skilled immigration include Kerr and Lincoln (2010), Kerr et al. (2011), Clemens (2012), and Foley and Kerr (2012). Broader work that examines general immigration using the LEHD includes Andersson et al. (2009, 2012). Olney (2012) considers how firm counts increase when immigration shocks impact a city. Acemoglu et al. (2012) consider skilled immigrants in reallocation of activity across firm. Work outside of the United States includes Nathan (2011), Barth et al. (2012), Åslund et al. (2012), and Choudhury (2012).

[7]Peri and Sparber (2009, 2011) provide evidence on this dimension.

lower cost resource may lead the firm to expand production to a degree (e.g., due to concavity in the firm's profit function resulting from monopolistic competition, fixed production factors, etc.). Thus, the strength of the response is necessary for separating these descriptions.

3 Firm-Level Employment Data

The next three sections provide our analyses of skilled immigrant hiring and employment outcomes. We first discuss how we select firms for our panel, the LEHD data set construction, our definitions of employee hiring and departures, and descriptive statistics on our sample. The next section presents our empirical framework and OLS estimation results. Section 5 then describes the construction of our IV framework and presents the estimation results.

3.1 Firm Panel Selection

Our sample focuses on large U.S. employers and major U.S. patenting firms. We select these two facets of firm behavior as the criteria for choosing our firm sample since employment and innovation outcomes are frequently emphasized in debates on skilled immigration to the United States. Throughout much of this paper, we analyze these two groups together as there is extensive overlap; where warranted, we also report separate results for each group. We describe here the selection of our initial sample and the creation of composite firms that account for major corporate restructuring.

We identify major employers using the Census Bureau data and available public records. While our analysis mostly focuses on employee records contained in the LEHD data set, we describe shortly the partial coverage of the LEHD data across the United States. To ensure that our sample of firms is not biased by the states included in the LEHD sample, we develop a candidate firm list using nationally-based employment records and then restrict the sample to those firms among the candidates that satisfy a certain coverage ratio in LEHD states.

Our specific procedure starts with the Census Bureau's Longitudinal Business Database (LBD) that contains annual employment records for all establishments in the United States. We link the name of each establishment to the LBD from the Standard Statistical Establishment List. Summing across establishments, we compile the top 100 employer names in every year from 1990 to 2008. We also supplement this list with firm names not contained in the first step but that rank in the top 100 U.S. firms for worldwide sales or employment contained in Compustat over the full 1990-2008 period or that were a Fortune 200 company in 2009. The additions with these latter two steps are fairly small in number, as most of these firms are picked up by the LBD employer name search directly, and are meant to ensure the robustness of the sample design for including major employer firms. Moreover, Census Bureau restrictions do not allow us to publish the names of the firms in our sample, but these latter two targeted lists are publicly available. We exclude from our sample several temporary help agencies that are among the top employer firms.

For our major patenting firms, we first extract from the USPTO data set—which we discuss in detail in Section 7—all patent assignee names that account for more than 0.05% of patents applied for during the 2001-2004 period. Given that roughly half of USPTO patents are filed by foreign inventors and firms, we restrict the patents to those with inventors residing in the United States at the time of their USPTO application. We then identify firm names in the Census Bureau that are close matches to the USPTO data using name-matching algorithms and manual searches. We distinguish among potential matches using features like the firm's location in the Census Bureau data and the inventor's location in the patent data.[8]

With this assembled list of names, we next define firms and collect the Census Bureau firm identifiers and the federal Employer Identification Number (EIN) associated with them. In many cases, we have multiple firm identifiers and EINs for these entities. We use this manual approach, rather than directly using the Census Bureau firm identifiers from top employment companies in the raw data, in part due to the fact that we observe cases where the provided firm identifiers display irregular properties (e.g., employment shifting briefly to another entity and back). While labor intensive, this approach ensures very consistent firm definitions for both our top employer and major patenting firms.

We also use this manual approach as a means to account for major corporate restructurings during our sample period. Our 1995-2008 sample contains some significant mergers and acquisitions, corporate spin-offs, and similar events that can create discontinuous changes in firm employment patterns. To address this, we create composite firms that combine the records of both entities before and after the major corporate restructuring. For example, if two firms merge in 2001, we combine their records in the 1995-2000 period. We create these composite firms with a hinge date of 2005. That is, if the corporate restructuring occurs in 2005 or prior, we correct for it. If the event falls after 2005, we do not correct for it and instead end the firm record prematurely if need be. While it is impossible for us to account for every event within these firms, as some acquisitions are too small to detect, we have sufficiently invested in this process that we either correct or can confirm major employment shifts accounting for more than a quarter of the firm's workforce. An example of the latter confirmations is the identification of a large-scale corporate lay-off for which no correction is appropriate.[9]

Following these steps, our base sample contains approximately 450 composite firms. These firms account for a large share of economic activity. Our sample contains 10%-20% of all employment spells in the LEHD, depending upon the state, and 20%-30% of all workers in the LEHD are employed by these firms at some point during the sample period. The firms account for over

[8]The name-matching algorithms are described in detail in an internal Census Bureau report by Ghosh and Kerr (2010). This patent matching builds upon the prior work of Balasubramanian and Sivadasan (2011) and Kerr and Fu (2008). The list of included patenting firms does not depend much upon the years employed, and we find a similar sample set when using patenting over the 1995-2008 period, for example.

[9]Unidentified restructurings will result in measurement error in our immigrant hiring variables. This measurement error will be non-classical, with a bias towards the typical employment ratios of acquired firms.

one-third of U.S. patenting. On average, our composite firms contain roughly 3.5 Census Bureau firm identifiers and 58 federal EINs. The sector composition of the sample is approximately 30% manufacturing; 25% wholesale and retail trade; 30% finance, insurance, real estate, and services; and 15% elsewhere.[10]

3.2 LEHD Employment Data Description

We source employment records from the LEHD database housed by the U.S. Census Bureau. The LEHD contains linked employer-employee records for all private-sector firms covered by state unemployment insurance reporting requirements. The LEHD does not contain public sector workers at present. There are currently 29 states participating in the LEHD database; these states are indicated by the shaded areas in Figure 1. The employment records for all states extend through 2008 at present, but the starting dates differ by state. Appendix Table 1 lists the start date of each state. Our primary sample uses a balanced panel of 18 states that have reporting starting by 1995. These states are indicated by a star in Figure 1, and they notably include big (and high-immigration) states like California, Florida, Illinois, and Texas. Examples of major states not included are New York, Michigan, and Pennsylvania. We use the full 29-state sample in robustness checks that utilize a firm-state-year as the observation.

Taking our targeted firm list described in the prior subsection, we use the LEHD's Business Register Bridge (BRB) file to link in the employment records contained in the LEHD. The primary basis in the LEHD for identifying employer-employee linkages is the state employer identification number (SEIN) that identifies individual establishments. The BRB includes for each SEIN the associated federal EIN and Census Bureau firm identifier by year. From the BRB, we collect the SEINs that are associated with our firms at any point in time. This collection of complete SEIN records is important as firms upon occasion change SEINs for reasons unrelated to our interests, and these legal adjustments could otherwise be confused with actual changes in the company's employment dynamics. With the collected SEINs, we then prepare the employment records for our firm sample. We need each SEIN to be uniquely associated with a firm, and therefore we research any overlapping identifiers and assign them to the appropriate company.[11]

On average, our composite firms contain roughly 200 SEINs; these firms account for 1%-3% establishment-quarter records in the LEHD depending upon the state. For each SEIN, the employer characteristics files provide the establishment's industry, county location, and total annual payroll and employment. We also collect the unique employee identifiers by SEIN, which

[10] The count of 450 firms may appear to be less than expected given our description. It is important to note that the initial LBD draw is based upon firm names, and different spellings of the same firm create overlaps. There is also substantial persistence from year-to-year in top U.S. employers. This is additionally due in part to the creation of composite firms.

[11] These overlaps are typically due to companies purchasing a subset of operations from another company. We assign these operations to the company who purchased them. If we cannot verify the incident leading to the overlap, we generally assign the SEIN to the company that appeared to have it most recently. In some unclear cases, we discard the SEIN entirely after ensuring that it does not contain a significant number of employees relative to the overall company size.

are used to collect associated worker employment histories from the individual employment histories files.

In addition, the individual characteristics files contain important person-level information collected mainly through the Social Security Administration, Statistical Administrative Records system (StARS), and the Unemployment Insurance Administration. The person-level characteristics contained in the LEHD include gender, date of birth, date of death, place of birth, citizenship, and race. The place-of-birth variable is at the country level (or even sub-country level), and we utilize this variation extensively below. This is also our primary technique for identifying an immigrant. The citizenship variable is coded similar to that in the decennial Census. As such, we can group workers as belonging to one of three categories: U.S. citizens from birth, naturalized U.S. citizens, and non-citizens. The data unfortunately do not distinguish temporary visa holders versus permanent residents among non-citizens. We use these data to define a worker as an immigrant if they are a naturalized citizen or a non-citizen.

We merge these person-level characteristics into their quarterly employment histories that contain their total earnings by employer. Given the LEHD's limitations for describing worker education levels, we use a worker's long-term earnings to assign skill levels in our analysis. 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. The LEHD reports wages by quarter, and we define this threshold using quarterly observations expressed in annualized terms. Periods when the worker is not observed in the LEHD are not used for this calculation. To put the $50,000 figure in perspective, the USCIS 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. Earnings are deflated to 2008 values using the Bureau of Labor Statistics' All Urban Consumers CPI series. We only consider workers aged 18-64 in our project.[12]

Our final step for the key employment composition variables aggregates the assembled worker records into the employment composition of the company by year. The construction from the micro-data allows us to analyze several dimensions simultaneously (e.g., native workers over 40-years old earning $50,000). Our primary empirical approach considers firm-years as the unit of observation. For these analyses, we only include the states present in the LEHD since 1995 for calculating employment patterns. Thus, we use a balanced state panel for drawing data (the firm panel itself is unbalanced). We also discuss below a robustness check that uses a firm-state-year panel with all 29 states available.

[12] We find similar results to those presented below when using alternative approaches to define skilled workers. These include using initial salaries to define skilled workers or when using the imputed education variable in the LEHD data. The imputed education variable is developed using the decennial Census and employee traits observable in the LEHD. We use this variable only to a limited extent given that many traits correlated with immigration are used in the imputation procedure, but similar patterns are evident when defining skilled workers through bachelor's educations.

3.3 Definitions of Employee Hiring and Departures

One of the main focus points is on the hiring of skilled immigrant workers, and it is thus important to describe more extensively the traits of this work and the nuances imposed by the LEHD's structure. We define the hiring of a worker as the first time that the worker is paid a salary by a given firm. We define the departure of an employee from a firm as the final time that a person is paid a wage. It is important to emphasize that we do not observe whether the employee's departure was voluntary or whether the employee was dismissed by the firm. We create these identifiers 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 re-hiring. We cannot distinguish hiring and departures at the sample end-points, and so we drop the extreme years when required.

The LEHD's structure allows us to observe workers within the firm regardless of state. We do not consider employee migration across states within the same firm to be a worker departure and re-hiring. As noted, however, we observe employment for firms in 29 states in the LEHD. Thus, we cannot capture this feature if the within-firm migration is to or from a non-LEHD state. For this reason, we restrict our sample to 319 firms that 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 threshold is to have greater power for the IV estimations. These thresholds are calculated from the LBD where we observe the full employment counts of the firm by state.

A similar issue relates to how we define our immigrant hiring and departures. Portions of our analysis below analyze immigrant hiring by firms regardless of how long they have been employed in the United States, and this variable is precisely defined subject to the above limitation. We focus on young immigrants to model closely the skilled immigrant group most debated and influenced by immigration policy—over 90% of H-1B visa grants are to workers under 40 years of age. Much of the policy debate, however, is on new-arrival immigrant hiring (e.g., hiring a new H-1B worker). We thus test the robustness of the core definition based upon immigrants' ages to a second variant that defines a new-arrival immigrant hire as the first time an immigrant worker is observed in the LEHD regardless of firm. To account for the hiring of foreign students enrolled at U.S. universities, which are a substantial component of the skilled immigrant hiring for the U.S. overall, we also require in this definition that the worker meet the annualized $50,000 salary threshold for two consecutive quarters so as to minimize the impact of summer internships. We are again limited by the fact that a new immigrant hire may have an unobservable work history in a non-LEHD state before joining a firm in the LEHD sample.

Finally, when analyzing hiring and departing, we use a simple decomposition of employment changes for a firm as: 1) Hires in continuing firm-states, 2) Departures in continuing firm-states, and 3) Non-organic changes due to firms entering or leaving states completely. The first two components are our central focus. The third component is mostly outside of the scope of our conceptual model, and unreported tests find these non-organic changes mostly uncorrelated with our variables of interest.

3.4 CPS-LEHD Match Occupations

Unfortunately, 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 1986-1997 Current Population Surveys (CPS) and the LEHD. The CPS is a random sample of individuals, and our firms employ 25,765 workers who were surveyed by the CPS and have median annualized earnings during the 1995-2008 period of \$20,000 or more. In total, these workers comprise 132,507 person-year observations during our sample period. While we do not observe time-varying information, we utilize below the worker's primary occupation at the time of the CPS survey response to identify workers connected to STEM occupations. In our main employment analyses, we use this STEM variable as one approach to measuring the firm's dependency on the H-1B program. 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 the workers were connected to STEM occupations when the CPS survey was conducted.

3.5 Descriptive Statistics

Appendix Table 2 provides descriptive statistics. There are 319 firms in our core sample, and 129 firms in our subsample of top patenting firms. Our firms average about 22,000 employees in the 18 core states of the LEHD, with an underlying range of less than 200 employees to several hundred thousand. Within these firms, 50% of the workforce is classified as skilled workers by achieving a median annual earnings of \$50,000 or more during the 1995-2008 period, with an underlying range of 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%. The rate of skilled worker hiring and departing is 13% and 14%, respectively.

4 Firm-Level OLS Employment Analysis

This section defines our estimating framework and provides OLS results.

4.1 Estimation Framework for Employment Analysis

Our primary estimating equation takes the form,

$$Y_{f,t} = \beta \cdot \ln(Emp_{f,t}^{YSI}) + \nu \cdot X_{f,t} + \phi_f + \eta_{i,t} + \epsilon_{f,t},$$

where $\ln(Emp_{f,t}^{YSI})$ 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 sector in which the firm employs the most workers in the initial period. The sectors are grouped as manufacturing; wholesale and retail trade; finance, insurance, real estate, and services; and other. As firms span multiple sectors, we also include in regressions an interaction of linear time trends with the firm's initial share of employment in the first three sector groups. We further include a linear time trend for the firm's initial technology intensity measured as patents per skilled worker.[13]

Our estimations first-difference the above equation,

$$\Delta Y_{f,t} = \beta \cdot \Delta \ln(Emp^{YSI}_{f,t}) + \nu \cdot \Delta X_{f,t} + \eta_{i,t} + \hat{\epsilon}_{f,t}, \tag{1}$$

with the covariates in the $X_{f,t}$ appropriately adjusted and $\hat{\epsilon}_{f,t} = \epsilon_{f,t} - \epsilon_{f,t-1}$.[14] Regressions contain 3,374 observations, cluster standard errors at the cross-sectional dimension of the firm, and are weighted by the log initial young skilled immigrant employment in the firm. The regression weights 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 estimations 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 controls noted earlier. First, we include in many specifications a control for the log change in total firm size. This control includes workers of all wage levels. Second, following the influential work of Card (2001) and related papers, we include several measures related to the general employment conditions in the local area in which the firm operates. Firms often have multiple facilities, and they may shift activity across locations depending upon conditions. We thus calculate these controls using the initial counties in which the firm is operating, and we take weighted averages across these counties using the initial employment distribution of the firm. Our local area controls include the 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 on firm activity.

Third, following the influential work of Borjas (2003) and related papers, we construct a measure that reflects the potential impact on the firm from national immigration trends by age-education cells. We use the LEHD's education estimates for this work. We build six cells that cross our young and older age groups with three education levels (i.e., high school diploma or less, some college, college degree). We then calculate the firm's initial skilled employment

[13] When calculating initial values of firms, we use the first three years the firm is observed.

[14] The efficiency of this first-differences form versus 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 0.75, while 0.22 is evident in the first-differenced form.

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. Our age-education immigration factor sums over these six groups, interacting each firm's initial distribution with the national growth by cell.

Finally, we include as controls two measures that are similar to the supply-push framework defined by Card (2001). We start by classifying countries into 12 basic groups that are built upon ethnic and geographic lines.[15] We then calculate each firm's initial skilled immigrant distribution across groups. We also 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 the firm with the growth of skilled immigrant workers at the national level by group. We use an identical procedure to also construct a supply-push factor directed at lower-skilled immigration to the firm based upon the initial composition of the firm's lower-skilled workers and their national trends. The factors help control for the well-documented networking or clustering by ethnicity and country-of-origin in the workplace.[16] We also describe below how the skilled immigration factor is particularly important for our IV estimations.

4.2 OLS Employment Estimations

Table 1 provides our baseline OLS results using specification (1). Column headers indicate the outcome variables $Y_{f,t}$ considered by each specification, and the title of each panel describes the sample employed and the included controls $X_{f,t}$. Column 1 of Panel 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 covariates. The β coefficient is strong and well measured. As both measures are in logs, the β coefficient 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, with the demarcation between older and younger workers at age 40. Column 3 finds 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 (0.02).

The next three columns of Table 1 document changes in some simple employment traits of the firm's skilled workforce. Across the sample in Panel A, a 10% increase in young skilled immigrant employment for the firm corresponds with 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

[15] Six 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 due to their high importance to U.S. 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 dispersed group of 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.

[16] See, for example, Mandorff (2007), Andersson et al. (2009, 2012), and Åslund et al. (2012).

effect from 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 U.S. employment of the firm, including lower-skilled workers, and the skilled immigrant share. A 10% increase in skilled immigrant employment for the firm correlates with a 6% increase in total firm employment, and 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. Panel B then adds the basic controls to the estimation framework, which do not materially influence the estimated elasticities from Panel A.

Panel C further adds the log contemporaneous change in aggregate firm size, which has a much more substantive effect on the coefficient estimates. The overall employment elasticity in Column 4 declines to 0.22. Thus, after conditioning on aggregate firm size, a 10% increase in the young skilled immigrant workforce of the firm correlates to a 2% increase in the total skilled workforce of the firm. Looking at Columns 1-3, this expansion strongly favors young natives and older immigrants compared to older natives, with elasticities for the former two groups more than three times stronger. Accordingly, Columns 4-7 show stronger shifts in the immigrant and older worker shares of the firm. Panel C is our preferred specification that we focus on more later in the analysis. Finally, Panel D finds similar effects when looking at the subsample of top patenting firms, with even stronger differences evident across different worker types.

Appendix Table 3 reports the complete set of coefficient values for Columns 1-4 of Panel C. Estimated coefficients for the covariates are reasonable in direction and magnitude. Interestingly, and matching much of the prior literature, the supply-push immigration factor has positive explanatory power, the immigration factor based upon the firm's local area has a relatively small elasticity, and the age-education immigration factor based upon national age-education cells has a stronger negative effect on native employment growth. While the inclusion of the controls does not substantially change our analysis for how immigration employment shapes the firm's workforce, comparing for example Panels A and B of Table 1, they certainly remain important overall.

4.3 OLS Hiring and Departing Estimations

Tables 2a and 2b next consider the hiring and departing of various worker groups contemporaneous with the hiring of young skilled immigrants. We continue to use specification (1), with the key regressor being $\Delta \ln(Hiring_{f,t}^{YSI})$. 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 does not restrict on new-arrivals, but includes any immigrant regardless of how long they have been working in United States. The Panels A-D are defined exactly as in Table 1.

Columns 1-4 consider as outcomes the log hiring of groups, with Column 4 simply a placeholder for now since the right-hand-side variable is the same as the potential outcome variable. Elasticities on this margin are similar to that measured for the total change in the workforce in Table 1. In Panel C, a 10% increase in young skilled immigrant hiring is associated with a 5%-6% increase in older and younger native hiring. There is not as large of a difference between Panels B and C as the firm size control has less bite on the isolated hiring margin. These estimates are again precisely measured. Columns 5-8 consider as outcomes the log departing rates of groups. Panels A and B find no material changes in leaving rates associated with increased young skilled immigrant hiring. Panels C and D condition on changes in overall firm size, and they find a decline in departing rates when young skilled immigration hiring increases.[17]

Table 2b then relates these hiring changes to changes in the overall composition of the firm's skilled workforce, similar to Table 1. The coefficient estimates are substantially lower here than in Table 1 due to our focus just on the changes in the hiring dimension rather than net changes in overall employment. The main specification in Panel C suggests that a 10% increase in the hiring of young skilled immigrants increases the total skilled workforce of the firm by about 0.2%. Growth is strongest in the immigrant worker group documented in Column 4, but it is also present for the younger natives and older immigrant workers in Columns 2 and 3. On the other hand, Column 1 does not find any associated growth for older native workers, and there is evidence of a decline among top patenting firms.

Appendix Tables 4a and 4b repeat this analysis without the log transformation of variables. While the non-log format introduces scale effects, it is useful to consider them given that advocacy group claims about skilled immigration effects are often expressed in raw counts. The hiring of one young skilled immigrant worker is associated with a total organic employment expansion of 4.8 workers. This includes about 1.6 older native workers, 1.8 younger native workers, 0.4 older immigrant workers, and a net young skilled immigrant worker addition of a little less than one worker after accounting for departures. More important, the overall depiction of the results is quite similar to the log format. The lower elasticity of older natives in the log format reflects in part the larger base of older natives in the workforce.

4.4 OLS New-Arrival Hiring Estimations

Tables 3a and 3b repeat the analysis conducted in Tables 2a and 2b with the key regressor now being the log rate of hiring of new-arrival skilled immigrant workers. These new-arrivals are defined such that this in the first time that we observed the immigrant working in LEHD states with substantial earnings for two quarters (defined as such to allow for a new-arrival by a student joining the workforce full-time after prior summer internships). In Table 3a, we again observe increased native hiring contemporaneous to the higher immigrant hiring. With the restricted

[17] Departure rates for young skilled immigrants in Column 8 are possible due to 1) the departure of immigrants already working in the firm and 2) short employment spells where a worker is hired and departs in the same year.

new-arrivals regressor, we can also quantify changes in overall young skilled immigrant hiring in Column 4, which is the strongest expansion of the worker groups. Similar to before, Columns 5-8 find reduced departure rates. In Table 3b, we quantify that a 10% increase in the hiring rate of new-arrival immigrants is associated with a small increase in the total skilled workforce of the firm. The largest percentage growth is again among the young immigrant group, not surprisingly, but positive growth is also observed for older immigrants and young natives. Once again, conditional on firm size, older native employment does not expand.

4.5 OLS Robustness Checks

The OLS patterns overall speak to increased hiring and employment of natives when the skilled immigrant workforce of a firm expands. These results are robust to a number of different approaches. To mention a few key ones, we find similar results using a firm-state approach that allows us to include all 29 states. The elasticity estimates are somewhat lower with this approach than in the firm panel, which may indicate that the firm as a whole operates differently compared to individual units (e.g., shifting production across facilities). We intend to further investigate this feature in future work. 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 previous section.

5 Firm-Level IV Employment Analysis

The OLS patterns documented in Section 4 are striking and novel to observe. There are, however, two clear concerns. First, the hiring of young skilled immigrants is likely to be endogenous to other factors influencing the firm. These omitted variable biases could be upwards or downwards in direction. For example, an upward bias might result from the firm having a new product that it wants to launch, and so the firm hires 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. The broad comparability of elasticities in Table 1 for total worker expansion and skilled worker expansion suggest this concern might be particularly true for OLS estimations that do not condition on aggregate firm size. On the other hand, a downward bias can emerge to the extent that 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 overcoming these types of labor market frictions (e.g., Borjas 2001, Kerr 2010b, Ruiz et al. 2012).

The second concern is more mundane but also important. While building from the microdata, our right-hand-side variables are measured with error. There are two types of measurement error present. First, we will have some degree of classical measurement error due to inaccurate reporting (e.g., an individual's place of birth is inaccurately transcribed). This measurement error downward biases coefficient estimates towards zero. Second, we could potentially have non-classical measurement error that results from corporate restructurings or acquisitions that we have not been able to account for with our composite firms. This type of measurement error will not bias us towards zero, but instead upwards to a degree that depends upon how similar the employment distributions of corporate restructurings are to the base firms. As one specific example, if the acquired employment structures are exact matches to the base firm structures, the bias is towards one. This section develops and presents IV estimations to address these concerns.

5.1 H-1B Population IV Design

Before jumping into the specifics of the H-1B program and our IV design, it is helpful to start with an overview of what the instruments are attempting to accomplish. To this extent, it is useful to consider first our control variable that is the supply-push immigration factor for skilled workers. Recall that this factor interacts the initial place-of-birth distribution of the firm's skilled workers with the aggregate changes across LEHD states in the extent to which there is skilled immigration to the United States from various countries. This factor is a strong predictor of increased young skilled immigrant employment in the firm, and one potential route would have been to use this supply-push factor as an instrument. In doing so, we would have had two potential concerns to address. The first would have been whether the initial distribution of country groups for skilled immigrants used in the interaction is instead correlated with something else that is affecting the measured outcomes. The second challenge of this type of instrument is that the national trends used for immigration groups may be endogenous to the needs or opportunities of the firms that employ them. For example, immigration flows from Japan to the United States may be higher when firms that rely heavily on skilled Japanese workers have strong opportunities (and perhaps recruit them). Thus, even though we would have instrumented for the direct hiring of the firm, the instrument's reliance on the national trends might not be a complete solution.

A stronger IV scenario would instead be mandated rates of immigration to the United States by country. U.S. immigration policy does not generally contain such tight, country-specific controls on immigration, but it does provide some empirical footholds through the H-1B visa program, the largest program for skilled immigration to the United States. We describe next the H-1B program in greater detail, and then we develop several instruments to analyze the employment relationship of firms. The construction of our instruments will be conceptually similar to the supply-push framework that is frequently employed, but we will seek to use the program's legal structure to deal with some of the concerns that would have existed on a traditional supply-push framework.

The H-1B visa is a temporary immigration category that allows U.S. 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 like 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. Approximately 40% and 10% of H-1B recipients over 2000-2005 came from India and China, respectively. Shares for other countries are less than 5%. Over 90% of H-1B visas are for workers less than 40 years old.

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 three-year term are exempt, and the maximum length of stay on an H-1B visa is thus six years. While most aspects of the H-1B program have remained constant since its inception, the cap has fluctuated significantly. Figure 2 uses fiscal year data from the United States Citizenship and Immigration Services (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 the cap over the next five years to 195,000 visas. These short-term increases were allowed to expire during the United States' high-tech downturn, when visa demand fell short of the cap. The cap returned to the 65,000 level in 2004 and became binding again, despite being subsequently raised by 20,000 through an "advanced degree" exemption.[18]

While the cap is well known, H-1B entry rates and population stocks are not definitively published. 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, the latter outflows require combining available statistics with modelling 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 Lowell's updated estimates provided to us for this research. The H-1B population grew rapidly in the late 1990s before leveling off after 2000. The lack of growth immediately after 2000 can be traced to weak U.S. employment opportunities for scientists and engineers during the high-tech recession. When demand returned, however, the reduced supply of H-1B visas restricted further growth.

These changes in the size of the H-1B program, driven in large part by legislative changes and numerical limits, provide an attractive alternative to using national immigration trends by country. We thus construct six instruments that are similar in spirit to the supply-push framework but that are more exogenous. The basic approach for the construction of each of these instruments is to first measure a fixed dependency of a 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 skilled immigrant employment in the firm.

We measure the fixed dependency of the firm in three ways. Our primary measure is the

[18] Kerr and Lincoln (2010) provide a more extended discussion of these features.

log ratio of the firm's Labor Condition Applications (LCAs) to skilled employment in 2001. To obtain an H-1B visa, an employer must first file an LCA with the U.S. Department of Labor (DOL). The primary purpose of the LCA is to demonstrate that the worker in question will be employed in accordance with U.S. 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 it receives, numbering 1.8 million for 2001-2006. These records include firm names and proposed work locations, and we use these records to describe firm dependencies (in LEHD states) from the earliest year that is available electronically (2001). It is important to note that this measure does not indicate granted visas, but instead the demand that firms have for the visas. Application fees are significant, and thus counts of applications are likely reliable measures of firm demand.

We complement this LCA-based measure with two other firm measures that are likely to indicate sensitivity to changes in the 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 are from these economies. Likewise, as the program is particularly important for STEM occupations, we define a third measure as the share of the firm's workers in STEM occupations where we are able to observe occupations for a firm via the LEHD-CPS match. We measure this in the first three years where matched employees are observed, which may be later than the typical initial period. Given the time-invariant occupation code and the limited 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 0.59 between the LCA-based measure and the initial Chinese and Indian share, 0.45 between the LCA-based measure and the initial STEM occupation share, and 0.59 between the initial Chinese and Indian share and the initial STEM occupation share.

We then interact these three measures with two measures of the H-1B program's size, expressed in logs, to obtain six instruments in total. The first measure of program size is Lowell's H-1B population estimates. The second measure is a summation of the previous six years' numerical visa caps. These two size measures have advantages and liabilities. The Lowell estimates have the advantage that they accurately reflect the population's true development and in most phases experienced growth that was 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. The sum of the previous six years' caps is the mirror image of this. We use this measure since the H-1B visa is effectively of a length of six years (inclusive of visa renewal). On one hand, the advantage of this measure is that it is more exogenous. On the other hand, there is a key period in the early 2000s when the H-1B demand declined substantially at the same time that the cap rose substantially, and thus the six-year summation is not as reflective of the program's size.

5.2 H-1B IV Analysis

Tables 4a and 4b report our primary IV results that condition on firm size. The three instruments in Table 4a use Lowell's population estimate for the interaction term, while those in Table 4b use the six-year summations of previous caps. Within both tables, Panel A presents results that use the LCA-based dependency measure, Panel B presents results that use the initial Chinese/Indian share of skilled workers, and Panel C presents results that use the initial STEM worker shares. The fit of the first stage estimations, indicated on the tables beneath each panel, pass standard criteria. They tend to be stronger for the population-based instruments compared to the summations of the previous six years' caps. The first-stages also tend to be weaker for the occupation-based measure, which is not surprising given the measurement error noted above.

The second-stage estimations resemble and differ from the OLS estimates in meaningful ways. For convenience, these results are summarized visually in Figures 3a and 3b along with the OLS results. Space constraints in the figures require that we use the short-hand of IV1-IV3 to report the outcomes from Panels A-C, respectively, from Table 4a. IV4-IV6 likewise denote Panels A-C from Table 4b.

Similar to the OLS estimations, the IV results in Figure 3a suggest an expansion in the total size of the skilled workforce of the firm after conditioning on aggregate firm employment changes. The IV results tend to be moderately larger than OLS. The more interesting heterogeneity comes when looking at the different worker groups. Four of the six IV estimations suggest no growth in older native employment is connected to the hiring of young skilled immigrant workers; the other two suggest modestly higher growth but are not significantly different from OLS. On the other hand, IV results suggest that young native employment responses in OLS were downwardly biased, perhaps due to young skilled immigration being used for situations where young native workers were difficult to hire. Finally, IV results for older skilled immigrants are comparable to OLS but with wider confidence bands. Figure 3b shows the consequence of these IV corrections for our key ratios. IV estimations find that immigrant worker shares among skilled employees grow somewhat more than OLS indicates, but the differences are small. On the other hand, the IV estimations find sharper declines in older worker employment shares than OLS exhibits.

Tables 5a and 5b extend the primary LCA-based IV analysis with the H-1B population and six-year cap summations, respectively. Panel A of both tables shows results that use the subsample of top patenting firms only, and Appendix Tables 5a and 5b provide all six IV variations with this subsample, similar to Tables 4a and 4b. The patterns are quite similar in this subsample, and it is also evident that the differences in behavior between the top patenting firms and the rest of the sample play an important role in describing the age tilt of the firms. Panel B finds similar results with unweighted specifications. Panel C includes 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. We also find similar results dropping firms that lobby about H-1B visas. Panel D replaces the total firm size control with a control based upon the growth of medium-skilled workers, defined to be those with median annualized earnings between $25,000 and $50,000, and finds similar effects. Finally, Panel E reports similar results using a balanced panel of firms present across the full sample period.

Table 5c provides a version of Table 4a without the aggregate firm size control. For this unconditional analysis, we do not report IV results using six-year cap summations as these latter instruments are too weak. This performance difference across the instruments goes back to the behavior of the H-1B cap during the high-tech recession. When using the Lowell H-1B population trends, the IV estimations are less reliant on a firm size control as the instruments are not predicting substantial firm growth during the high-tech recession. Using the more exogenous cap summations to model the program's size, we are able to model successfully the behavior of the skilled workforce in the firm after conditioning out the firm's overall growth path but not independently of this baseline control.

The raw estimates of employment size changes in Tables 5c are mixed across the instruments. Two of the three instruments continue to find total growth in the skilled workforce of the firm, with the LCA-based dependency predicting only very small additions. The evidence for increases in total firm size are more ambiguous, except that all three instruments agree that the OLS results with respect to aggregate firm size are upwardly biased. With the IV correction, only one of the total firm size estimates is statistically different from zero. On the other hand, the adjustments in the basic traits of the firms due to young skilled immigration are confirmed by all three instruments as these ratios implicitly remove firm size. We again find in Columns 5-7 and 9 increases in the immigrant share of skilled workers, a shift in the age structure towards younger workers, and an increase in the skilled worker share of the firm's total workforce.

6 Occupation-Level Estimations

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

6.1 Occupation-Level Elasticities of Substitution by Age

Starting with Borjas (2003), a number of studies within the immigration literature consider elasticities of substitution using a CES production function. Skipping some of the theoretical background that is provided, for example, by Borjas et al. (2012), we focus on a central regression in this technique that estimates the elasticity of substitution between worker groups along a specified dimension. For our age-related purposes, this estimation takes the form,

$$\ln(Wage_{a,t}) = \gamma \cdot \ln(Emp_{a,t}) + \phi_a + \eta_t + \epsilon_{a,t},$$

where a indicates worker ages 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 much (a γ coefficient of zero). This logic can be expressed as the elasticity of substitution $-1/\gamma$, with higher elasticities indicating easier substitution.

We apply this model at the occupational level using bachelor's level workers in the CPS from 1995-2008. We consider workers aged 20-59 and define four age categories as 20-29, 30-39, 40-49, and 50-59. We group the CPS's base occupations into larger groups to provide sufficient observations and more meaningful comparisons. The elasticities with respect to age are substantially higher in the STEM-related fields among these 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 five and seven, including lawyers, accountants, administrators, and doctors. Some occupations like teachers have basically no elasticity of substitution along the age dimension.

Higher elasticities of substitution by age for STEM give one indication as to why older natives may experience displacement from young 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 the bachelor's educated branch only, and we allow for different elasticities over ages by occupation. Finding a very high elasticity of substitution by age in an occupation would suggest that immigrants in one age group of the occupation can substitute equally well for natives in other ages groups as they can for natives in their own age group. This would provide a more rigorous framework for thinking about why young immigrants may substitute more for older natives in one occupation versus another.[19]

6.2 Departure Rates by Occupation

With this background, Table 6 provides some simple estimations of departure rates by occupation within our firms and how they correlate with young skilled immigration. We stress again that

[19] Appendix Figure 1 provides related evidence from the 2000 Census of Populations of a flatter wage profile with age in STEM fields compared to other occupations with similar education levels. See also Brown and Linden (2011) and Wadwha (2010).

occupation is observed once during the 1986-1997 period for the individual, and we are applying that past trait forward to the 1995-2008 period. Our sample includes native 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 dataset comprises 132,507 person-year observations from 25,765 workers.

Our specification is a linear probability model where the outcome variable is an indicator variable for an individual departing from his or her firm. The key explanatory variable is the growth in young skilled immigrant employment in the firm by year. To study occupational and age differences in an intuitive format, we interact this immigration regressor with three indicator variables for 1) older worker in STEM occupations, 2) young worker in STEM occupations, and 3) older worker 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 6 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. This baseline is 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 shows this pattern in a second way where 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 correlated 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 based upon salary levels (time varying, taken from the LEHD). We define higher 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 the 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. This is robust in Column 4 to including age-occupation fixed effects. In Column 4, 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 different from each other at 0.102 (0.039) and 0.086 (0.027), respectively.

We have extended this set of work in several ways. First, Column 5 examine firm-level of hiring of these matched workers and does not this pattern, indicating 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 6.1. We adopt Table 6's indicator variable approach for reported results given its intuitive nature. Figure 4 also provides some graphical evidence from the public CPS files. 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 LCA applications the firm makes in 2001. Using the elasticities calculated in Section 6.1, we identify the weighted elasticity of substitution by age across the applications the firm makes. The differentials across salary levels are almost three times higher for firms who 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 be an important moderating effect for how firm employment structures are influenced by young skilled immigration.

7 Firm-Level Patenting Estimations

This section describes our patenting estimations. We first describe the patent data and the identification of the probable ethnicities of U.S. inventors. We then provide an analysis that links the hiring of skilled immigrants to changes in firm patenting outcomes.

7.1 Patenting Data Description

Our innovation data come from the individual records of all patents granted by the USPTO from January 1975 to May 2009. This database was first developed by the NBER and was subsequently extended by HBS Research to include patenting in recent years. Each patent record provides information about the invention and the inventors submitting the application. Hall et al. (2001) provide extensive details about these data, and Griliches (1990) surveys the use of patents as economic indicators of technology advancement. We collect from this database the patents that are 1) filed by inventors living in the United States at the time of the patent application, and 2) assigned to industrial firms. In a representative year, 1997, this group comprised about 75 thousand patents. We use the date of patent applications to identify the timing of innovative activity. While we have patents granted through 2009, there is substantial attrition in counts for the 2005-2008 period as many applications are still being processed by the USPTO. We thus conduct patent-based analyses across the 1995-2004 period.

Each patent lists at least one and often several inventors and includes information on the location and employer of each inventor. The immigration status or ethnicity of inventors is not listed on patents, but it is possible to determine their probable ethnicity through their names.

The matching approach exploits the fact that people with particular first names and surnames are likely to be of a certain ethnicity and makes use of two databases of ethnic names originally developed for marketing purposes (e.g., Melissa Data Corporation, LSDI). The procedures have also been extensively customized for the USPTO data. The process affords the distinction of nine ethnicities: Anglo-Saxon, Chinese, European, Hispanic, Indian, Japanese, Korean, Russian, and Vietnamese. The name match rate is 99%.[20]

7.2 Patenting Estimations

Table 7 provides OLS results on patenting outcomes. We focus this exercise on the 129 top patenting firms that are included in our firm panel. This group meets four minimum thresholds: 1) obtaining more than 100 U.S. patents during the sample period, 2) having a minimum annual patent count above three patents, 3) having more than one Anglo-Saxon ethnicity inventor in each year, and 4) having more than one non-Anglo-Saxon ethnicity inventor in each year. These thresholds are designed to identify higher quality and consistent firm observations for the specification variants we analyze below (which are in logs and thus create difficulties for handling zero-valued observations). This group is identical to the top patenting subsample analyzed in prior sections. Appendix Table 2 continues to provide descriptive statistics. On average, these firms have 217 patents in each year. The inventor workforce is 69% Anglo-Saxon ethnicity and 31% non-Anglo-Saxon ethnicity. Of this latter group, roughly half of the inventors are of Chinese and Indian ethnicity. These shares and their further ethnic divisions are reflective of the broader STEM workforce evident in the Census of Populations, and the responses of inventors with Anglo-Saxon ethnic names can serve as a viable proxy for the experiences of citizen inventors.

We use an estimation framework similar to specification (1), with the outcome variable now being changes in the log number of patents in the United States. The first column of Table 7 shows that a 10% increase in the skilled immigrant employment by firms correlates with a 1%-2% increase in total firm patenting. These estimates are statistically different from zero in Panels A and B; they are not statistically different from zero after the firm size control is introduced in Panel C. This first column only considers firm patenting in the LEHD states over which we can measure skilled immigration, and Panel B shows comparable figures if instead using aggregate U.S. patent counts for these firms. The remainder of the columns use patenting in LEHD states only.[21]

Columns 3 and 4 divide patents into contributions linked to Anglo-Saxon ethnicity inventors versus non-Anglo-Saxon ethnicity inventors. We apportion patents with multiple inventors such

[20] Kerr (2007, 2008, 2010a) and Kerr and Lincoln (2010) provide details on the matching process, list frequent ethnic names, and provide descriptive statistics and quality assurance exercises. Agrawal et al. (2008) undertake a similar strategy.

[21] We have investigated longer lag structures and not found anything especially noteworthy beyond the first-differenced results. Most empirical studies find that contemporaneous R&D investments have the most important impact for rates of technology formation at the firm level (e.g., Pakes and Griliches 1980, Hausman et al. 1984, Hall et al. 1986). Kerr and Lincoln (2010) also observe a similar pattern with respect to skilled immigration and patenting at the city level.

that each patent receives equal weight. We likewise apportion the contributions of individuals with multiple or ambiguous ethnic matches using the underlying probabilities identified. In Panels A and B, patenting expansion is evident among both ethnic groups. In Panel C, after we introduce the aggregate firm size control, a stark difference becomes evident with a very high elasticity of ethnic innovation to growth in the young skilled immigrant workforce. On the other hand, only a trace increase in patenting by Anglo-Saxon ethnicity inventors is observed. Thus, most of the increase in firm patenting appears directly linked to the immigrants themselves.[22]

The last three columns split patents for a firm in a second way. Column 5 considers patents where the ethnic composition of inventors is heavily of Anglo-Saxon origin (specifically, that 80% or more of the ethnic composition across inventors is Anglo-Saxon). In Column 6, we describe collaborative patenting that involves at least one Anglo-Saxon inventor and one non-Anglo-Saxon inventor. This decomposition shows that much of the increase in Anglo-Saxon innovation comes through patents that are collaborations with non-Anglo-Saxon inventors. Column 7 again finds a large increase in patents with inventors that are mostly of non-Anglo-Saxon ethnic origin.

In addition to Table 7's depiction, we calculated a variety of traits about patents to test whether the patents associated with Anglo-Saxon inventors differ substantially from those associated with non-Anglo-Saxon inventors. These traits included standard quality measures from the patent literature like citation counts and patent claims (normalized by technology class and year). They also include measures of the age of the technology class in which the patent was being made and the ages of technologies cited by patent in the USPTO filing. Other measures considered how closely connected the patent was with the prior work of the firm through self-citations and whether the patent was mainly intended for exploitation or exploration purposes (e.g., Akcigit and Kerr 2010). Across these dimensions and others, there appears to be very little difference across the patents filed by different ethnicities. There is some evidence that ethnic inventors may build upon more recent technologies than Anglo-Saxon inventors, but given the null results on the many other dimensions analyzed, the most reasonable conclusion is that the patents are overall quite similar. This is important as it suggest claims about complementarity between citizens and skilled immigrants need to rely on a quantity argument rather than a quality dimension with respect to patenting.

We have also examined the IV specifications surrounding patenting. These results provide some directional confirmation but are not tabulated due to their general imprecision. Our highest quality IV elasticity estimate is 1.171 (0.583) and 1.145 (0.592) for total patenting with the LCA-based instruments that employ the Lowell population trend and cap summation, respectively. Some of the expansion in coefficient size is likely linked to the local average treatment effect of the H-1B program being used for STEM fields. But the standard errors are generally too

[22] This connection is also important from a methodology perspective. Multiple studies use probable ethnicities based of off individuals' names to ascertain traits of workers where detailed characteristics are otherwise scarce. To the best of our knowledge, this approach has not been extensively validated at the firm level using administrative records. As a second example, the elasticity of Chinese and Indian patenting to the growth of young Chinese and Indian skilled workers in the firm is 0.54 (0.18).

large compared to the baseline OLS estimates to afford causal claims with this approach. Thus, the best connection this study can establish is through the tight connection of ethnic names on patents with the growth of young skilled immigrant employment in the firm. The relative differences across the ethnic groups are informative of the experiences of American workers.

8 Conclusions

In summary, the results of this paper provide a multi-faceted view of the impact of young skilled immigrants on the employment structures and patenting outcomes of U.S. firms. There is consistent evidence linking 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 generally consistent evidence, once including aggregate firm size controls or instrumenting for immigrant employment, that older native employment expands very little, which is different from the other employment groups. Unlike 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 departure rates for older STEM occupations may be higher, which would connect to the higher age elasticity of substitution in these fields. Among patenting firms, the increased skilled immigration is also associated with greater levels of invention. These gains again appear to mainly follow from increased contributions of immigrants. Some collaboration across ethnicities is evident, and new innovations tend to be comparable in quality to the prior work of the firm.

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. The firm is the key actor for skilled immigration, and substantial portions of the U.S. immigration framework like the H-1B visa program have been designed to allow U.S. firms to choose (with approval constraints) the immigrants that they want to hire and to give the firm a special relationship with the immigrant for a period if time while in the United States. Given this system and the fact that the size of the program is determined by legislation, it is imperative to understand the motivations of the firm and the economics of skilled immigration within the firm. Some of the most prominent features of this analysis would have been obscured with standard approaches to immigrant effects. Our results have important implications for the competitiveness of U.S. firms, the job opportunities of natives and immigrants employed by the firm, our larger national innovative capacity (e.g., Furman et al. 2002), and much beyond. This study is a first step towards this characterization, and we hope that future work continues to discern the effects of skilled immigration within firms.

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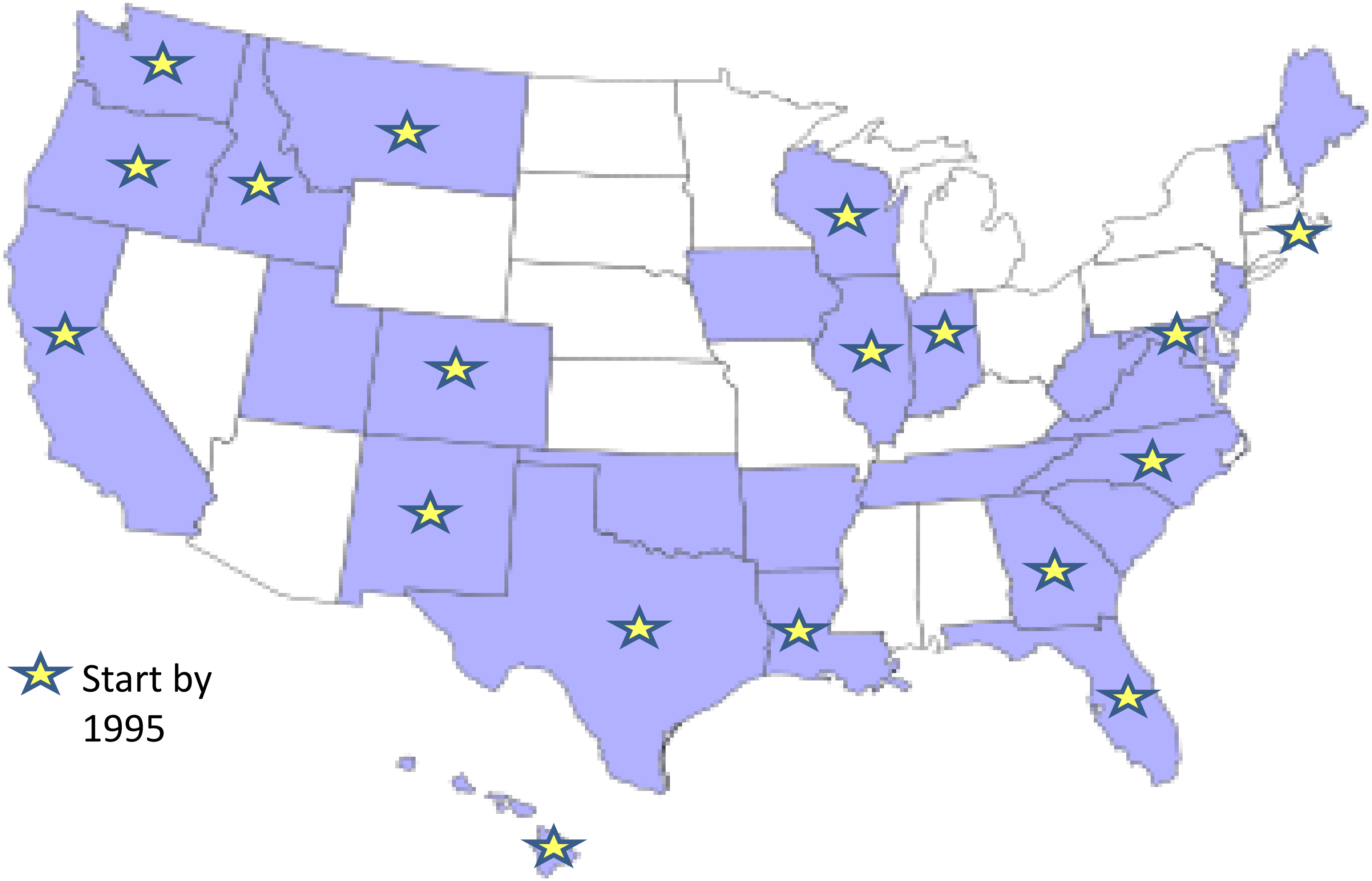
[70] Stephan, Paula, and Sharon Levin, "Exceptional Contributions to US Science by the Foreign-Born and Foreign-Educated", *Population Research and Policy Review* 20:1 (2001), 59-79.

[71] Wadhwa, Vivek, "Silicon Valley's Dark Secret: It's All About Age", TechCrunch Post (2010).

Figure 1: LEHD State Coverage

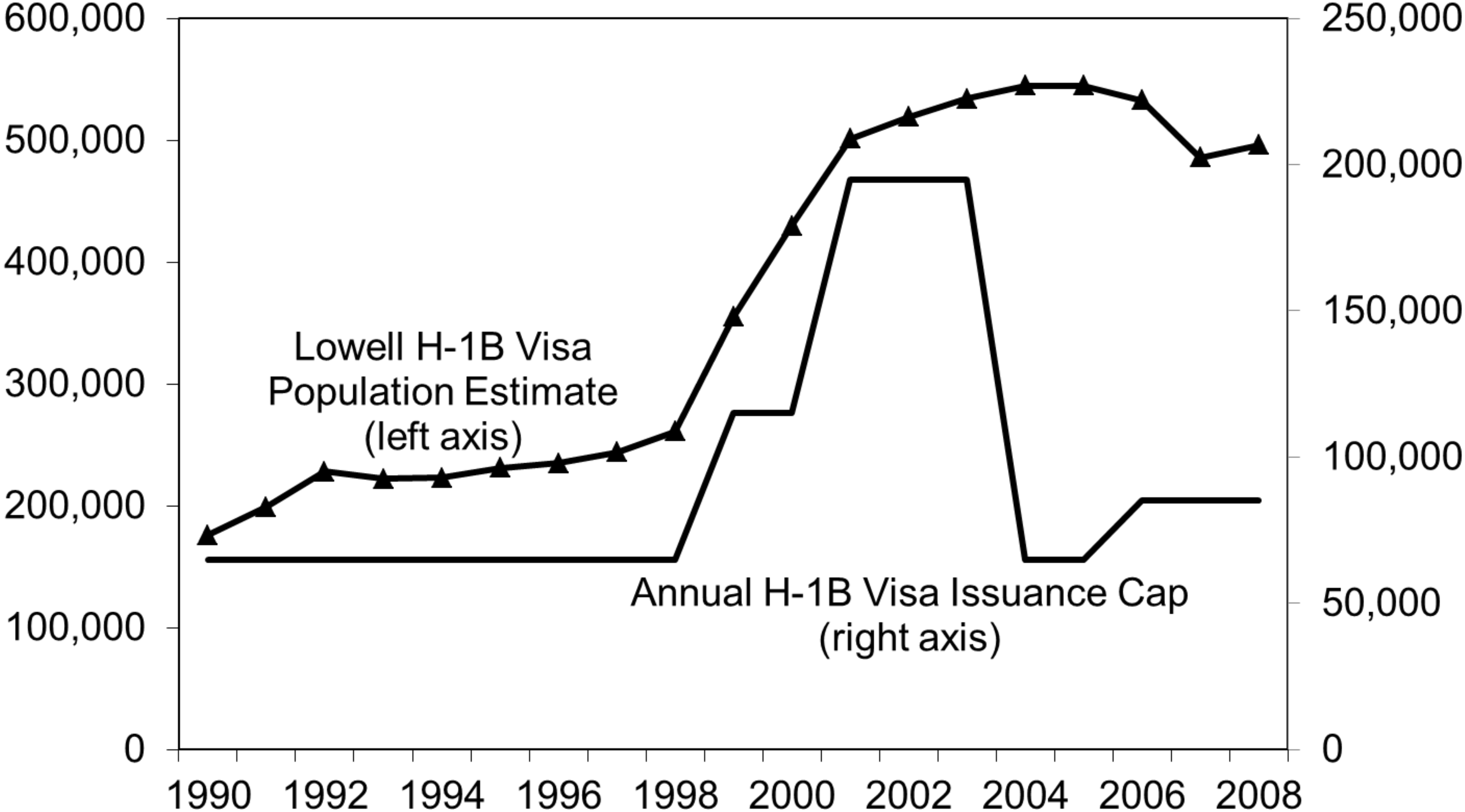
Stars indicate primary sample of 18 states whose coverage begins by 1995



Notes: The figure indicates with shading the states that are covered by the LEHD. Alaska is not covered. Stars indicate the 18 states whose coverage begins by 1995 that constitute our primary sample. Coverage for all states ends in 2008.

Figure 2: H-1B population estimates and numerical caps

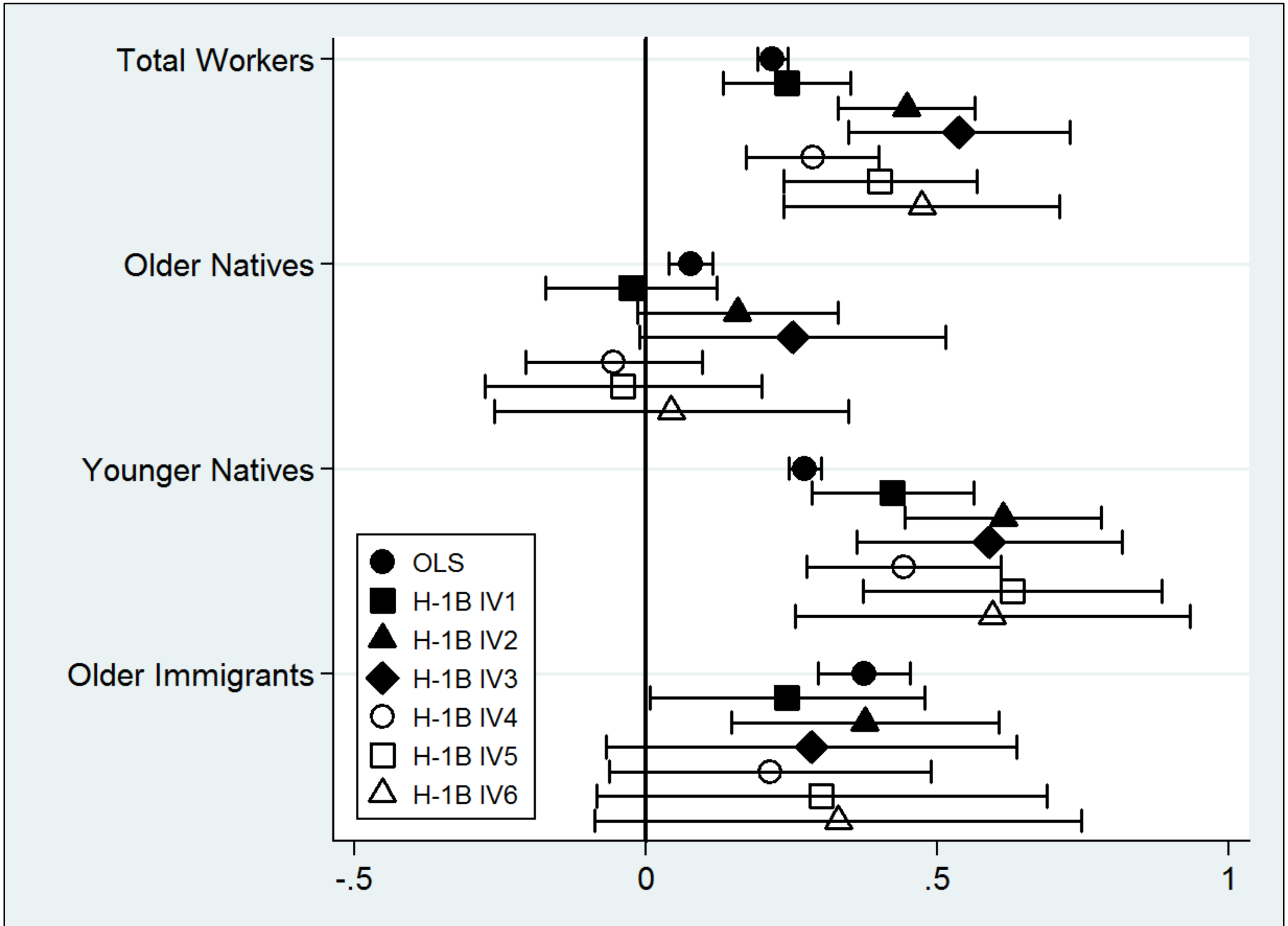
Population estimates on left-hand axis; numerical caps on right-hand axis



Notes: Figure plots H-1B population estimates and numerical caps by USCIS fiscal year.

Figure 3a: Impact for skilled groups conditional on firm size

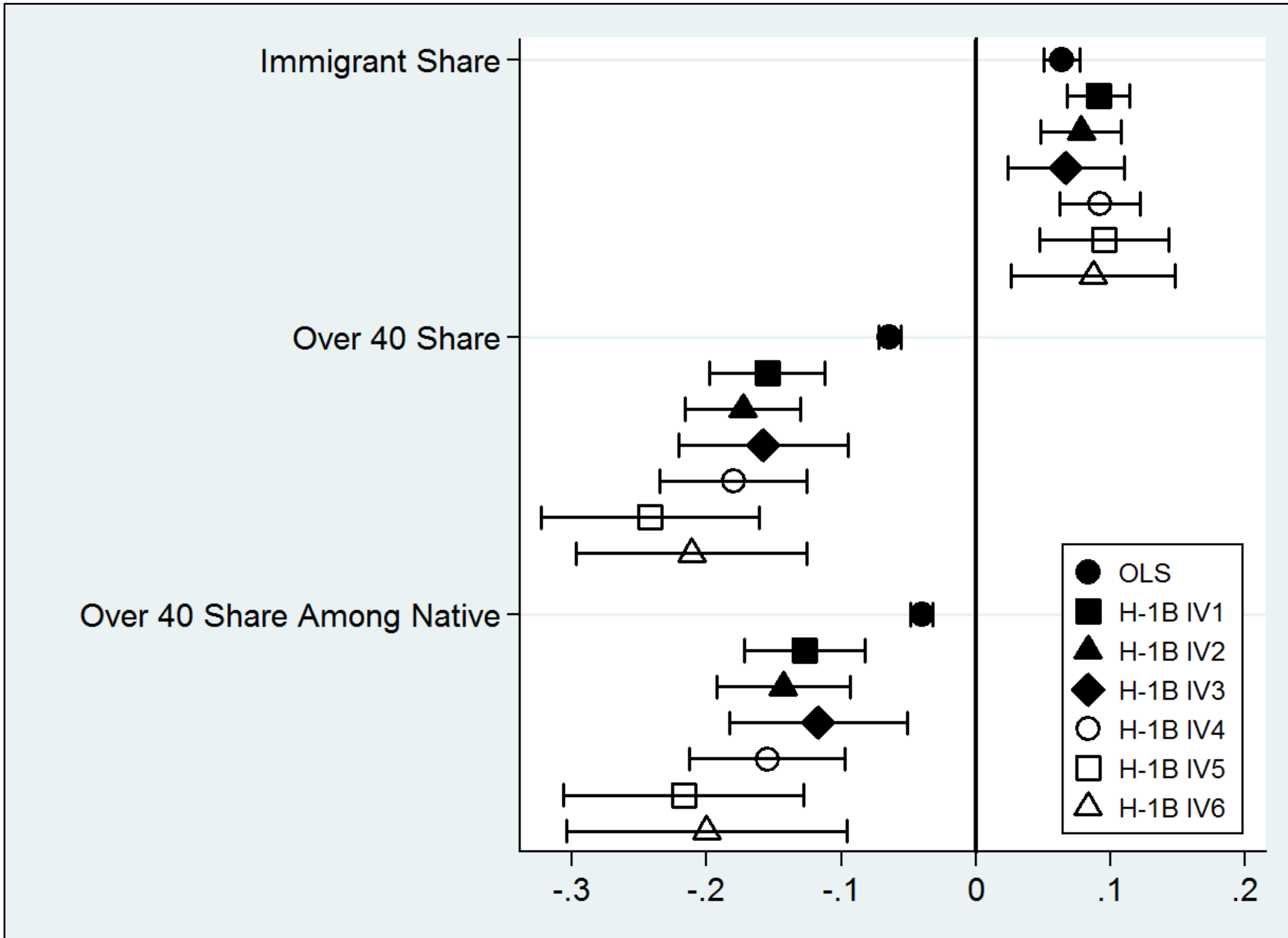
Elasticities of employment measures to log young skilled immigrant workers



Notes: Figure plots coefficient estimates and 90% confidence intervals from Tables 1a, 4a, and 4b. H-1B IVs interact a fixed dependency on the program with changes in the program's size. The fixed dependency for IV1 and IV4 is measured through LCA applications, for IV2 and IV4 through the firm's initial share of skilled immigrant employment that is of Chinese and Indian ethnicity, and for IV3 and IV6 through the firm's initial share of STEM occupations in STEM fields. IV1-IV3 use Lowell's H-1B population estimate for the second part of the interaction; IV4-IV6 use the summation of the previous six years' H-1B caps. Regressions include controls identified in the tables.

Figure 3b: Impact for skilled worker traits conditional on firm size

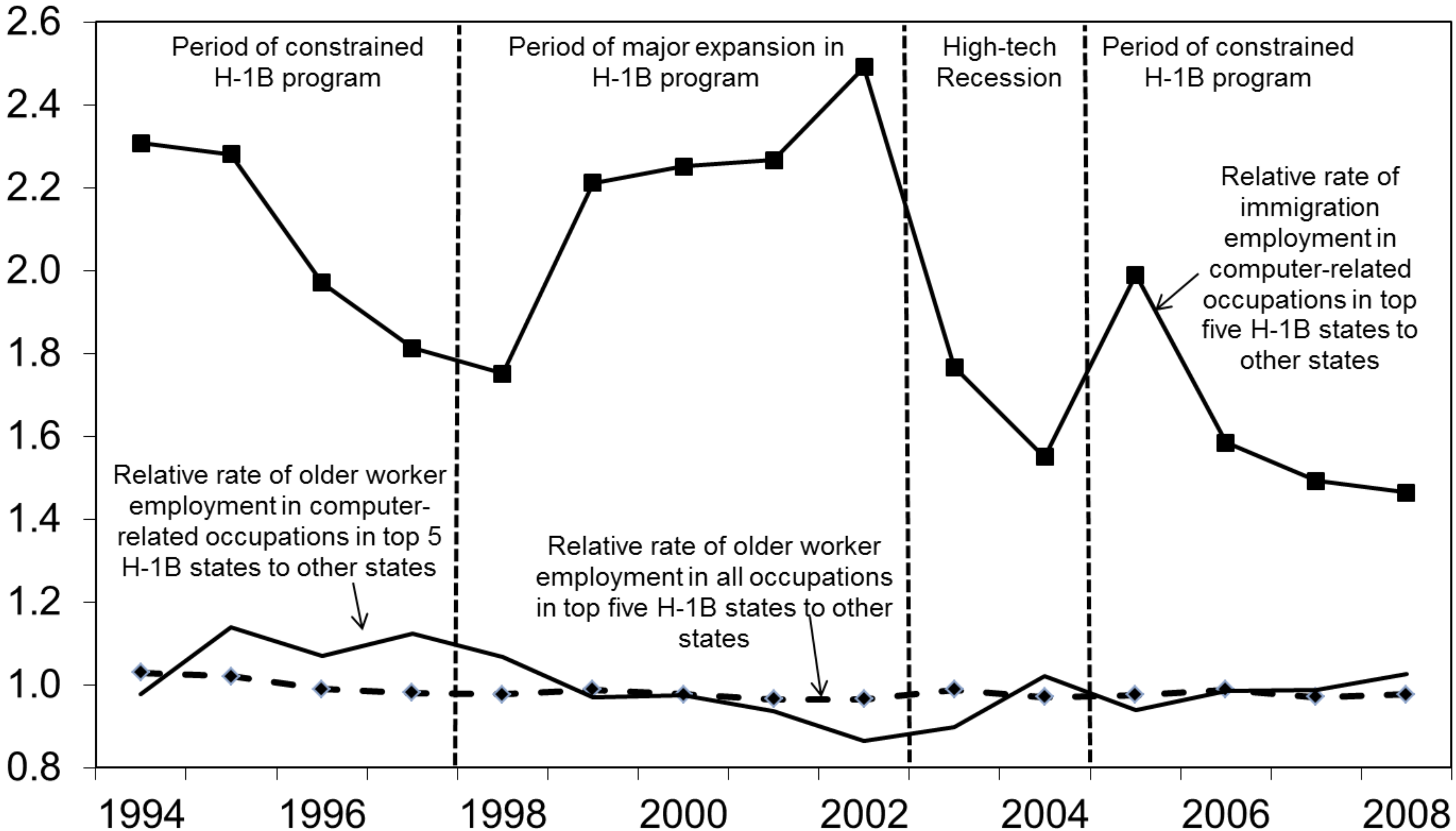
Elasticities of share measure to log young skilled immigrant workers



Notes: See Figure 3a.

Figure 4: Immigration and age profiles in computer occupations

National trends from CPS comparing top five H-1B states to the rest of country



Notes: Relative rates for older workers are calculated by comparing the share of workers aged 40-65 in the top 5 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 exercises on the levels between 2002 and 2003 as the CPS is redesigned this period.

Appendix Figure 1: Wage profiles by age in skilled occupations

2000 Census of Populations using workers with bachelor's educations or higher

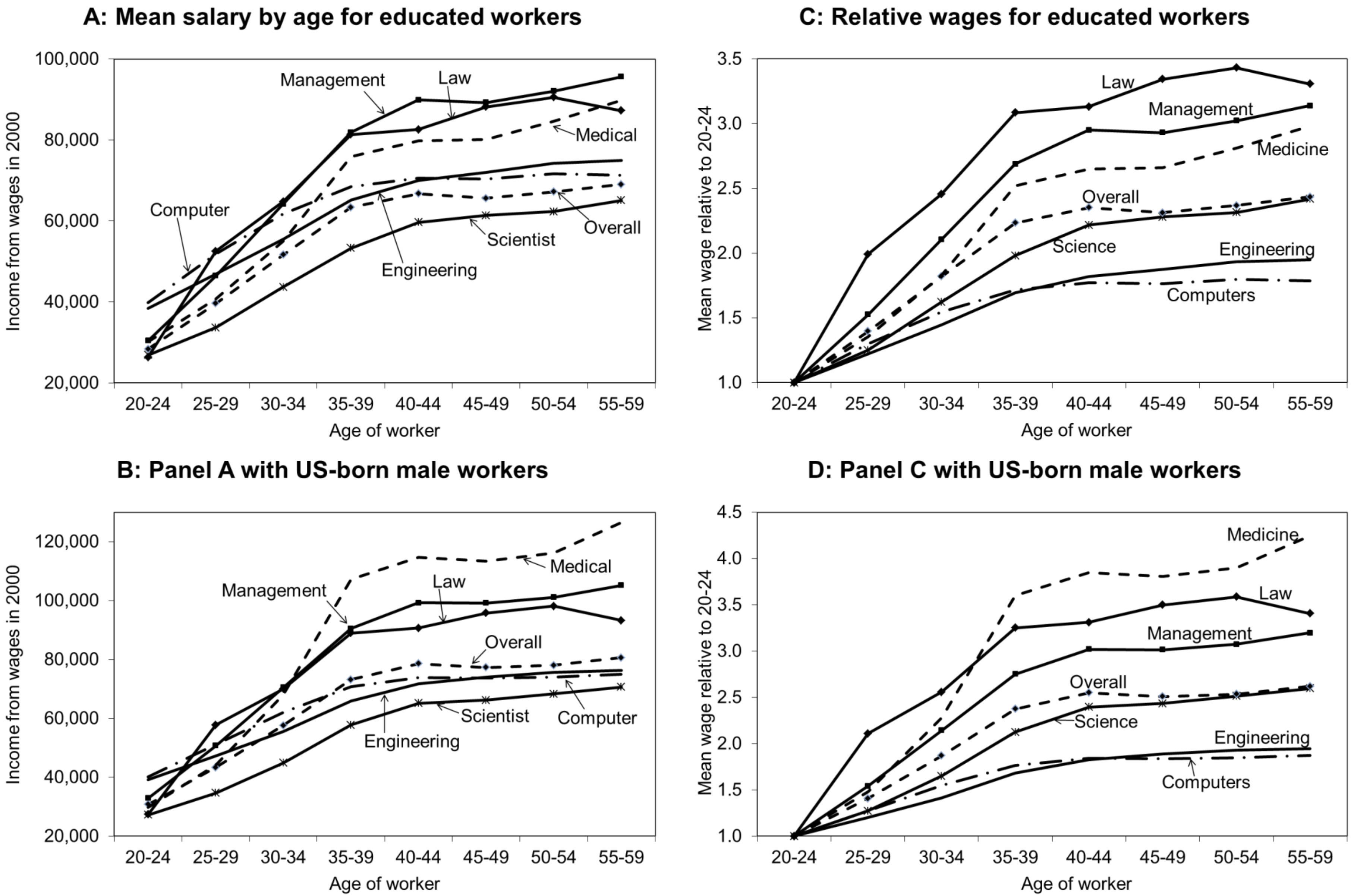


Table 1: OLS estimations of young skilled immigrant employment and skilled employment structures

	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	Young natives	Older immigrants	Total					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: OLS estimations with no controls								
Δ Log employment of young skilled immigrants	0.578	0.673	0.719	0.637	0.031	-0.031	-0.019	0.585	0.011
	(0.022)	(0.021)	(0.045)	(0.020)	(0.005)	(0.003)	(0.003)	(0.022)	(0.005)
	Panel B: OLS estimations with base controls								
Δ Log employment of young skilled immigrants	0.564	0.656	0.709	0.626	0.032	-0.031	-0.019	0.574	0.012
	(0.021)	(0.020)	(0.045)	(0.020)	(0.005)	(0.003)	(0.003)	(0.022)	(0.006)
	Panel C: Panel B including the contemporaneous change in aggregate firm size								
Δ Log employment of young skilled immigrants	0.077	0.273	0.374	0.217	0.064	-0.064	-0.040	n.a.	n.a.
	(0.023)	(0.017)	(0.048)	(0.016)	(0.008)	(0.005)	(0.005)		
	Panel D: Panel C restricted to top patenting firm sample								
Δ Log employment of young skilled immigrants	-0.042	0.232	0.521	0.165	0.097	-0.084	-0.060	n.a.	n.a.
	(0.060)	(0.032)	(0.057)	(0.038)	(0.008)	(0.011)	(0.013)		

Notes: OLS estimations consider the relationship between the change in log employment of young skilled immigrants and the change in log employment of other skilled and lower-skilled workers in the firm in the same year. 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 U.S. 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. Younger workers are those less than 40 years old. Outcome variables are indicated by column headers. Panel 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. Panel C further includes the contemporaneous change in the overall size of the firm, incorporating lower-skilled employees in the firm. Regressions contain 3,374 and 1,002 observations in Panel A-C and D, respectively; are weighted by log initial young immigrant skilled employment in the firm; and cluster standard errors by firm.

Table 2a: OLS estimations of worker hiring and departing margins

	Δ Log hires of skilled worker group:				Δ Log departures of skilled worker group:			
	Older natives	Young natives	Older immigrants	Young immigrants	Older natives	Young natives	Older immigrants	Young immigrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Panel A: OLS estimations with no controls			
Δ Log hiring of young skilled immigrants	0.579	0.591	0.672	n.a.	-0.008	0.027	-0.001	0.085
	(0.026)	(0.024)	(0.030)		(0.020)	(0.020)	(0.027)	(0.026)
					Panel B: OLS estimations with base controls			
Δ Log hiring of young skilled immigrants	0.577	0.584	0.670	n.a.	-0.021	0.012	-0.013	0.069
	(0.027)	(0.024)	(0.030)		(0.020)	(0.020)	(0.027)	(0.027)
					Panel C: Panel B including the contemporaneous change in aggregate firm size			
Δ Log hiring of young skilled immigrants	0.493	0.511	0.618	n.a.	-0.182	-0.140	-0.171	-0.079
	(0.028)	(0.024)	(0.033)		(0.021)	(0.022)	(0.029)	(0.028)
					Panel D: Panel C restricted to top patenting firm sample			
Δ Log hiring of young skilled immigrants	0.547	0.577	0.719	n.a.	-0.261	-0.217	-0.289	-0.168
	(0.057)	(0.043)	(0.052)		(0.045)	(0.040)	(0.056)	(0.044)

Notes: See Table 1. 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 2b: Continuation of Table 2a

	Δ Log employment of older native skilled workers	Δ Log employment of young native skilled workers	Δ Log employment of older skilled immigrant workers	Δ Log employment of young skilled immigrant workers	Δ Log total employment of skilled workers
	(1)	(2)	(3)	(4)	(5)
	Panel A: OLS estimations with no controls				
Δ Log hiring of young skilled immigrants	0.100	0.122	0.125	0.194	0.115
	(0.009)	(0.009)	(0.011)	(0.011)	(0.009)
	Panel B: OLS estimations with base controls				
Δ Log hiring of young skilled immigrants	0.095	0.115	0.120	0.190	0.110
	(0.009)	(0.008)	(0.010)	(0.011)	(0.009)
	Panel C: Panel B including the contemporaneous change in aggregate firm size				
Δ Log hiring of young skilled immigrants	-0.001	0.021	0.024	0.102	0.016
	(0.003)	(0.003)	(0.006)	(0.007)	(0.003)
	Panel D: Panel C restricted to top patenting firm sample				
Δ Log hiring of young skilled immigrants	-0.012	0.016	0.011	0.081	0.009
	(0.004)	(0.006)	(0.009)	(0.008)	(0.003)

Notes: See Table 2a.

Table 3a: OLS estimations of worker hiring and departing margins using new-arrivals

	Δ Log hires of skilled worker group:				Δ Log departures of skilled worker group:			
	Older natives	Young natives	Older immigrants	Young immigrants	Older natives	Young natives	Older immigrants	Young immigrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: OLS estimations with no controls							
Δ Log hiring of new-arrival skilled imm.	0.203	0.218	0.298	0.370	-0.009	0.000	-0.009	0.004
	(0.017)	(0.017)	(0.019)	(0.019)	(0.015)	(0.013)	(0.019)	(0.017)
	Panel B: OLS estimations with base controls							
Δ Log hiring of new-arrival skilled imm.	0.198	0.211	0.293	0.364	-0.017	-0.007	-0.016	-0.005
	(0.018)	(0.017)	(0.020)	(0.019)	(0.015)	(0.013)	(0.020)	(0.017)
	Panel C: Panel B including the contemporaneous change in aggregate firm size							
Δ Log hiring of new-arrival skilled imm.	0.130	0.148	0.239	0.312	-0.089	-0.076	-0.087	-0.076
	(0.017)	(0.016)	(0.020)	(0.019)	(0.016)	(0.014)	(0.021)	(0.018)
	Panel D: Panel C restricted to top patenting firm sample							
Δ Log hiring of new-arrival skilled imm.	0.125	0.208	0.266	0.414	-0.150	-0.117	-0.196	-0.132
	(0.035)	(0.031)	(0.040)	(0.030)	(0.034)	(0.031)	(0.045)	(0.035)

Notes: See Table 1. OLS estimations consider the relationship between log changes in new-arrival skilled immigrant hiring and log changes in the hiring/departures of other skilled workers in the firm in the same year. New-arrival immigrants are those employed for the first time in the 29 LEHD states.

Table 3b: Continuation of Table 3a

	Δ Log employment of older native skilled workers	Δ Log employment of young native skilled workers	Δ Log employment of older skilled immigrant workers	Δ Log employment of young skilled immigrant workers	Δ Log total employment of skilled workers
	(1)	(2)	(3)	(4)	(5)
			Panel A: OLS estimations with no controls		
Δ Log hiring of new-arrival skilled imm.	0.048	0.054	0.061	0.076	0.053
	(0.006)	(0.005)	(0.007)	(0.006)	(0.006)
			Panel B: OLS estimations with base controls		
Δ Log hiring of new-arrival skilled imm.	0.046	0.051	0.059	0.074	0.050
	(0.006)	(0.005)	(0.007)	(0.006)	(0.005)
			Panel C: Panel B including the contemporaneous change in aggregate firm size		
Δ Log hiring of new-arrival skilled imm.	-0.002	0.004	0.011	0.025	0.004
	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)
			Panel D: Panel C restricted to top patenting firm sample		
Δ Log hiring of new-arrival skilled imm.	-0.008	0.007	0.005	0.033	0.005
	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)

Notes: See Table 3a.

Table 4a: IV estimations of young skilled immigrant employment using H-1B population estimates

	Δ Log employment of skilled worker group: Older natives	Young natives	Older immigrants	Total	Δ Immigrant share of skilled workers	Δ Older worker share of skilled workers	Δ Older worker share of native skilled workers	Δ Log average age of skilled workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: IV using log LCA/employee dependency in 2001 interacted with log annual H-1B populations							
Δ Log employment of	-0.025	0.423	0.242	0.242	0.091	-0.155	-0.127	-0.028
young skilled immigrants	(0.089)	(0.084)	(0.143)	(0.066)	(0.014)	(0.026)	(0.027)	(0.013)
Exogeneity test p-value	0.145	0.020	0.254	0.547	0.021	0.000	0.000	0.377
	First stage: t-statistic 7.49, F-statistic 41.58							
	Panel B: IV using initial Chinese/Indian skilled shares interacted with log annual H-1B populations							
Δ Log employment of	0.157	0.613	0.376	0.447	0.078	-0.173	-0.143	-0.027
young skilled immigrants	(0.104)	(0.102)	(0.139)	(0.071)	(0.018)	(0.026)	(0.030)	(0.014)
Exogeneity test p-value	0.317	0.000	0.986	0.000	0.295	0.000	0.000	0.508
	First stage: t-statistic 7.47, F-statistic 42.90							
	Panel C: IV using initial STEM occupation shares interacted with log annual H-1B populations							
Δ Log employment of	0.252	0.589	0.284	0.537	0.067	-0.158	-0.117	0.001
young skilled immigrants	(0.159)	(0.138)	(0.213)	(0.115)	(0.026)	(0.038)	(0.040)	(0.020)
Exogeneity test p-value	0.106	0.004	0.608	0.000	0.877	0.001	0.005	0.242
	First stage: t-statistic 4.81, F-statistic 17.98							

Notes: See Table 1. 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 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 Panel C of Table 1a. The null hypothesis in Wu-Hausman exogeneity tests is that the instrumented regressors are exogenous.

Table 4b: IV estimations of young skilled immigrant employment using H-1B cap summations

	Δ Log employment of skilled worker group: Older natives	Young natives	Older immigrants	Total	Δ Immigrant share of skilled workers	Δ Older worker share of skilled workers	Δ Older worker share of native skilled workers	Δ Log average age of skilled workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: IV using log LCA/employee dependency in 2001 interacted with log annual H-1B cap summations							
Δ Log employment of	-0.055	0.442	0.213	0.286	0.092	-0.180	-0.155	-0.026
young skilled immigrants	(0.092)	(0.101)	(0.167)	(0.069)	(0.018)	(0.033)	(0.035)	(0.015)
Exogeneity test p-value	0.184	0.068	0.327	0.297	0.092	0.000	0.000	0.645
	First stage: t-statistic 5.22, F-statistic 26.99							
	Panel B: IV using initial Chinese/Indian skilled shares interacted with log annual H-1B cap summations							
Δ Log employment of	-0.039	0.629	0.301	0.402	0.095	-0.242	-0.217	-0.041
young skilled immigrants	(0.144)	(0.155)	(0.234)	(0.100)	(0.029)	(0.049)	(0.054)	(0.021)
Exogeneity test p-value	0.373	0.007	0.733	0.054	0.165	0.000	0.000	0.270
	First stage: t-statistic 4.42, F-statistic 17.10							
	Panel C: IV using initial STEM occupation shares interacted with log annual H-1B cap summations							
Δ Log employment of	0.043	0.594	0.330	0.473	0.087	-0.211	-0.200	0.006
young skilled immigrants	(0.184)	(0.205)	(0.253)	(0.143)	(0.037)	(0.052)	(0.063)	(0.028)
Exogeneity test p-value	0.834	0.052	0.870	0.034	0.406	0.000	0.000	0.338
	First stage: t-statistic 3.51, F-statistic 9.75							

Notes: See Table 4a. Instruments use the summation of the previous six years' H-1B caps as a second version of the program's national size.

Table 5a: Extensions on IV estimations with LCA dependencies and H-1B populations

	Δ Log employment of skilled worker group: Older natives	Young natives	Older immigrants	Total	Δ Immigrant share of skilled workers	Δ Older worker share of skilled workers	Δ Older worker share of native skilled workers	Δ Log average age of skilled workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Using top patenting firm sample				
Δ Log employment of	0.168	0.284	0.721	0.266	0.125	-0.056	-0.011	0.010
young skilled immigrants	(0.126)	(0.136)	(0.214)	(0.092)	(0.020)	(0.031)	(0.039)	(0.018)
Exogeneity test p-value	0.061	0.632	0.178	0.192	0.131	0.276	0.089	0.008
				First stage: t-statistic 5.21, F-statistic 17.82				
				Panel B: Excluding sample weights				
Δ Log employment of	-0.035	0.398	0.212	0.237	0.092	-0.151	-0.125	-0.026
young skilled immigrants	(0.097)	(0.094)	(0.167)	(0.075)	(0.016)	(0.029)	(0.030)	(0.014)
Exogeneity test p-value	0.085	0.033	0.357	0.549	0.003	0.000	0.000	0.368
				First stage: t-statistic 5.44, F-statistic 29.50				
				Panel C: Including control for LCA-based dependency (time trend)				
Δ Log employment of	-0.163	0.536	0.097	0.376	0.073	-0.251	-0.246	-0.062
young skilled immigrants	(0.199)	(0.183)	(0.329)	(0.131)	(0.029)	(0.079)	(0.084)	(0.031)
Exogeneity test p-value	0.116	0.264	0.139	0.702	0.702	0.000	0.000	0.075
				First stage: t-statistic 3.27, F-statistic 9.79				
				Panel D: Using medium-skilled workers for size control				
Δ Log employment of	-0.051	0.410	0.223	0.224	0.093	-0.159	-0.131	-0.029
young skilled immigrants	(0.161)	(0.111)	(0.180)	(0.123)	(0.017)	(0.034)	(0.033)	(0.013)
Exogeneity test p-value	0.000	0.328	0.004	0.001	0.000	0.000	0.000	0.197
				First stage: t-statistic 4.84, F-statistic 23.36				
				Panel E: Examining a balanced panel of firms				
Δ Log employment of	-0.063	0.388	0.149	0.198	0.095	-0.162	-0.125	-0.029
young skilled immigrants	(0.096)	(0.089)	(0.149)	(0.072)	(0.015)	(0.028)	(0.028)	(0.013)
Exogeneity test p-value	0.058	0.106	0.073	0.834	0.005	0.000	0.000	0.362
				First stage: t-statistic 5.94, F-statistic 35.21				

Notes: See Table 4a.

Table 5b: Extensions on IV estimations with LCA dependencies and 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	Δ Log average age of skilled workers
	Older natives	Young natives	Older immigrants	Total				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Using top patenting firm sample								
Δ Log employment of young skilled immigrants	0.056	0.257	0.528	0.193	0.133	-0.078	-0.020	0.002
	(0.114)	(0.134)	(0.166)	(0.073)	(0.021)	(0.034)	(0.042)	(0.019)
Exogeneity test p-value	0.450	0.842	0.968	0.759	0.099	0.831	0.236	0.063
First stage: t-statistic 5.37, F-statistic 31.92								
Panel B: Excluding sample weights								
Δ Log employment of young skilled immigrants	-0.084	0.464	0.175	0.287	0.100	-0.185	-0.166	-0.031
	(0.110)	(0.142)	(0.220)	(0.085)	(0.023)	(0.044)	(0.046)	(0.016)
Exogeneity test p-value	0.093	0.036	0.399	0.280	0.013	0.000	0.000	0.368
First stage: t-statistic 3.93, F-statistic 15.37								
Panel C: Including control for LCA-based dependency (time trend)								
Δ Log employment of young skilled immigrants	-0.145	0.513	0.118	0.386	0.084	-0.246	-0.236	-0.040
	(0.157)	(0.185)	(0.270)	(0.123)	(0.033)	(0.073)	(0.080)	(0.024)
Exogeneity test p-value	0.186	0.131	0.354	0.155	0.456	0.000	0.000	0.417
First stage: t-statistic 2.97, F-statistic 9.25								
Panel D: Using medium-skilled workers for size control								
Δ Log employment of young skilled immigrants	0.121	0.537	0.349	0.400	0.075	-0.149	-0.129	-0.024
	(0.114)	(0.092)	(0.148)	(0.085)	(0.015)	(0.030)	(0.032)	(0.012)
Exogeneity test p-value	0.019	0.646	0.107	0.450	0.041	0.000	0.000	0.450
First stage: t-statistic 4.77, F-statistic 22.71								
Panel E: Examining a balanced panel of firms								
Δ Log employment of young skilled immigrants	-0.102	0.388	0.053	0.231	0.094	-0.190	-0.153	-0.026
	(0.098)	(0.107)	(0.175)	(0.069)	(0.020)	(0.036)	(0.038)	(0.015)
Exogeneity test p-value	0.098	0.270	0.076	0.783	0.059	0.000	0.000	0.634
First stage: t-statistic 4.82, F-statistic 23.17								

Notes: See Table 4b.

Table 5c: IV estimations of Table 4a without firm size control

	Δ Log employment of skilled worker group: Older natives	Young natives	Older immigrants	Total	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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: IV using log LCA dependency in 2001 interacted log annual H-1B populations									
Δ Log employment of young skilled immigrants	-0.189	0.333	0.119	0.123	0.105	-0.180	-0.148	-0.174	0.053
	(0.302)	(0.183)	(0.275)	(0.223)	(0.029)	(0.054)	(0.048)	(0.280)	(0.034)
Exogeneity test p-value	0.000	0.004	0.001	0.000	0.000	0.000	0.000	0.000	0.181
First stage: t-statistic 3.93, F-statistic 10.36									
Panel B: IV using initial Chinese/Indian skilled shares interacted with log annual H-1B populations									
Δ Log employment of young skilled immigrants	0.449	0.740	0.597	0.632	0.051	-0.110	-0.090	0.381	0.096
	(0.115)	(0.083)	(0.104)	(0.081)	(0.014)	(0.022)	(0.022)	(0.108)	(0.026)
Exogeneity test p-value	0.137	0.220	0.215	0.926	0.035	0.000	0.000	0.005	0.000
First stage: t-statistic 6.77, F-statistic 32.38									
Panel C: IV using initial STEM occupation shares interacted with log annual H-1B populations									
Δ Log employment of young skilled immigrants	0.330	0.630	0.360	0.583	0.060	-0.140	-0.104	0.115	0.143
	(0.261)	(0.170)	(0.297)	(0.167)	(0.028)	(0.057)	(0.049)	(0.291)	(0.063)
Exogeneity test p-value	0.116	0.841	0.047	0.714	0.121	0.000	0.001	0.001	0.001
First stage: t-statistic 2.82, F-statistic 5.36									

Notes: See Table 4a.

Table 6: OLS estimates of departure rates by occupation, age, and salary level

	(0,1) Worker departs from the firm				Column 4 with DV of (0,1) worker hired in year
	Estimation including age and year fixed effects	Estimation including age and firm-year fixed effects	Estimation including age and firm-year fixed effects	Estimation including age-occupation and firm-year fixed effects	
	(1)	(2)	(3)	(4)	(5)
Δ Log hiring of young skilled immigrants in the firm	-0.072 (0.025)	(Reference category: young, non-STEM occupations)			
x older worker in STEM occupations	0.073 (0.038)	0.056 (0.032)			
x higher wage			0.119 (0.041)	0.102 (0.039)	-0.005 (0.036)
x lower wage			-0.076 (0.074)	-0.089 (0.079)	-0.020 (0.059)
x younger worker in STEM occupations	0.056 (0.045)	0.025 (0.041)			
x higher wage			0.015 (0.044)	0.013 (0.039)	-0.043 (0.057)
x lower wage			0.060 (0.092)	0.033 (0.096)	0.075 (0.088)
x older worker in non-STEM occupations	0.021 (0.020)	0.011 (0.018)			
x higher wage			0.086 (0.026)	0.086 (0.027)	-0.004 (0.033)
x lower wage			-0.024 (0.023)	-0.023 (0.023)	-0.061 (0.027)

Notes: 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 1986-1997 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 $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 are clustered by firm. In columns 1 and 2, differences across groups are not statistically significant. In columns 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.

Table 7: OLS log estimations of skilled immigration employment and patenting

	Δ Log total firm patenting in LEHD states	Δ Log total firm patenting including non-LEHD states	Δ Log patenting by inventors of Anglo-Saxon ethnicity	Δ Log patenting by inventors of non-Anglo-Saxon ethnicity	Collaborative patenting: Δ Log patenting by Anglo-Saxon inventors only	Collaborative patenting: Δ Log patenting by inventors with collaboration of both ethnic groups	Collaborative patenting: Δ Log patenting by non-Anglo-Saxon inventors only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A: OLS estimations with no controls				
Δ Log employment of young skilled immigrants	0.227	0.191	0.223	0.314	0.186	0.374	0.311
	(0.084)	(0.077)	(0.084)	(0.108)	(0.088)	(0.112)	(0.128)
			Panel B: OLS estimations with base controls				
Δ Log employment of young skilled immigrants	0.229	0.184	0.200	0.384	0.145	0.408	0.339
	(0.091)	(0.082)	(0.093)	(0.118)	(0.101)	(0.116)	(0.138)
			Panel C: Panel B including the contemporaneous change in aggregate firm size				
Δ Log employment of young skilled immigrants	0.132	0.122	0.048	0.511	0.013	0.360	0.654
	(0.135)	(0.118)	(0.146)	(0.200)	(0.175)	(0.209)	(0.239)

Notes: See Table 1. Panel includes major patenting firms only. The dependent variable in column 1 includes all patents filed by the firm, using application years to date innovative activity, filed from the core 18 LEHD states. Column 2 examines all United States patenting. Columns 3 and 4 split these patents into the portion contributed by inventors of Anglo-Saxon ethnicity and those of non-Anglo-Saxon ethnicity. Each patent receives equal weight, with the contributions of multiple inventors on a patent allocated with proportionate shares. Columns 5-7 similarly split patents by the degree of collaboration. Column 5 includes patents where Anglo-Saxon contributions comprise 80% or more of the total inventor group on the patent. Column 6 includes patents with two or more inventors, where Anglo-Saxon and non-Anglo-Saxon contributions are both evident. Column 7 considers patents with mostly or exclusively non-Anglo-Saxon contributions.

Appendix Table 1: Entry dates of LEHD states

1995 and earlier	1996	1997	1998	1999	2000	2001	2002
California	Maine	West Virginia	Iowa	Utah	Oklahoma		Arkansas
Colorado	New Jersey		South Carolina		Vermont		
Florida			Tennessee				
Georgia			Virginia				
Hawaii							
Idaho							
Illinois							
Indiana							
Louisiana							
Maryland							
Montana							
New Mexico							
North Carolina							
Oregon							
Rhode Island							
Texas							
Washington							
Wisconsin							

Appendix Table 2: Descriptive statistics for sample

	Full Sample		Top Patenting Sample	
	Mean	Standard Deviation	Mean	Standard Deviation
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%
Initial LCA dependency	0.8%	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%
Patent count per year			217	379
Anglo-Saxon inventor share			68.8%	14.1%
non-Anglo-Saxon inventor share			31.3%	14.1%
Chinese/Indian inventor share			15.3%	10.4%
Collaborative: Anglo-Saxon only			52.7%	17.5%
Collaborative: Both groups			32.4%	12.7%
Collaborative: non-Anglo-Saxon only			15.9%	12.2%

Appendix Table 3: Full coefficient values for Columns 1-4 in Panels C of Table 1a

	Δ Log employment of older native skilled workers	Δ Log employment of young native skilled workers	Δ Log employment of older immigrant skilled workers	Δ Log total employment of skilled workers
Δ Log employment of young skilled immigrants	0.077	0.273	0.374	0.217
	(0.023)	(0.017)	(0.048)	(0.016)
Δ Log total employment of firm	0.847	0.666	0.583	0.712
	(0.042)	(0.024)	(0.048)	(0.026)
Δ Supply-push skilled immigration factor	0.071	0.049	-0.130	0.163
	(0.094)	(0.113)	(0.161)	(0.068)
Δ Supply-push lower-skilled immigration factor	-0.284	0.116	-0.318	-0.126
	(0.273)	(0.349)	(0.453)	(0.235)
Δ Log local employment	0.021	0.040	0.037	0.019
	(0.012)	(0.016)	(0.021)	(0.008)
Δ Log local immigrant share	-0.014	-0.023	0.031	-0.009
	(0.026)	(0.029)	(0.038)	(0.017)
Δ Log local workers over 40 share	0.608	0.486	0.473	0.285
	(0.296)	(0.338)	(0.580)	(0.202)
Δ Age-education immigration factor	-0.979	-0.192	-1.505	-0.046
	(0.205)	(0.207)	(0.635)	(0.147)
Patent intensity of the firm (linear time trend)	0.334	0.326	0.237	0.164
	(0.080)	(0.085)	(0.092)	(0.052)

Notes: See Table 1. Regressions also include unreported sector-year fixed effects, where the sector is defined to be the dominant sector of the firm, and time trends interacted with the firm's initial share of employment in each sector.

Appendix Table 4a: OLS non-log estimations of worker hiring and departing margins

	Δ Hires of skilled worker group:				Δ Departures of skilled worker group:			
	Older natives	Young natives	Older immigrants	Young immigrants	Older natives	Young natives	Older immigrants	Young immigrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: OLS estimations with no controls				
Δ Hiring of young skilled immigrants	1.240	1.899	0.346	n.a.	-0.063	0.259	-0.013	0.079
	(0.272)	(0.249)	(0.047)		(0.129)	(0.129)	(0.025)	(0.028)
				Panel B: OLS estimations with base controls				
Δ Hiring of young skilled immigrants	1.251	1.891	0.347	n.a.	-0.077	0.240	-0.019	0.072
	(0.272)	(0.238)	(0.047)		(0.131)	(0.116)	(0.025)	(0.028)
				Panel C: Panel B including the contemporaneous change in aggregate firm size				
Δ Hiring of young skilled immigrants	1.108	1.807	0.330	n.a.	-0.480	0.008	-0.077	0.017
	(0.253)	(0.236)	(0.043)		(0.200)	(0.107)	(0.036)	(0.029)
				Panel D: Panel C restricted to top patenting firm sample				
Δ Hiring of young skilled immigrants	0.945	1.740	0.301	n.a.	-0.619	-0.081	-0.093	0.033
	(0.279)	(0.277)	(0.040)		(0.268)	(0.091)	(0.048)	(0.021)

Notes: See Table 2a.

Appendix Table 4b: Continuation of Appendix Table 4a

	Δ Employment of older native skilled workers	Δ Employment of young native skilled workers	Δ Employment of older skilled immigrant workers	Δ Employment of young skilled immigrant workers	Δ Total employment of skilled workers
	(1)	(2)	(3)	(4)	(5)
	Panel A: OLS estimations with no controls				
Δ Hiring of young skilled immigrants	1.303	1.640	0.358	0.921	4.222
	(0.293)	(0.188)	(0.056)	(0.028)	(0.489)
	Panel B: OLS estimations with base controls				
Δ Hiring of young skilled immigrants	1.329	1.651	0.366	0.928	4.274
	(0.296)	(0.188)	(0.057)	(0.028)	(0.496)
	Panel C: Panel B including the contemporaneous change in aggregate firm size				
Δ Hiring of young skilled immigrants	1.589	1.799	0.407	0.983	4.777
	(0.346)	(0.216)	(0.063)	(0.029)	(0.593)
	Panel D: Panel C restricted to top patenting firm sample				
Δ Hiring of young skilled immigrants	1.563	1.821	0.394	0.967	4.745
	(0.431)	(0.277)	(0.071)	(0.021)	(0.734)

Notes: See App. Table 4a. Columns consider the total changes in skilled worker counts among continuing states for the firm over which the skilled immigrant hiring is defined. Coefficient values in Column 5 equal the sum of Columns 1-4.

Appendix Table 5a: IV estimations Table 4a using top patenting firm sample

	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 average age of skilled workers
	Older natives	Young natives	Older immigrants	Total				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: IV using log LCA/employee dependency in 2001 interacted with log annual H-1B populations							
Δ Log employment of young skilled immigrants	0.168	0.284	0.721	0.266	0.125	-0.056	-0.011	0.010
	(0.126)	(0.136)	(0.214)	(0.092)	(0.020)	(0.031)	(0.039)	(0.018)
Exogeneity test p-value	0.061	0.632	0.178	0.192	0.131	0.276	0.089	0.008
	First stage: t-statistic 5.21, F-statistic 17.82							
	Panel B: IV using initial Chinese/Indian skilled shares interacted with log annual H-1B populations							
Δ Log employment of young skilled immigrants	0.357	0.534	0.751	0.428	0.097	-0.065	-0.030	0.031
	(0.157)	(0.118)	(0.169)	(0.092)	(0.021)	(0.030)	(0.038)	(0.021)
Exogeneity test p-value	0.001	0.007	0.139	0.001	0.981	0.480	0.308	0.000
	First stage: t-statistic 5.94, F-statistic 25.82							
	Panel C: IV using initial STEM occupation shares interacted with log annual H-1B populations							
Δ Log employment of young skilled immigrants	0.484	0.268	0.736	0.547	0.122	-0.026	0.045	0.049
	(0.293)	(0.201)	(0.288)	(0.181)	(0.037)	(0.054)	(0.068)	(0.036)
Exogeneity test p-value	0.002	0.827	0.342	0.001	0.386	0.127	0.016	0.001
	First stage: t-statistic 3.84, F-statistic 10.26							

Notes: See Table 4a.

Appendix Table 5b: IV estimations Table 4b using top patenting firm sample

	Δ Log employment of skilled worker group: Older natives	Young natives	Older immigrants	Total	Δ Immigrant share of skilled workers	Δ Older worker share of skilled workers	Δ Older worker share of native skilled workers	Δ Log average age of skilled workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: IV using log LCA/employee dependency in 2001 interacted with log annual H-1B cap summations							
Δ Log employment of	0.056	0.257	0.528	0.193	0.133	-0.078	-0.020	0.002
young skilled immigrants	(0.114)	(0.134)	(0.166)	(0.073)	(0.021)	(0.034)	(0.042)	(0.019)
Exogeneity test p-value	0.450	0.842	0.968	0.759	0.099	0.831	0.236	0.063
	First stage: t-statistic 5.37, F-statistic 31.92							
	Panel B: IV using initial Chinese/Indian skilled shares interacted with log annual H-1B cap summations							
Δ Log employment of	0.224	0.536	0.869	0.252	0.161	-0.075	-0.023	0.079
young skilled immigrants	(0.242)	(0.247)	(0.356)	(0.131)	(0.047)	(0.059)	(0.072)	(0.053)
Exogeneity test p-value	0.295	0.207	0.299	0.618	0.135	0.875	0.572	0.002
	First stage: t-statistic 2.90, F-statistic 6.29							
	Panel C: IV using initial STEM occupation shares interacted with log annual H-1B cap summations							
Δ Log employment of	0.332	0.429	1.083	0.459	0.158	-0.067	-0.033	0.008
young skilled immigrants	(0.336)	(0.273)	(0.495)	(0.220)	(0.055)	(0.077)	(0.091)	(0.065)
Exogeneity test p-value	0.211	0.476	0.144	0.142	0.211	0.795	0.717	0.013
	First stage: t-statistic 2.37, F-statistic 3.95							

Notes: See Table 4b.