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For my Family.

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ABSTRACT

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This dissertation consists of three essays examining the effects of high-skilled immigration on various economic outcomes within the receiving country. In the first essay, I study how skilled immigrants affect wages and employment in US industries during 1995-2007, using novel microdata on approved H-1B visas. These data show that most H-1B employers specialize in the production of high-skilled services used as inputs by other businesses. In light of this, I consider the downstream effects of skilled immigrants on industry labor market outcomes: how wages and employment in an industry respond to immigration shocks to its suppliers. The identification strategy relies on large policy changes to the annual limit on H-1B admissions. I find that higher admissions lead to higher mean wages in exposed downstream industries. Also rising with downstream exposure are the wages of high-skilled, STEM, and low-skilled workers, and the employment of high-skilled and STEM workers. These findings indicate that higher admissions increase average wages by increasing worker compensation but also by changing the composition of employment in exposed industries. While immigration status is not observable in my data, my estimates suggest that higher admissions benefit US native workers because exposed downstream sectors hire few immigrants.

In the second essay, I use the administrative data mentioned above to examine how skilled immigrants affect the employment prospects of young skilled natives in US states during 2000-2009. My identification strategy uses a decline in the supply of visas to a state caused by (1) changes in national immigration policy, and (2) tougher competition in the market for visas as demand by the largest H-1B employer increased

dramatically. I show robust evidence that increased hiring of skilled foreign workers lowers employment of young college-educated natives. Consistent with previous work, I find no effect on total college-educated employment.

In the last chapter, I consider how rising skilled immigration during 1995-2007 affected service offshoring in US industries. Using the H-1B microdata, I document a large increase in the employment of skilled immigrants in tradeable service sectors during 1995-2007. Because skilled immigration may be endogenous to offshoring, I develop instruments that use variation in H-1B inflows that depend on (1) the annual limit on H-1B admissions set by government policy and (2) US macroeconomic conditions. These national shocks have differential effects across industries because some industries are always more exposed to skilled immigration than others. I find that higher skilled immigrant flows lead to higher offshoring in highly exposed industries.

1. HIGH-SKILLED IMMIGRANTS, WAGES AND EMPLOYMENT IN US INDUSTRIES

1.1 Introduction

A significant portion of the skilled immigrants that join the US labor market do so through the H-1B visa program. In regards to the regulation of the program, there is much public debate as to whether an increase in the annual cap on admissions would prove beneficial to US workers. Arguments on both sides tend to center around how the hiring of H-1Bs affects the opportunities of US workers within a firm (Pekkala Kerr, Kerr, and Lincoln 2014). Noting that H-1Bs are primarily employed in STEM occupations[1]—a critical input to technology creation and dissemination—proponents argue the cap is too low, preventing US firms from hiring the workers they need to innovate (Gates 2008). A low cap curtails innovation by US firms and thus reduces employment prospects for US natives. Conversely, opponents claim such a shortage does not exist, but rather that firms prefer to hire foreign workers to cut labor costs (Matloff 2003; Hira 2010). In seeking to advance the public debate, a recent body of academic literature evaluates the impact of skilled immigrants on US workers by focusing on their effects on the receiving firm.[2][3] While it is clearly important to understand how immigrants directly affect employment outcomes within a firm, a focus solely on the firm overlooks supplier-buyer links that exist between firms. These economic linkages can transmit shocks affecting a particular firm to other firms in their

[1]STEM occupations require training in Science, Technology, Engineering, and Mathematics.
[2]See Pekkala Kerr, Kerr, and Lincoln 2014; Ghosh, Mayda, and Ortega 2014; and Doran, Gelber, and Isen 2014.
[3]An important parallel literature takes the city as the unit of analysis (see Peri, Shih, and Sparber 2014, 2015). These studies may capture downstream effects to the extent that H-1B firms interact with businesses based on location. Nonetheless, as noted in Pekkala Kerr, Kerr, and Lincoln (2014), top H-1B employers operate across different regions. It is reasonable to assume their supply chains will extend across multiple regions as well.

supply chain. The findings of this study suggest that the indirect effects of skilled immigration are at least as important as the direct effect studied in the current literature.

In this paper, I study the *downstream* effects of skilled immigrants on the US labor market. That is, how labor conditions in an industry respond to immigration shocks to its upstream suppliers. In particular, I quantify the downstream effects of changes in H-1B employment from 1995 to 2007. To identify these effects, I use instruments that capture variation in H-1B employment caused by policy changes to the annual cap on admissions. During 1995–2007, the US Congress raised the cap from 65,000 visas per year to a high of 195,000 and then lowered it to the original 65,000. In the sectors most exposed to the program, variation in the cap led to large changes in the employment of foreign workers. Measuring these changes requires data on the employment and wages of H-1B workers by industry-year. However, government agencies do not report industry-level summaries, and the administrative data needed to generate the summaries are not publicly available.[4] Under a Freedom of Information Act Request to the US Citizenship and Immigration Service (USCIS), I obtain microdata on approved H-1B visas. To measure downstream shocks, I combine the H-1B data with intermediate input usage by industry from input-output accounts.

Though perhaps not evident at first glance, shocks to H-1B employers are likely to have strong consequences downstream. From the USCIS data, we find that most H-1B industries are skilled labor intensive service sectors that supply intermediate inputs to a wide range of businesses throughout the economy. The professional and business services (PBS) sector obtains over two-thirds of H-1B visas with around 60% of all petitions granted to firms in information technology (IT) consulting, engineering services, R&D services, and management consulting.[5] As their name suggests, PBS firms specialize in the production of services used as inputs by other businesses.

[4]Because these administrative records were not made available until recently, most of the previous literature has not used this rich data source. Exceptions are recent working papers by Doran, Gelber, and Isen, 2014, and Peri, Shih, and Sparber, 2015.
[5]In the next section, I document the sectoral composition of H-1B workers in more detail.

Berlingieri (2014) reports that in 2002, firms consumed 83% of gross PBS output as intermediate inputs compared to only 44% of the output of the average sector. Moreover, business services are general purpose inputs and thus are used by a wide range of businesses throughout the economy.[6][7] The fact that PBS firms use high-skilled labor intensively compounds the prospect of strong downstream effects. Because production relies heavily on high-skilled labor, a higher supply of skilled foreign workers can meaningfully increase output supply in these sectors, and improve the economic opportunities of their downstream customers.

While immigration shocks likely improve profitability in downstream industries, the effect on labor demand is unclear. To illustrate this point, I sketch a simple model to describe how upstream shocks affect labor demand downstream. Assume we have a single upstream sector that transforms H-1B labor into an intermediate input. Downstream industries combine these inputs with domestic labor to produce final goods. An increase in H-1B admissions boosts intermediate output supply and propagates downstream in the form of a lower price. The fall in price has two opposing effects on downstream labor demand, and the sign of the total effect depends on which of the two effects is stronger. First, there is a negative effect based on the substitutability between labor and intermediates. The fall in price lowers production costs, however, allows the industry to expand and thus increases demand for all inputs. The model also predicts a larger downstream effect for industries that use intermediates more intensively. This prediction motivates how I measure downstream shocks to an industry: I first multiply the direct shocks to the industry's suppliers by their share in total intermediate input costs, and then sum across all suppliers. My

[6]As discussed in Acemoglu et al.(2012), in the US economy a small set of industries play a key role as intermediate input suppliers. Berlingieri (2014) documents the evolution of forward linkages—a metric of the importance of a sector in the supply chain—for the US economy during the 1948-2002 period. In the past several decades, business services has become the sector with the highest forward linkage becoming more influential than other traditionally well-connected sectors such as transportation.

[7]Since H-1Bs are highly concentrated in a few industries, but their employers supply a great number of sectors, many of the of the most exposed industries downstream hire few or no H-1B workers directly, including many four-digit NAICS industries in wholesale, retail, mining, and other business services.

empirical approach relates these shocks with annual changes in industry log wages and log employment.

I begin my analysis using data on average wages and employment from the Labor Productivity and Costs (LPC) program administered by the Bureau of Labor Statistics (BLS). The sample consists of 137 LPC industries from 1995 to 2007. I find a positive and statistically significant downstream effect on average wages. A one standard deviation increase in downstream exposure increases wage growth in an industry by .44 percentage points. In the period from 2000 to 2001, the increase in wages is 1 percentage point higher for an industry in the 80th percentile of exposure than for an industry in the 20th percentile. The results are robust to controlling for industry output and pre-trends in wages, IT capital intensity, and even more demanding industry-specific time trends. I find no evidence of downstream effects on total employment.

A disadvantage of the LPC data is that its industry coverage misses the great majority of H-1B employment, and thus I cannot estimate the direct impact of skilled immigration shocks. While the main contribution of this paper is to account for downstream effects—since direct effects are already studied in other settings—it is useful to estimate both effects to compare their economic magnitude. To estimate direct effects, I extend the analysis using data from the Occupational Employment Statistics (OES) program.[8] The OES samples more industries than the LPC and includes most H-1B employers. I find a positive direct effect on average wages albeit less than half of the magnitude of the indirect effect. A one standard deviation increase in direct exposure increases wage growth in an industry by .18 percentage points.

The estimated downstream effect on average wages suggests that lifting the current level of the cap would benefit US workers. Such policy recommendation may be misleading if for example, skilled immigration strongly harms certain groups of workers but benefits other groups in a way such that its total effect on average wages

[8]The OES is also administered by the BLS.

is positive. To address this possibility, using occupational data on wages and employment from the OES, I examine how downstream effects vary with worker characteristics. I find that the wages of high-skilled, STEM, and low-skilled workers rise with downstream exposure. On the employment side, I find positive effects for high-skilled and STEM workers. These findings suggest that higher admissions increase average wages by increasing worker pay but also by changing the labor composition of exposed downstream industries towards high-skilled and STEM employment. Lastly, I find a strong direct impact on the employment of high-skilled and STEM workers. This finding indicates that average wages increase in directly exposed industries mostly through changes in the employment mix.

This paper fits into the larger high-skill immigration literature that examines the effect on other outcomes such as innovation and productivity (Kerr and Lincoln 2010, Hunt and Gauthier-Loiselle 2010, and Moser, Voena, and Waldinger 2012, Borjas and Doran 2012).[9] More broadly, I add to the literature that studies the labor market effects of immigrants.[10] My contribution is to account for an indirect effect of immigration that takes place because of the interconnection of industries through input-output linkages. In its account of indirect effects, this paper is similar to Cortes (2008) who argues that low-skill immigration to a city lowers the prices of unskilled-intensive sectors and indirectly benefits consumers of these goods.

This paper is also related to industry and firm level studies that explore how foreign workers affect domestic labor markets through input trade and offshoring (e.g., Feenstra and Hanson 1997,1999; Ottaviano, Peri, and Wright 2013; Hummels, Jorgensen, Munch, and Xiang 2014; Ebenstein, Harrison, McMillan and Phillips 2014).[11] I complement this literature by accounting for the role of foreign workers in the domestic sourcing of intermediate inputs. My employment results are consistent with Crino (2010)—and with most of the literature on offshoring—who finds that service

[9]See surveys by Nathan(2013), Kerr (2013) and Chapter 8 in Borjas(2014)

[10]The seminal contributions are Card (2001) and Borjas(2003). See also surveys by Friedberg and Hunt (1995), Lewis and Peri (2014), and Chapters 3-6 in Borjas (2014).

[11]See Feenstra and Hanson (2003) , Harrison, McLaren, and McMillan (2011) and Hummels, Munch, and Xiang (2014) for surveys on offshoring and labor markets.

offshoring increases employment in skilled versus less skilled occupations. In this study, however, I find evidence that the wages of low-skill workers are positively affected, which is an unusual finding in the literature on globalization.[12]

Lastly, this paper is related to a recent empirical literature that quantifies the impact of shocks that originate in some US industries and propagate to others through the input-output network. Acemoglu, Autor, Dorn, Hanson, and Price (2015) show evidence that increased exposure to imports from China in some manufacturing sectors has effects on employment in industries not directly exposed to import competition. In addition to Chinese import shocks, Acemoglu, Akcigit, and Kerr (2015) consider the propagation of three other types shocks: changes in spending by the federal government, shocks to total factor productivity, and changes in patenting rates by foreign countries. They find that the network effects are larger than the direct impact of the shocks. I extend this literature by estimating downstream effects for a different type of industry shock: skilled immigration shocks.

The paper is organized as follows. Section 2 provides background on the H-1B program and describes the data used in the study. Section 3 discusses the model, how to measure downstream shocks, and the empirical strategy. Section 4 presents the results and various robustness exercises. Section 5 concludes.

1.2 H-1B Visa Background and Data Sources

1.2.1 H-1B Visa Background and Data

The H-1B visa grants temporary working rights to high-skill foreign workers, with most H-1B recipients having at least a bachelor's degree.[13] In general, more than half of successful applicants are in Science and Engineering or computer related professions (Kerr and Lincoln, 2010). The program came into effect under the Immigration Act

[12]This discrepancy, however, may take place because I include in my analysis many non-traded sectors (e.g. wholesale and retail), which are intensive in low-skilled labor but also in intermediate service inputs.

[13]In general, more than half of successful applicants are in Science and Engineering or computer related professions (Kerr and Lincoln, 2010).

of 1990. At this time, the US Congress set a cap of 65,000 on the number of new visas to be issued in any given fiscal year (FY). Figure 1.1 shows the numerical cap and the approximate number of cap-bound visas issued in each fiscal year from 1990 to 2008. During the first years of the program, visa demand was lower than the numerical cap. By the middle of the 1990s, the cap became binding and was temporarily increased to 115,000 for 1999 and 2000,[14] and further raised to 195,000 for fiscal years 2001, 2002, and 2003. H-1B demand plummeted in the aftermath of the 2001-recession. Because of the decrease in demand, the cap was not reached in fiscal years 2002 and 2003. As a consequence, in 2004 the cap returned to its current level of 65,000, though, in the 2006 fiscal year, an additional 20,000 additional visas were reserved for workers with graduate degrees from US universities. Since returning to a lower level in 2004, the cap has been binding every year.[15][16]

My empirical strategy leverages these large policy-driven changes in H-1B employment for identification. Measuring these employment shocks to an industry is challenging because government agencies do not keep track of the number of H-1B workers that are in the US at any given point in time (GAO 2011).[17] Since industry stocks are unknown, my empirical approach measures shocks in first differences. I estimate changes in industry stocks using microdata on all approved visas for initial employment subject to the cap. These data are from the form I-129: "Petition for a Nonimmigrant Worker." A firm must file an I-129 application form with the US

[14]This took place under the American Competitiveness and Workforce Improvement act of 1998

[15]Under the American Competitiveness in the Twenty-First Century Act of 2000, government and some nonprofit research organizations, as well as universities, became exempt from the cap so that the number of visas issued exceeds the cap in many years. In my data, I cannot distinguish which visas are cap-exempt. In Figure 1.1, I report an approximate number of cap-bound visas issued by excluding firms in Healthcare and Education from the computation.

[16]For FY 2006, however, an additional 20,000 additional visas were reserved for workers with graduate degrees from US universities.

[17]There are *national* estimates of the H-1B population, however. Influential work by Kerr and Lincoln (2010) uses an estimate of the population developed by Lowell (2000). Estimating the population requires combining H-1B gross inflow data with assumptions about the rates at which the stock is depleted.

Citizenship and Immigration Service (USCIS) to obtain an H-1B visa.[18] Since these records are not publicly available, I obtain them directly from the USCIS under a Freedom of Information Act request. In addition to employer characteristics such as name, location and four-digit NAICS industry, each I-129 record contains information on worker occupation, age, country of origin, and annual wages. The data span the fiscal years 1998–2012.[19]

Figure 1.2 describes the sector composition of H-1B workers subject to the cap. To construct the figure, I use the I-129 data on over 2.5 million petitions approved H-1B visas from 1998 to 2010.[20] The figure underscores how H-1B employment is highly concentrated in professional and business services (PBS). PBS industries obtain around 72 percent of all petitions. If we include financial services in this group, business services account for close to 80 percent of all applications. The manufacturing sector as a whole takes only 13 percent of all petitions. About half of those petitions are granted to firms in computer and communications manufacturing (e.g. semiconductors, computer and peripheral equipment manufacturing, etc.). Figure 1.3 shows the percentage of H-1B petitions for the top 25 four-digit NAICS sectors. The pattern outlined in the figure further details how the H-1B program is used primarily by business services sectors. While Computers Systems Design (IT consulting) takes the lions share of petitions (45%), the list includes 18 other business services sectors.

1.2.2 Labor Outcome Data and Input-Output Accounts

I obtain annual data on industry wages and employment from two sources: the Labor Productivity and Costs (LPC) program and the Occupational Employment

[18]If the cap has not yet been exhausted, and admission requirements are met, the USCIS approves the petitions. Petitions are approved on a first-come-first-served basis, so that visas are granted irrespective of firm or worker characteristics such as industry or occupation.

[19]For 1995–1997, the first three years in my analysis, I only know the total number of visas awarded in each year. For each industry, I estimate the number of visas for these years by multiplying these totals with the industrys share of total visas in 1998.

[20]The figure does not include visas granted to Healthcare and Education because these sectors became fully or partially exempt from the cap through the American Competitiveness in the Twenty-First Century Act of 2000.

Statistics (OES) program.[21] The LPC includes total labor compensation, total employment and nominal and real output. I construct industry average wages by dividing labor compensation by total employment. For the most part, I restrict the sample to industries for which data are available at the four-digit NAICS, to match the level of aggregation in the H-1B data for a total of 137 industries. The data span the period from 1987 to 2013 and cover most industries in manufacturing, retail and wholesale, mining, and utilities. The LPC sample, however, does not include a sizeable number of H-1B industries.[22] For this reason, testing for the direct impact of the program—the effect on the industries that directly hire H-1Bs—is not well-suited using the LPC data. Thus, I only address direct effects when using the OES sample.

The OES series contains wages and employment for over 800 occupations and covers most H-1B industries absent in the LPC.[23] . Its primary disadvantage is that the first year in the series is 1997. As explained below, this limits the set of robustness exercises that can be performed using the OES data. For this reason, I first establish the robustness of the baseline results on average wages and employment using the LPC data. I then use the OES data first to estimate direct effects and then to test for differential effects based on worker characteristics such as skill level.

Lastly, I characterize linkages between industries using data from the annual input-output (IO) tables, which are available from the Bureau of Labor Statistics (BLS).[24]

1.3 Methodology

This section outlines the approach I follow to estimate downstream effects, that is, how labor demand in an industry responds to immigration shocks to its *upstream* suppliers. In Section 3.1, I use a simple partial equilibrium model to motivate the em-

[21]Both datasets are published by the Bureau of Labor Statistics

[22]The data excludes most PBS and finance industries.

[23]See the appendix for a full description of industries covered in each dataset

[24]Unfortunately, data for retail and wholesale –some of the largest purchasers of service inputs from H-1B industries– are aggregated at the two-digit NAICS. To disaggregate input purchases for these sectors, I use information from the 2007 Annual Surveys of Retail and Wholesale, which contains detailed estimates of selected expenditures by four-digit NAICS subsectors on many high-skill service inputs. Details of this procedure can be found on the Appendix.

pirical specification and to provide guidance on how to measure downstream shocks. Section 3.2 explains in detail how I measure these shocks. The last subsections show the estimating equation and discuss threats to identification.

1.3.1 Framework

Consider an economy with I final good industries and a single industry (H-1B industry) that produces intermediate goods (H-1B intermediates). All industries are perfectly competitive. Each industry $i = 1, ..., I$ combines labor (L_i) and H-1B intermediates (M_i) to produce a final output (q_i). In this simple setting, all final good industries are downstream in the supply chain from the H-1B industry. The production function for final good i is given by

$$q_i = A_i(\alpha^i_L L_i^{\frac{\sigma-1}{\sigma}} + \alpha^i_M M_i^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \tag{1.1}$$

where A_i is productivity and $\alpha^i_L, \alpha^i_M \in (0, 1)$ are industry-specific distribution parameters which allow for input intensity to vary across industries. The elasticity of substitution $\sigma > 0$ is fixed across industries.

Each industry i faces a downward sloping output demand curve given by $q_i^D(p_i) = {p_i}^{\eta_Y} exp(a_i)$, where $a_i > 0$, and p_i is the price of output. The elasticity of output demand $\eta_Y < 0$ is fixed across industries. Each industry faces an upward sloping labor supply curve of the form $L_i^S(w_i) = {w_i}^{\mu} exp(b_i)$, where $b_i > 0$, and w_i is the wage. The elasticity of labor supply $\mu > 0$ is fixed across industries.

The H-1B industry uses only H-1B workers (L_H) in the production of M. Production takes place as

$$M = \alpha_H L_H \tag{1.2}$$

where $\alpha_H > 0$ is an efficiency constant. All industries face a common price for M, p_M. Sectors are small so that for a given p_M they face an infinitely elastic supply of M. The output demand curve for M is downward sloping and is given by: $M^D(p_M) = \sum_{i \in I} M_i^D(p_M)$. H-1B workers supply labor inelastically and their stock is a function of government policy. In particular, the government can increase the size of the stock by allowing immigration to take place. Initially, admission levels are set at 0. In equilibrium, factors are paid their marginal productivity, profits are zero and markets clear.[25]

I am interested in how shocks to the stock of H-1B workers affect the labor outcomes of industries downstream. In the model, this happens when the government lifts admission levels, where higher admissions imply larger shocks. Suppose that the government raises admission levels. From (1.2), we see that this leads to an increase in intermediate output supply. Since the intermediate output demand curve is downward-sloping, higher supply decreases the market clearing price p_M. From the standpoint a downstream industry, higher admissions act as a (exogenous) positive shock to input prices and leads to higher usage of intermediates.

The effect on labor demand, however, is ambiguous. To see this, note that for a given wage level, the cross-elasticity of labor demand with respect to p_M is given by[26]

$$\eta_{LM}^i = (|\eta_q| - \sigma) \cdot s_M^i \tag{1.3}$$

where $s_M^i = \frac{p_M M_i}{p_i q_i}$ is the cost share of M in industry i. Equation (1.3) separates the total effect from a price change into two opposing effects: substitution and scale. The substitution effect occurs because a change in p_M induces the industry to use more M at the expense of L, as M has become relatively cheaper. A fall in p_M, however, implies lower production costs which lead to an expansion in output, in-

[25]Wages need not equalize across-industries because of imperfect labor mobility or other labor market frictions.
[26]Equation (1.3) is similar to Hammermesh [1993, p. 24]

creasing demand for all inputs. Labor demand increases if the scale effect dominates the substitution effect, that is, if $|\eta_Y| > \sigma$.[27]

Even though the model is silent about the sign of η^i_{LM}, it predicts, unambiguously, a stronger effect for industries that are initially more exposed to the program. This is because industries use H-1B intermediates with different intensities (s^i_M), and $|\eta^i_{LM}|$ is large if s^i_M is large.[28] The intuition behind this prediction is simple. Technological differences lead some industries to initially use relatively more of a certain input. An immigration-related shock originates upstream and propagates down the supply-chain in the form of a uniform reduction in the price faced by all downstream industries. Those initially more exposed are more affected by the common price change. This prediction guides how I construct downstream shocks.

1.3.2 Measuring Downstream Shocks

For simplicity, in the theory setting just described, I have assumed that immigration shocks originate in a single upstream industry. Because there are multiple H-1B industries, to implement (1.3) empirically, I first map the various shocks originating upstream into a single value. I measure the downstream skilled-immigration shocks for each industry i in the following two steps. First, I define the *direct* shock to industry j as the change in production costs in j associated with higher H-1B employment. This quantity is given by

$$\Delta D_{jt} = \frac{\Delta H_{jt}}{Y_{jt-1}} \tag{1.4}$$

where ΔH_{jt} is the change in the H-1B wage bill between t and $t-1$, and Y_{jt-1} is the value of shipments in j at time $t-1$. As mentioned in the data section, estimates of H-1B employment and wages at the industry level are not available. To proxy for

[27] Naturally, the effect on equilibrium wages and employment will depend on the slope of the labor supply curve. Since is positive, however, if labor demand increases then wages and employment will also increase, and vice versa.

[28] To be precise, in this model, shares vary over industries on the basis of differences in the distribution parameters (technology) but also because of equilibrium wages can vary across industries.

change in the H-1B wage bill ΔH_{jt}, I use the wages of all H-1B workers in industry i that received a cap-bound visa for initial employment and the employment contract starts at time t, h_{jt}. I measure this proxy using the I-129 microdata.[29]

Since the model tell us that direct shocks to industry j impact its downstream customers differentially, the second step is to scale ΔD_{jt} by the share of j in total intermediate use in i, α_{ijt}. To get a single number for each industry-year, I sum over all H-1B industries j that supply to i.[30][31] Specifically, the downstream shock to i at time t, is given by

$$\Delta ID_{it} = \sum_j \alpha_{ij0} \times \Delta D_{jt} = \sum_j \alpha_{ij0} \times \frac{h_{jt}}{Y_{jt-1}} \tag{1.5}$$

where $\alpha_{ij0} = \dfrac{m_{ij0}}{\sum_j m_{ij0}}$, and m_{ij0} is the value of intermediates from j consumed by i in 1995. Using this methodology, we see that a downstream sector i will be highly exposed to the H-1B program if it uses inputs intensively from sectors that are *directly* exposed to the program. Data on the value of intermediates purchased (m_{ij0}) and output (Y_{jt-1}) come from the annual IO use tables from the BLS, where m_{ij0}, is the *use* value. This approach to constructing downstream shocks is closely related to Acemoglu, Autor, Dorn, Hanson, and Price (2015); and Acemoglu, Akcigit, and Kerr (2015).

[29]The Appendix documents features of these direct shocks. In general, sectors experiencing the highest shocks will also be those with the highest raw H-1B counts, as described in Figure 1.3 (e.g. IT consulting experiences the largest direct shocks).

[30]In some cases, I weight the direct shocks by the share of total industry output instead of the share of total intermediate usage. The results do not change significantly based on this choice of normalization.

[31]I restrict the set of H-1B industries j to those in high-skill service sectors since I cannot disaggregate many input purchases for four-digit wholesale and retail industries. This is because the expenditure data in the Annual Surveys of Retail and Wholesale do not include information for manufacturing inputs. Though, as discussed above, most H-1Bs are employed in high-skill service sectors so that, excluding wholesale and retail, the two measures are strongly positively correlated.

1.3.3 Specification

In this section, I outline the approach I follow to estimate the downstream effects of the H-1B program – the effect on wages and employment in an industry caused by immigration shocks to the industry's suppliers. My specifications exploit differences in downstream shocks across industries and over time.

I take to the data specifications of the form:

$$\Delta y_{it} = \delta_t + \beta_{Downstream} \Delta ID_{it} + \alpha C_{it} + \varepsilon_{it} \tag{1.6}$$

where y_{it} stands for the annual log change of the outcome of interest for industry i between 1995 and 2007. The error term is given by ε_{it}. Since we estimate our $\beta_{Downstream}$ coefficient using a first-differenced specification, we have already controlled for time invariant differences across industries that may bias our estimates. The variable δ_t controls for common shocks to industries in a given time interval. Thus identification relies on within industry variation in outcomes over time while accounting for shocks common to all industries in a given time period. The downstream shock variable ΔID_{it} is as described above but rescaled by its sample standard deviation to aid with interpretation of the $\beta_{Downstream}$ coefficient. The variable C_{it} is a vector of controls described in more detail below.

Identification of the $\beta_{Downstream}$ coefficient requires that downstream shocks are not correlated with the error term in (1.6). The observed upstream shocks ΔD_{jt}, however, may also be a function of latent demand shocks that cause wages and employment. For example, assume that changes in consumer preferences favor industries intensive in intermediates from H-1B employer j. To meet higher output demand, these industries hire more workers but also buy more intermediates from j. In turn, to meet higher intermediate demand, industry j increases H-1B employment leading to higher ΔD_{jt} and thus to higher ΔID_{it}. In this scenario, unobserved shocks create a positive link between the measured downstream shocks and the changes in labor demand that we observe. If we then relate ΔID_{it} with changes in labor outcomes across industries as in (1.6), we may overstate the effect of downstream shocks.

To minimize these concerns, I develop two instruments that capture exogenous variation in downstream shocks. To construct the variables, I first develop instruments for the direct shocks and follow a similar approach as in (1.5) to construct the downstream instruments. The idea behind the first direct instrument is that because of fixed differences in production technology some industries always obtain more visas than others.[32] Thus, these industries always receive a larger share of the annual cap irrespective of the relative economic conditions they face.[33] With this in mind, I instrument the actual change in H-1B employment ΔH_{jt} with the change in H-1B employment that would take place if we distributed the cap across industries based on their historical exposure to foreign workers. Specifically, letting $\frac{h_{i0}}{\sum_k h_{k0}}$ stand for the share of the wage bill received by i in a year in the pre-sample, the first instrument for $\Delta D_{it} = \dfrac{h_{it}}{Y_{it-1}}$ is given by

$$\Delta D_{it}^{IV_1} = \frac{\frac{h_{i0}}{\sum_k h_{k0}} \times cap_t}{Y_{i0}} = \frac{1}{\sum_k h_{k0}} \times \Delta D_{i0} \times cap_t \tag{1.7}$$

where cap_t is the level of the cap at t, and ΔD_{i0} is the shock to j in the first year of the sample. To improve the predictive power of the instrument, I measure $\frac{h_{i0}}{\sum_k h_{k0}}$ with data on all visas granted in the first two years in my data (i.e. I use visas issued for initial employment in 1998 and 1999, as well as visas renewed in those years).

As shown in Figure 1.1, in most years in my sample, the cap binds or is very close to the total number of visas issued. However, for fiscal years 2002 and 2003, two of the three years the cap was at its highest point, the total number of visas granted

[32]For example, some industries always use more STEM workers than others so that their quantity demanded for H-1Bs is always higher: the IT consulting sector always requests more H-1B workers than the Legal Services sector. Other industry characteristics may also generate these differences. For example, some industries have stronger ties to foreign countries perhaps because firms in the industry have affiliated partners in those countries. For firms in these industries it is less costly to find and recruit foreign workers and thus hire relatively more of them.

[33]Similarly, given an increase in the cap, we would expect the change in H-1B employment to be even larger for these industries, and these changes to also be independent of the relative economic conditions industries face.

fell far below the cap. As a consequence, for these two years, the first instrument is not a reasonable approximation of direct shocks. To increase predictive power in periods when the cap does not bind, my instrumental variable strategy includes a second variable given by

$$\Delta D_{it}^{IV_2} = \Delta D_{i0} \times \pi_t \tag{1.8}$$

where π_t is a dummy variable for the 2001–2002, and 2002–2003 periods.[34]

To construct the downstream shocks we follow a similar approach as before. The downstream instruments are given by

$$\Delta ID_{it}^{IV_1} = \sum_j \alpha_{ij0} \Delta D_{jt}^{IV_1} = \sum_j \alpha_{ij0} \times \Delta D_{j0} \times cap_t = \Delta ID_{i0} \times cap_t \tag{1.9}$$

and

$$\Delta ID_{it}^{IV_2} = \sum_j \alpha_{ij0} \Delta D_{jt}^{IV_2} = \sum_j \alpha_{ij0} \times \Delta D_{j0} \times \pi_t = \Delta ID_{i0} \times \pi_t \tag{1.10}$$

where the weights α_{ij0} are as previously defined but are now fixed at their value in 1995. I measure the weights in the pre-sample to account for endogenous changes in the input structure of industries which may bias my estimates.

Note that because the weights α_{ij0} and the direct shocks ΔD_{j0} are fixed in the cross-section, we can write the instruments as the interaction between the aggregate component of the instruments and the downstream shock in the first period ΔID_{i0} (I refer to ΔID_{i0} as industry i's downstream dependency). To get an idea of the industries that experience the largest downstream shocks in my sample, Table 1.1 reports the downstream dependencies ΔID_{i0} for the top 40 industries.[35] Note that

[34] Below, I show that the results are robust to fitting the model without the 2001–2002, and 2002–2003 intervals, and to estimating the model from 1995 to 2001.

[35] In the Appendix, I report dependencies for the top 25 industries in both the OES and LPC datasets. As mentioned above, the great majority of LPC industries are included in the OES and

industries on the list are almost exclusively in the service sector. This is reasonable given that most H-1B industries are service providers and service inputs constitute a small share of total intermediate usage in the manufacturing sector. Nevertheless, on this list, we find that a wide range of service sectors enter the top rankings. Naturally, some of these sectors will also be highly exposed to the H-1B program directly in part because industries tend to consume inputs from related industries intensively. Many industries in PBS, information, and finance are both directly and indirectly exposed to the H-1B program. Highlighted in Table 1.1, however, are industries that hire few or no H-1B workers: about half of the industries on the list are not directly exposed to the program including many four-digit industries in wholesale, retail, mining, and other business services. The Appendix reports the least dependent industries. These industries are almost exclusively in low-skill manufacturing although a handful of retailers and the Forestry and Logging industry also make the list.

The patterns of dependency in Table 1.1 underscore why accounting for downstream effects is important in the context of the H-1B program. In particular, H-1B employers are highly concentrated in a few industries and therefore only affect these few industries directly. However, H-1B employers specialize in the production of services consumed as inputs by other businesses. Since these services are used in production in many different ways, H-1B employers have customers in virtually all sectors of the economy.

In light of their role as input suppliers, if higher immigration increases the ability of H-1B employers to sell inputs to their customers, the shocks may reach many industries with little exposure to the original shocks. Since business services use skilled labor intensively, this is a likely scenario given an increase in the H-1B quota. That is, because production of IT services is strongly reliant on skilled labor, it is likely that increasing the supply of foreign IT consultants leads to higher IT output, lower prices, and affects labor outcomes in industries that use these services. Because

thus for the most part the lists differ to the extent that some industries are covered in the OES but not in the LPC.

many sectors of the economy consume IT services, shocks to IT-service providers presumably affect many industries not directly exposed to the H-1B program.

Figure 1.4 shows the explanatory power of the cap-based instrument. The scatter plot relates the explanatory variable ΔID_{it} with the instrumental variable in (1.7) and represents the first-stage in the empirical model described above, without including control variables, and excluding the years when the cap does not bind (i.e. excludes the 2001–2002, and 2002–2003 periods). Each dot stands for one of 2460 industry-year observations. I multiply the variables by one thousand to improve the readability of the graphs. The slope of the regression line is .48 and is estimated precisely with a robust t-statistic of 10.47. The corresponding r-squared is .68.

1.3.4 Alternative Hypotheses

I now discuss threats to identification. Recall that to estimate the causal effect of downstream shocks on industry labor outcomes we must first address the fact that intermediate input choice may be endogenous to shocks to labor demand. To deal with this issue, I follow the instrumental variables approach previously described. Nonetheless, identification still requires our instruments to be uncorrelated with said shocks to labor demand. One concern is that the downstream dependency metric ΔID_{i0} captures other industry differences that may independently generate the patterns of wage and employment growth we observe. For instance, industries experiencing positive productivity or shocks to output demand, in the years prior to the increase in the H-1B cap, may have simultaneously increased their intensity of usage of H-1B inputs as well as their demand for labor. If these positive shocks are persistent over time—that is, if these same set of industries continued to experience these positive shocks (e.g. to output demand or productivity)—our tests will return upwardly biased estimates of the effect of interest.

I address these issues in several ways. First, I include in the regressions variables meant to capture an industry's expected growth in outcomes given the growth trajectory observed before the increase in the cap. I include this measure to account for trends in wages and employment that pre-date the change in H-1B policy but may correlate with the instrument. I construct these measures as the mean annual log change in wages and employment, from 1990 to 1995 (or to up to 1999, the year of the first increase in the cap). By including these variables in the regressions, the identification of the effect only uses deviations in outcome growth from the trend observed before the change in H-1B admission policy. Similarly, in a more stringent specification, I augment the estimating equation with industry-specific fixed effects. This last exercise is equivalent to including industry-specific time trends because my empirical models are expressed in first-differences.[36] Finally, I include industry output as a control to account for time-varying shocks to output demand which, if correlated over time, may affect our estimates. On this same note, I exclude from the analysis industries that may be particularly prone to persistent positive demand shocks during the period (e.g. information, computers, and other ICT industries).

An additional possibility is that investment in IT capital assets, induced by rapidly falling IT equipment and prepackaged software prices, explains the patterns of labor outcome growth which are driving the results.[37] For instance, given that IT prices are falling throughout the sample period, it is possible that IT-intensive industries were better equipped to take advantage of falling IT prices and thus benefitted disproportionately more than other industries. We must address this possible scenario since the downstream dependency measure correlates with pre-sample IT capital intensity due to strong H-1B employment by IT capital producers (IT consulting, computers, software, telecoms, etc.). However, this correlation is unlikely to be one-to-one for two reasons. First, the weighting scheme used to scale intermediate input consumption is specific to the H-1B program. IT capital services such as IT consulting receive much larger weights than other IT capital sectors such as computer manufacturing

[36]Industry-specific trends take care of the issue if the correlated shocks are relatively constant over time.

[37]Stiroh (2002) argues that most of the productivity acceleration in the 1990s occurred in IT-producer and IT-using industries.

and semiconductors. Second, other business services sectors, which are not IT capital producers, play a significant role in the program. For this reason, it is implausible that IT capital accounts for the entire effect presented in the next section. Nevertheless, to further mitigate these concerns, the regressions in the next section control for trends in IT capital usage.

A related concern is that supply side factors –that also put downward pressure on the prices of business services– happened concurrently with the relaxation in admission levels. In the context of the model discussed above, technological change (a shock to α_H) could have also increased output supply of business services. To fix ideas, consider the following scenario: if IT consulting prices are mostly driven by the same factors that drive the fall in IT hardware and software, our results may arise from the steady decline in price of IT capital. The price of IT consulting services, however, is mostly driven by the price of labor services provided by workers in computer occupations. Consistent with this statement, although during the 1990s the price of IT hardware and software fell dramatically, the price of IT Consulting did not (see Jorgenson 2001).

1.4 Results

In this section, I present estimates of the downstream effects of the H-1B program on wages and employment. Before reporting the results, let us pause to discuss the order in which I carry out my tests. As mentioned in the data section, the OES and LPC datasets include industry average wages and total employment but differ in other aspects. Specifically, the OES has data on occupations and larger industry coverage but covers a shorter time span—the first year reported in the OES is 1997 versus 1987 in the LPC. Since we want to identify our effect using the policy changes beginning in 1999, it is useful to have wage and employment data in the pre-treatment period to use as a baseline from which to evaluate subsequent changes. Similarly, the longer time span in the LPC data allows us to account better for pre-trends in wages and employment, which as mentioned above, may confound the estimates of downstream effects. The downside of using the LPC data is that since LPC industries only cover a small fraction of H-1B employment, estimates of the direct effects using these data are not very informative.

Although the main contribution of this paper is the identification of downstream effects—since the literature already addresses direct effects—it is useful to get a sense of the size of the direct effects in order to compare their magnitude with the downstream effects. In light of this, and of the restrictions imposed by my data, I proceed as follows. I first establish the robustness of the results on average wages and total employment using the LPC. I then estimate direct effects using the OES sample. Lastly, using data on occupational wages and employment from the OES data, I extend the analysis by considering how downstream effects vary with worker characteristics. Specifically, I examine how the wages and employment of high-skill, low-skill, and STEM workers employed in downstream industries respond to changes in the H-1B program.

1.4.1 Average wages and total employment

I now present estimates of the coefficient of interest, $\beta_{Downstream}$, which captures the downstream effects of the H-1B program. First, I report estimates from the baseline specification in Equation (1.6), which includes only period fixed effects as controls. I then include the additional controls meant to alleviate omitted variable concerns as discussed in Section 3.4. Table 1.2 reports results from estimating Equation (1.6) using 2SLS where the dependent variable is the yearly change in the log of average wages. Different columns represent different specifications. The sample is composed of 137 LPC industries for the period from 1995 to 2007. All specifications include period fixed effects and cluster standard errors at the industry level. I first discuss the results for wages and then for employment.

Column 1 in Table 1.2 shows the baseline 2SLS results. The results indicate a positive association between downstream shocks and average wage growth. The coefficients are economically meaningful and estimated precisely. The results suggest that a one standard deviation increase in industry downstream exposure leads to a .44 percentage point increase in wage growth. Consistent with the graphical evidence shown in Figure 1.4, the instruments are good predictors of downstream shocks with first-stage F-statistics always in excess of 50. These estimates are consistent with the hypothesis that increases in the H-1B population shift labor demand in downstream industries leading to higher wages.

Columns 2-6 introduce the additional set of controls, namely, nominal output and variables meant to capture pre-sample trends. In columns 2-6, I control for nominal output. In columns 3 and 4, I account for pre-trends in wages and employment where I construct the variables using data from 1990-1995 and 1990-1999, respectively. Column 5 controls for trends in IT capital defined as the log ratio of 1997 IT capital expenditures to total capital expenditures.[38] Data on capital expenditures come from the 1997 capital flow tables and are aggregated at the three-digit NAICS sector.[39] Column 6 includes industry fixed effects to account for linear time trends that are industry-specific.

As we include the various controls mentioned above, the estimated effect on wages remains qualitatively the same. From this set of controls, the wage trends, and the IT capital trends reduce the point estimates slightly to 0.32 - 0.42. The estimates for the coefficients of the controls enter with the correct sign and are significant at the 1 percent level, except for the coefficient on IT capital, which is significant at the 10 percent level. Industry fixed effects increase the point estimates to 1.7. This estimate is significant at the 10 percent level. The robustness of these results suggests that my estimates are not the product of pre-trends in wages. In the context of this study,

[38]This functional form follows Stiroh (2002).

[39]I develop two other measures of IT capital intensity. The two proxies use IT capital expenditures from the 2010 ICT survey from administered by the U.S. Census. I normalize IT capital expenditures by either total capital expenditures or total employment in 2010 and then take logs.

however, controlling for trends in wages and employment may underestimate the true impact of the program because growth rates may respond to changes in the supply of H-1B intermediate inputs.

The remaining columns in Table 1.2 show results from additional robustness exercises. Column 7 tests the sensitivity of the results to industry sample choice and column 8 to how we measure downstream shocks. Column 7 shows the point estimate from regressions omitting the five most dependent sectors. Though the estimated coefficient of .39 is a bit smaller than the baseline reported in the first column, it is the correct sign and is still highly significant. The stability of the estimates reported argues against the results being driven by outlier industries. In column 8, I now construct downstream shocks by weighing the direct shocks of supplying industries by the ratio of intermediate use to gross output instead of by the ratio of intermediate use to total intermediate use. In this case, the point estimate decreases slightly, and precision is largely unaffected. Column 9 shows an OLS estimate of similar magnitude to the 2SLS estimate, although a bit smaller, and with a larger standard error. In columns 10 and 11 we test the robustness of the results to excluding the time periods when the cap does not bind. For these two cases, the estimation takes place using a single instrument– the cap-based instrument. Column 10 excludes the 2001-2002 and the 2002-2003 periods from the estimation. Column 11 shows estimates using the period from 1995 to 2001. In both cases, the estimates are of similar magnitude as before and still highly significant.

It is worth mentioning that although I am not able to observe immigration status in my data, my estimates imply that the H-1B program indirectly benefits native US workers. First, there is little reason to believe that downstream shocks affect native and foreign workers differently. Second, my main results come from the LPC sample, which as previously mentioned does not include the industries that employ most high-skilled foreigners. Also, as is well-known, and documented in Cortes (2008), low-skilled foreign workers are heavily concentrated in sectors in low-skill manufacturing, agriculture, personal services, and construction. These sectors are some of the least exposed to downstream shocks. Thus, a significant portion of the gains implied by my estimates accrue to workers in sectors with little immigrant presence (e.g. retail and wholesale).

In column 12, we now explore the results using the larger OES sample. Recall that using this sample I can estimate direct effects. The sample now includes 48 additional industries including the largest H-1B employers for a total of 185 industries for the period 1997 to 2007. For example, we now have data on the IT consulting industry, and the R&D services industry. Using this larger sample, I find a wage estimate close in magnitude to those estimated using the LPC (the coefficient is .29 versus .44 in the baseline specification). The standard errors are larger, but the coefficient is still significant at the 5 percent level. The bottom row in column 12 shows the wage estimates for the direct shock of the program. As with the downstream shock variable, I normalize the direct shock variable by its sample standard deviation—which eases comparability of the magnitude of the direct effect with that of the indirect effect. I find a positive direct effect on average wages. However, the direct effect coefficient is smaller than the indirect effect coefficient. A one standard deviation increase in direct exposure is associated with a .18 percentage point increase in wage growth.

Table 1.3 shows results from estimating Equation (1.6) using 2SLS where the dependent variable is now the yearly change in the log of total employment. The estimates displayed in the table show a weak association between downstream shocks and employment growth. In columns 1-5, which include the set of controls, the estimate of the downstream shock is slightly negative but not significantly different from 0. The coefficients on output and wage growth are positive and highly significant, as expected. Once we include the industry fixed effects in column 6, the point estimate becomes more negative, but it is still not significantly different from 0. In Column 7, which omits the top 5 most dependent sectors in the LPC data, we see a change in the sign of the estimates, which are now positive and significant at the 1 percent level. In the last column, which uses the larger OES sample, I still find no evidence of downstream employment effects.

In contrast to the downstream effects, the direct effect on employment is positive and significant (t-ratio of 2.32). To find that direct shocks increase total employment is natural because total employment rises mechanically as industries employ more H-1B workers. For this reason, estimating the direct effects on employment in this study is problematic. In particular, because I do not observe immigration status, I cannot discern the effect on total employment for native workers.

To summarize, in this section I document a positive association between downstream shocks and wage growth. The results are robust to controlling for industry output and other potentially confounding trends. I find no consistent downstream effects on total employment with most specifications finding no effect. I find some evidence that direct shocks have a positive impact on employment and average wages.

1.4.2 High-Skill, Low-Skill and STEM wages and employment

In this section, I explore whether wages and employment outcomes respond to the H-1B program based on worker characteristics such as skill level and occupation (STEM versus non-STEM). In addition to showing how downstream effects vary with worker traits, this exercise is useful for another reason. The estimated positive downstream effects of the H-1B program on wages suggests that U.S. workers benefit from expansions in the H-1B program. This conclusion may be misleading if the program harms some groups of workers, but the effects are obscured within averages. For example, if H-1B inputs are substitutable with low-skilled tasks but complementary with high-skilled tasks, industries may substitute towards high-skilled labor, leading to higher average wages but obscuring the negative impact on low-skilled workers. This section contains a deeper analysis of this possible scenario. The occupational data on wages and employment I use in this section come from the OES. Because the OES contains data on industries that directly hire H-1B workers, I will also report estimates of the direct effect.

To approximate the wages and employment of high-skilled and low-skilled workers, I first categorize each 6-digit SOC occupation based on their skill level. I develop two proxies for occupational skill level as in Crino (2010), which label each occupation based on the average level of education of the workers employed in that occupation. The first proxy (Skill Proxy 1) defines high-skilled occupations as those with the average schooling level of a bachelor's degree or better.[40] The second proxy (Skill Proxy 2) defines high-skilled occupations as those with a share of college graduates in excess of 60 percent. I use STEM definitions from the BLS to classifiy occupations as STEM or non-STEM. I aggregate occupational wages and employment based on these proxies.

Motivating the empirical tests in this section is the same conceptual framework as that outlined in the theory section. That is, downstream shocks affect a subset of workers based on the degree of complementarity between that labor type and H-1B-related inputs. Moreover, the effect will vary across industries because industries differ in how intensively they use these inputs. Letting x denote high-skill, low-skill, or STEM workers, I run for each group separately, specifications of the form

$$\Delta y_{it}^{x} = \delta_t + \beta_{x,Downstream}\Delta ID_{it} + +\beta_{x,Direct}\Delta D_{it} + \varepsilon_{it}^{x} \tag{1.11}$$

where y_{it}^{x} is either the percentage change in wages for group x or the change in employment normalized by initial industry employment. We are now interested in the coefficients $\beta_{x,Downstream}$ and $\beta_{x,Direct}$ which capture the downstream effects and the direct effects, respectively. All specifications include period fixed effects δ_t and cluster standard errors at the industry level. The error term is given by ε_{it}^{x}. In the next section, I augment the specification in (1.11) with a set of control variables. I instrument for ΔID_{it} as in the previous section, and for the direct shocks $\Delta D_{it} = \dfrac{\Delta H_{it}}{Y_{it-1}}$, with the two direct instruments $\Delta D_{it}^{IV_1} = \Delta D_{i0} \times cap_t$, and $\Delta ID_{it}^{IV_2} = \Delta ID_{i0} \times \pi_t$, as defined in (1.7) and (1.8).

[40] I do this using the 2004 5% extract from the Public Use Microdata Series (PUMS, Ruggles et. al, 2008). A more detailed description is given in the appendix

Table 1.4 reports the 2SLS estimates of Equation (1.11). Column captions denote the dependent variable y_{it}^{x}. Panels A and B of Table 1.5 show the results for the first and second skill proxies, respectively. In each panel, the first row reports the downstream coefficient and the second row the coefficient for the direct effect. Columns 1-3 present the estimates for the log change in the wages of high-skilled, low-skilled and STEM workers, respectively. Columns 4-6 show estimates for the corresponding employment variables. Since the results are qualitatively the same in Panels A and B, I simply discuss the findings in Panel A.

Columns 1-3 of Table 1.4 show that downstream shocks increase the wages of high-skilled, low-skilled, and STEM workers. The coefficients are estimated precisely, and their magnitude is economically meaningful. A one standard deviation increase in industry downstream exposure leads to a .42 percentage point increase in the high-skilled wage. A similar increase in downstream exposure leads to a .27 percentage point increase in the low-skilled wage. These results suggest that, overall, inputs from H-1B industries are complementary with labor inputs. As well, the estimated wage gains imply that the results found in the previous section for average wages are not simply a consequence of changes in the employment mix within industries. In the second row of Panel A, we find little support for direct effects on wages with none of the estimates being significantly different from 0.

In columns 4 through 6 I find evidence that downstream gains in employment accrue to high-skill and STEM workers but not to low-skill workers. The coefficients on the high-skill and STEM employment variables are significant at the 1 percent level. A one standard deviation increase in downstream shocks to an industry is associated with an increase in the growth of high-skill employment by .08 percentage points of total employment. Taken together, the effect on average wages found in the previous section seems to arise from a combination of an increase in worker compensation and an increase in the employment of high-skill and STEM workers.

Moving to the second row of the panel, we find a positive direct effect on the employment of high-skill and STEM workers. For both high-skill and STEM employment, the direct effect is larger in magnitude than the indirect effect. A one standard deviation increase in direct shocks to an industry leads to an increase in the growth of high-skill and STEM employment by .15 and .23 percentage points of total employment, respectively. In both cases, the standard errors are extremely small with t-ratios larger than 8. Finding a strong response from skilled employment is not surprising given the mechanical correlation previously discussed. As before, I cannot determine the effect on natives because total STEM employment mechanically rises as H-1B employment rises.[41]

I now address the threats to identification previously discussed by performing a similar set of robustness checks as in the analysis undertaken using the LPC data. That is, I include the set of controls previously discussed, namely, expected measures of wages and employment growth, industry output, and IT capital intensity. Recall that controlling for pre-trends in wages and employment is problematic in the OES data because the first year in the sample is 1997. To incorporate these trends into the analysis in this section, I merge the LPC controls to the OES dataset. Because the most LPC industries are also sampled in the OES, the analysis that follows uses a smaller set of 124 LPC industries. As before, I do not report the direct effects since they are not very informative in the smaller LPC sample.

Table 1.5 reports the results using the smaller set of industries. As a point of reference, row A in Table 1.5 shows the baseline results from Table 1.4 row A, which use the main definition of skill, and include only period fixed effects as controls. In Row B, we introduce the additional controls using the LPC industries. The elasticities for all coefficients are in similar in terms of magnitude and significance as in the OES sample. For example, the coefficient for high-skill wages is .52 in the LPC sample and .42 in the OES sample, and is still highly significant with a t-ratio of 4.04. These estimates mitigate concerns that the results are contingent on sample selection. The coefficients for high-skill and STEM employment are still significant

[41]This would not be the case, however, if H-1B works fully displaced native workers. In this case, total employment would not change. There is little evidence that skilled workers displace native in the literature, however.

at the 1 percent level, but the coefficients fall from .08-.09 to .05. Row C shows that the results are nearly identical once we use the second skill proxy. Row D excludes STEM occupations when constructing the high-skill and low-skill wage and employment variables. In this case, the coefficient on high-skill employment is driven to zero suggesting that employment effects for high-skill workers are being driven by the effects on STEM occupations. The final row excludes the top 5 most dependent sectors. Overall, the point estimates are not substantially reduced compared to the baseline shown in Row A. However, the coefficient on STEM employment is now estimated quite imprecisely.

1.5 Conclusion

To my knowledge, this is the first study examining the relationship between skilled immigration and US labor market outcomes taking national industries as the unit of analysis. By focusing on industries, I can examine an indirect effect previously unexplored in the literature: the *downstream* effect of skilled immigrants. That is, how labor demand in an industry responds to immigration shocks to its upstream suppliers. Motivating this approach is the industrial composition of H-1B workers. In particular, H-1B employer industries are high-skilled labor intensive and supply intermediate service inputs to virtually all sectors of the US economy. Because these industries use skilled labor intensively, shocks to the supply of skilled labor likely translate into meaningful increases in output supply to the benefit of their many downstream customers.

Consistent with this idea, I find strong downstream effects on average wages, and these effects are larger than the corresponding direct effects. Although immigration status is not discernible in my data, the estimated downstream wage effects suggest that US natives benefit from higher admission rates because dependent downstream sectors tend to employ few immigrants. In an extension, I find evidence that downstream shocks affect average wages partly through an increase in worker compensation and partly through an increase in the employment of high-skilled and STEM workers. Lastly, I find evidence that average wages increase in directly exposed industries mostly through an increase in the employment of STEM and high-skilled workers.

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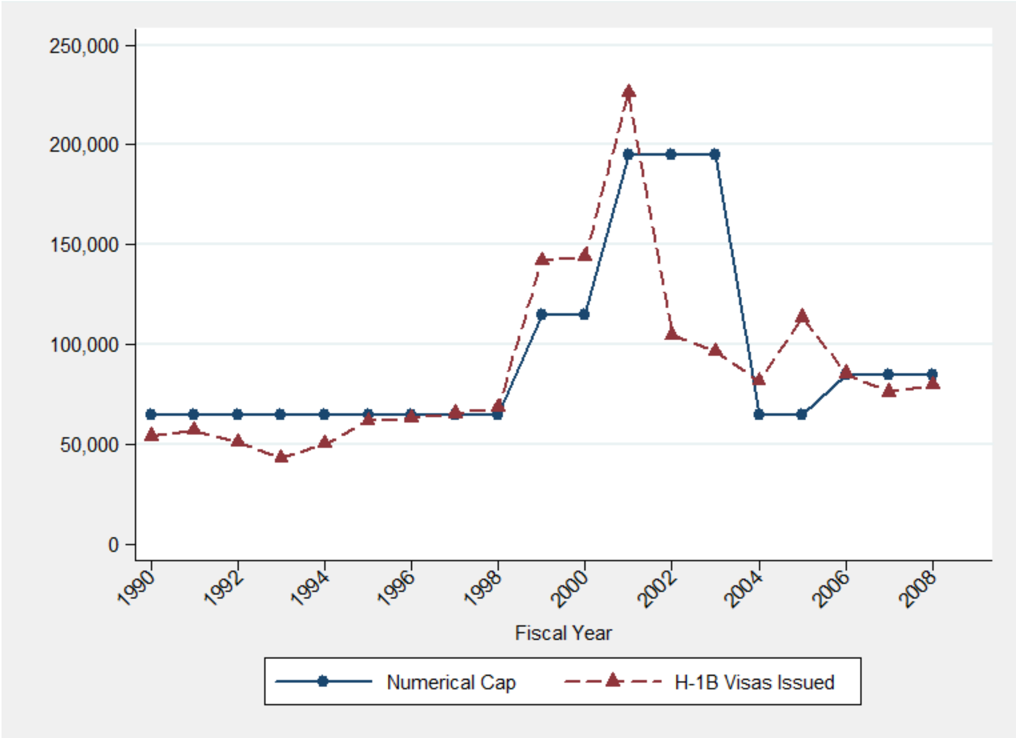

Fig. 1.1.. The H-1B numerical cap and number of approved visas subject to the cap, 1990-2008.

Notes: Figure 1.1 shows the evolution of the H-1B numerical cap and the actual number of visas issued subject to the cap for 1990-2008. The figure excludes visas issued to Healthcare and Education because these sectors became fully or partially exempt from the cap through the American Competitiveness in the Twenty-First Century Act of 2000. Data on aggregate visa issuances from 1990 to 1997 are taken from Kerr and Lincoln (2010). Data on aggregate visa issuances from 1998 to 2008 are computed using data from the Form I-129

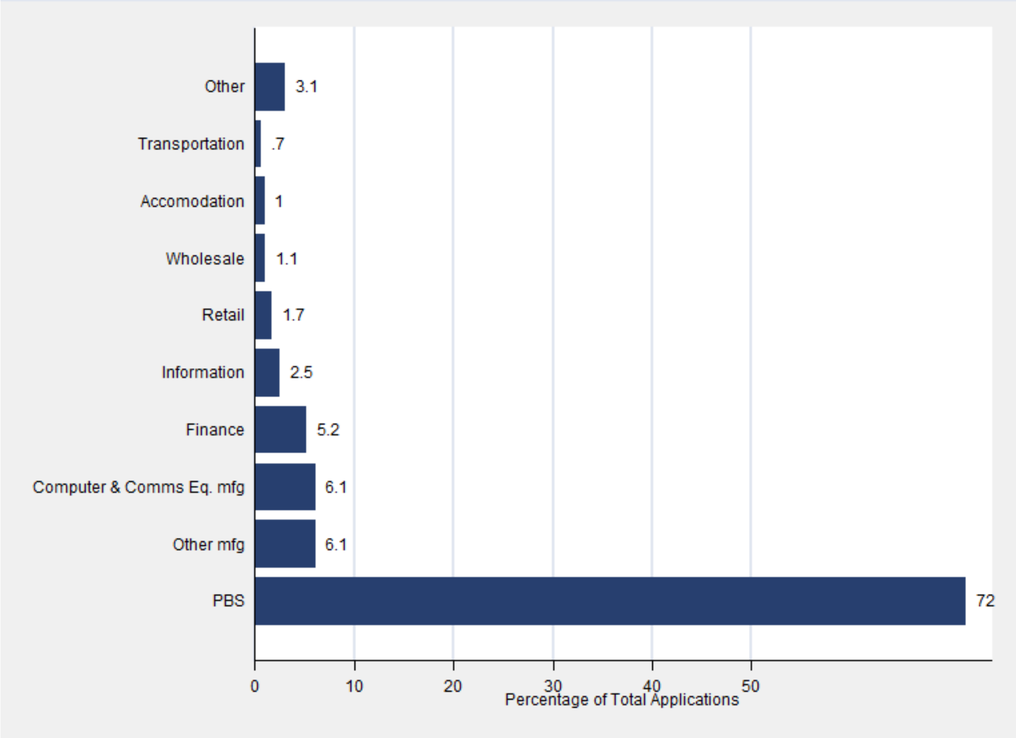

Fig. 1.2.. H-1B Applications by Major Sector, 1998-2010

Notes: Figure 1.2 reports the major sector (two-digit NAICS) distribution of over 2.5 million approved H-1B applications for 1998-2010. The data used includes new approved H-1Bs as well as those for continuing employment. The figure excludes Healthcare and Education, which became fully or partially exempt from the cap through the American Competitiveness in the Twenty-First Century Act of 2000. PBS stands for Professional and Business Services. Source: Form I-129 from the U.S. Citizenship and Immigration Service

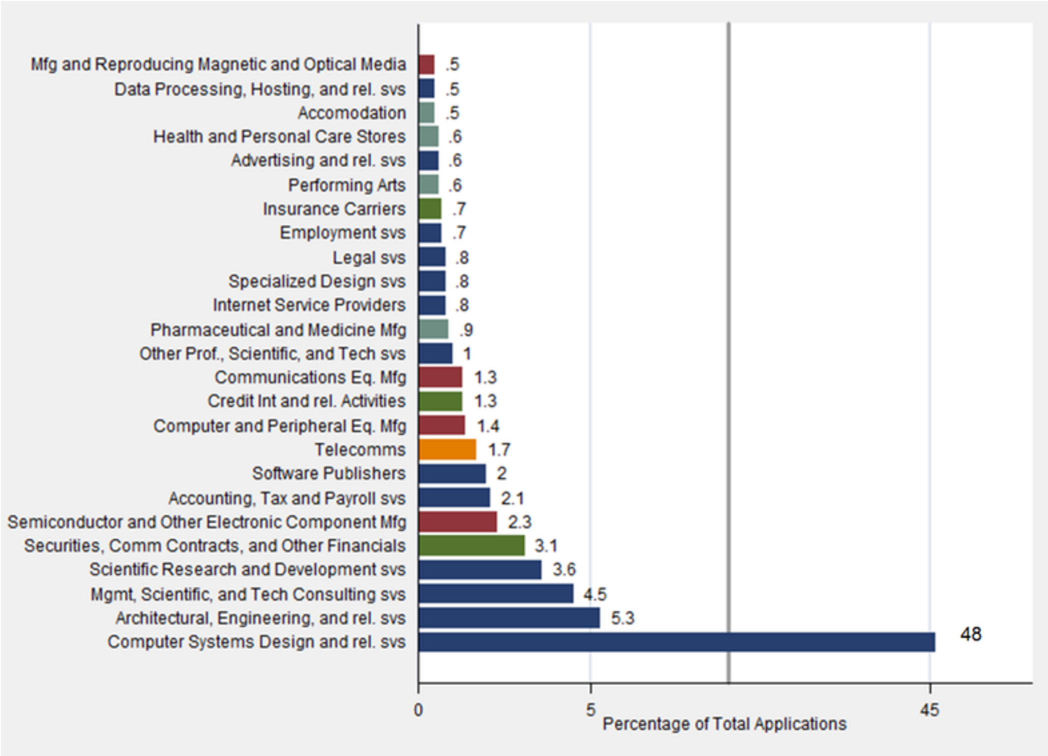

Fig. 1.3.. H-1B Applications by Detailed Sector, 1998-2010

Notes: Figure 1.3 reports the percentage of total H-1B petitions for the top 25 minor sectors (4-digit NAICS) for over 2.5 million approved H-1B applications for 1998-2010. The data used includes new approved H-1Bs as well as those for continuing employment. The figure excludes Healthcare and Education which became fully or partially exempt from the cap through the American Competitiveness in the Twenty-First Century Act of 2000. The vertical gray bar denotes a break in the x-axis created to save space. Each bar representing a minor sector is colored according to the major sector to which it belongs.
Source: Form I-129 from the U.S. Citizenship and Immigration Service

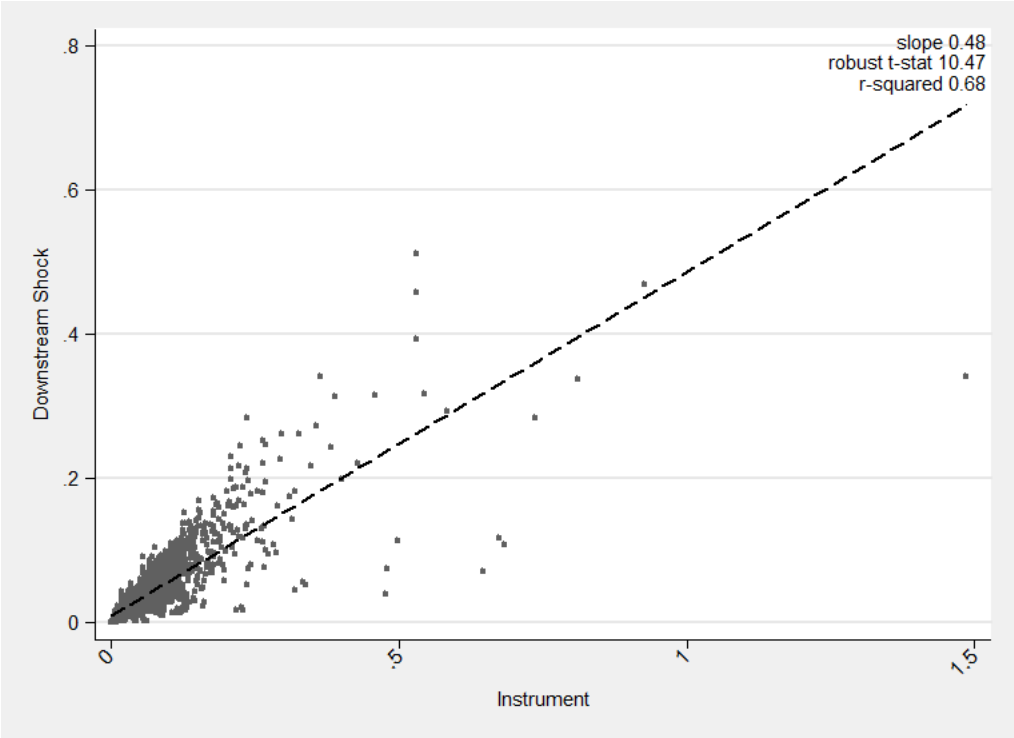

Fig. 1.4.. Downstream shock and Instrumental Variable

Notes: The scatter plot shows the relationship between the measure of industry downstream shocks and the instrumental variable. Each point in the scatterplot represents an industry-year pair for 185 industries for 1995-2007, excluding the years when the cap does not bind (i.e. 2002 and 2003). The downstream shock is scaled by 100 to improve readability. The t-statistics are computed using robust standard errors.
Source: Form I-129 from the U.S. Citizenship and Immigration Service

Table 1.1.. Most Indirectly Dependent Industries

#	Industry	Dep	#	Industry	Dep
1	**Metal ore mining**	5.1	21	**Automobile dealers**	0.9
2	Audio & video Eq. mfg	2.5	22	**Automotive parts, accessories, & tire stores**	0.9
3	**Beer, wine, & liquor stores**	2.3	23	**Beer, Wine, and Distilled Alcoholic Beverage whl**	0.9
4	Communications Eq. mfg	1.7	24	Funds, trusts, & other financial vehicles	0.9
5	**Shoe stores**	1.7	25	Industrial machinery mfg	0.8
6	**Electronics & appliance stores**	1.4	26	**Prof. and Coml. Equipment and Supplies whl**	0.8
7	Data Processing, Hosting, and rel. svs	1.3	27	Accounting, Tax & Payroll svs	0.8
8	**Facilities support svs**	1.2	28	**Farm Product Raw Material mch whl**	0.8
9	Computer systems design & rel. svs	1.2	29	**Investigation & security svs**	0.8
10	Architectural, engineering, & rel. svs	1.1	30	**Miscellaneous store retailers**	0.8
11	Navigational, medical, & control instruments mfg	1.1	31	**Business support svs**	0.8
12	Securities intermediation & rel. activities	1.1	32	Hardware & Heating Eq. & Supplies whl	0.8
13	Management of companies & enterprises	1.1	33	**Department stores**	0.8
14	**Electrical and Electronic Goods mch whl**	1	34	Legal svs	0.8
15	Metalworking machinery mfg	1	35	Newspaper & Book Publishers	0.8
16	**Paper and Paper Product whl**	1	36	Other Educational Services	0.8
17	Oil & gas extraction	1	37	**Furniture and Home Furnishing mch whl**	0.8
18	**Lessors of NonFinancial Intangible assets**	0.9	38	Employment svs	0.8
19	Agencies, brokerages, & other insurance rel. activities	0.9	39	**Health & personal care stores**	0.8
20	**Sporting goods, hobby, book, & music stores**	0.9	40	Mgmt, Scientific, & Tech Consulting svs	0.8

Notes: Table 1.1 presents the 40 most indirectly dependent industries in the Occupational Employment Statistics (OES) sample. H-1B indirect dependency is constructed using data on H-1B visas issued in 1998 and data from the 1997 Benchmark IO tables. The measure is scaled by 1000 to improve readability. Sectors are highlighted if they are not directly dependent on the H-1B program

Table 1.2.. Industry-Level Wage Regressions, LPC Sample

	Dependent variable: Δ Log Wage Bill per Worker											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
H-1B Downstream Shock	0.44***	0.44***	0.42***	0.32***	0.44***	1.70**	0.39***	0.39***	0.30***	0.54***	0.65***	0.29**
	(4.38)	(4.13)	(3.84)	(3.44)	(4.21)	(2.48)	(2.82)	(5.09)	(3.13)	(4.26)	(3.43)	(2.14)
Δ Log Output		0.17***	0.17***	0.17***	0.18***	0.17***						
		(8.12)	(7.81)	(7.69)	(7.83)	(6.56)						
Wage Growth (1990-1995)			0.18***									
			(2.97)									
Wage Growth (1990-1999)				0.35***								
				(3.56)								
IT Capital Control					0.17*							
					(1.79)							
H-1B Direct Shock												0.18**
												(2.13)
Other controls	No	No	No	No	Yes	No	No	No	No	No	No	No
Industry Fixed Effects	No	No	No	No	No	Yes	No	No	No	No	No	No
Number of observations	1780	1780	1780	1780	1637	1780	1715	1780	1780	1506	958	1840
Number of industries	137	137	137	137	126	137	132	137	137	137	137	185
F-Statistic	501.3	507.0	557.2	477.5	473.8	74.1	926.1	65.5	X	66.9	99.7	67.7

Notes: Each column in Table 1.2 presents the results from industry-year regressions using the change in the log wage bill per worker as the dependent variable from Labor Productivity and Cost (LPC) data over 1995 to 2007. To construct the downstream shock variable, I first interact the direct shocks to the industrys suppliers with their share in total intermediate input costs, and then sum across all suppliers. Direct shocks are defined as the change in the H-1B wage bill normalized by industry output. The first instrumental variable for downstream shocks interacts the indirect dependency measure with the cap. The second instrument interacts indirect dependency with a dummy that equals 1 for the 2001-2002 and 2002-2003 intervals. Indirect dependencies are constructed using data on H-1B visas issued in 1998-1999 and data from the 1997 Benchmark IO tables. All specifications are unweighted and include period and industry fixed effects. Standard errors are clustered at the industry level.

Table 1.3.. Industry-Level Employment Regressions, LPC Sample

	Dependent variable: Δ Log Employment											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
H-1B Downstream Shock	-0.08	-0.07	-0.00	-0.07	-0.07	-1.51	0.64***	-0.32*	0.24	-0.03	-0.28	0.52
	(-0.31)	(-0.36)	(-0.01)	(-0.46)	(-0.40)	(-1.12)	(3.80)	(-1.76)	(0.98)	(-0.13)	(-0.74)	(1.43)
Δ Log Output		0.21***	0.20***	0.19***	0.20***	0.14***						
		(6.37)	(6.19)	(6.12)	(6.24)	(4.59)						
Employment Growth (1990-1995)			0.39***									
			(5.58)									
Employment Growth (1990-1999)				0.57***								
				(6.98)								
IT Capital Control					-0.38*							
					(-2.30)							
H-1B Direct Shock												0.25**
												(2.32)
Other controls	No	No	No	No	Yes	No	No	No	No	No	No	No
Industry Fixed Effects	No	No	No	No	No	Yes	No	No	No	No	No	No
Number of observations	1780	1780	1780	1780	1637	1780	1715	1780	1780	1506	958	1840
Number of industries	137	137	137	137	126	137	132	137	137	137	137	185
F-Statistic	501.3	507.0	557.2	477.5	473.8	74.1	926.1	65.5	X	66.9	99.7	67.7

Notes: Each column in Table 1.3 presents the results from industry-year regressions using the change in log employment as the dependent variable from Labor Productivity and Cost (LPC) data over 1995 to 2007. To construct the downstream shock variable, I first interact the direct shocks to the industrys suppliers with their share in total intermediate input costs, and then sum across all suppliers. Direct shocks are defined as the change in the H-1B wage bill normalized by industry output. The first instrumental variable for downstream shocks interacts the indirect dependency measure with the cap. The second instrument interacts indirect dependency with a dummy that equals 1 for the 2001-2002 and 2002-2003 intervals. Indirect dependencies are constructed using data on H-1B visas issued in 1998-1999 and data from the 1997 Benchmark IO tables. All specifications are unweighted and include period and industry fixed effects. Standard errors are clustered at the industry level.

Table 1.4.. Indirect Impact of the H-1B program on the Wages and Employment of High-Skill, Low-Skill and STEM Workers

	Wages			Employment		
	High-Skill (1)	Low-Skill (2)	STEM (3)	High-Skill (1)	Low-Skill (2)	STEM (3)
Panel A: Skill Proxy 1						
H-1B Downstream Shock	0.42***	0.27***	0.27**	0.08***	0.14	0.07***
	(3.55)	(2.64)	(2.17)	(3.69)	(0.96)	(2.90)
Direct Shock	-0.05*	0.07**	0.08	0.15***	0.04	0.23***
	(-1.81)	(1.98)	(1.41)	(8.09)	(1.03)	(16.82)
Panel B: Skill Proxy 2						
H-1B Downstream Shock	0.32***	0.28***	0.27**	0.06***	0.16	0.07***
	(3.37)	(2.87)	(2.17)	(2.62)	(1.07)	(2.90)
Direct Shock	-0.03	0.10***	0.08	0.15***	0.05	0.23***
	(-1.37)	(2.85)	(1.41)	(9.29)	(1.17)	(16.82)

Notes: Each column in Table 1.5 presents the results from industry-year regressions using as the dependent variable the wages and employment of high-skill, low-skill and STEM workers as described on the column heading. Wage and employment data for 189 industries are from the Occupational Employment Survey (OES) over 1997 to 2007 for a total of 2013 observations. Rows A and C-E use the first skill definition obtained by averaging an occupations level of education with data from the 2000 Census. Row B uses the alternative definition. STEM classification of occupations comes from the BLS. Row C excludes STEM workers in the construction of high and low skill variables. Row D omits Information and Communications Technology sectors. The explanatory variable in rows A-D is the interaction of the log of the national H-1B population and the indirect dependency measure which is constructed using data from the 1997 Benchmark IO tables and data on H-1B visas issued in 1998. In row E, the explanatory variable is the interaction of the log of the national H-1B population with a dummy variable that collects industries into quintiles of indirect dependency. All specifications are unweighted, include year and industry fixed effects. Standard errors are clustered at the industry level.

Table 1.5.. Robustness Checks: OES data using LPC Industry Sample

	Wages			Employment			N
	High-Skill	Low-Skill	STEM	High-Skill	Low-Skill	STEM	
	(1)	(2)	(3)	(1)	(2)	(3)	
(A) Skill Proxy 1:	0.42***	0.27***	0.27**	0.08***	0.14	0.07***	185
OES Sample	(3.55)	(2.64)	(2.17)	(3.69)	(0.96)	(2.90)	
(B) Skill Proxy 1	0.52***	0.32***	0.22	0.05***	0.02	0.05**	124
	(4.04)	(3.37)	(1.56)	(2.85)	(0.22)	(2.30)	
(C) Skill Proxy 2	0.44***	0.31***	0.22	0.04**	0.03	0.05**	124
	(4.12)	(3.44)	(1.56)	(2.51)	(0.27)	(2.30)	
(D) Excluding STEM	0.53***	0.30***	0.22	-0.00	0.02	0.05**	124
	(5.04)	(3.40)	(1.56)	(-1.04)	(0.18)	(2.30)	
(E) Excluding 5 Most	0.62***	0.37***	0.39**	0.07**	0.19*	0.05	119
Dependent Sectors	(3.37)	(2.91)	(2.32)	(2.23)	(1.65)	(1.47)	

Notes: See Table 1.4. Each column in Table 1.5 presents the results using OES data but restricting the sample to the 143 industries in the LPC. Row A shows the results without the inclusion of controls. Rows B-E include controls for output and for expected wage and employment pre-trends.

2. SKILLED IMMIGRANTS AND THE EMPLOYMENT OPPORTUNITIES OF YOUNG SKILLED NATIVES IN US CITIES

2.1 Introduction

A large portion of the number of skilled guest workers joining the US labor market each year does so with an H-1B visa. A continuing debate exists over whether H-1B workers hurt or improve the employment prospects of US workers. Noting that most H-1Bs work in STEM occupations – a critical input to technology creation and dissemination – some argue the cap on admissions prevents firms from hiring the workers they need to innovate (Gates 2008). Others argue the cap is already too high, and there is no shortage of qualified natives willing to fill the positions taken by foreign workers (Matloff 2003, Lowell 2014). The program simply acts as a subsidy to companies at the expense of US workers.

In this study, I examine how high-skilled immigrants relate to the employment of US college-educated workers in US states. A novel feature of this study is a focus on how skilled immigrants affect the employment prospects of young natives within this demographic group[1]. I focus on young college-educated workers because their skills and work experience most closely resembles that of skilled immigrants and thus they are the most likely group to compete with skilled immigrants for jobs. Previous work that exploits differences in outcomes across local labor markets to identify the employment effects of high-skill immigration finds little evidence of displacement (Kerr and Lincoln 2010, Peri et al. 2014, 2015). These studies, however, do not consider how the effect may vary with age, which seems important in our context given that

[1] In a firm-level study, Pekkala Kerr, Kerr, and, Lincoln 2014, find some evidence that young-skilled immigrants increase the employment of young natives.

85 percent of H-1Bs are 35 or younger. My tests employ administrative data on all approved H-1B visas during 2000-2009 fiscal years. I obtain the data under a Freedom of Information Act Request from the US Citizenship and Immigration Service (USCIS).

Identifying the employment effects of skilled immigrants on US workers is challenging because variation in inflows across states may be caused by differences in their current economic environment. A shock to productivity in a state, for example, may increase demand for all labor inputs and thus immigrant inflows may be endogenous to the employment of domestic workers. To deal with this issue, I instrument inflows with two variables that take advantage of the fact that it was much more difficult to obtain visas in the 2005-2009 period than from 2000 to 2004.

The first instrument builds on the empirical methodology of Kerr and Lincoln (2010) who study the effect of H-1B workers on the rate of patenting and employment. The idea is to leverage large changes in the national availability of visas induced by changes in immigration policy. For the 2004 fiscal year, the cap was lowered from to 195,000 visas per year to 65,000, where it has remained since. The lowering of the cap had a stronger impact in states based on their initial exposure to the program. This differential decline in visas across states is arguably unrelated to changes in their relative economic opportunities.

Even though the first instrument is a good predictor of H-1B inflows, we can leverage an additional source of aggregate variation to improve its explanatory power. Unique to this paper, is a second instrumental variable that uses changes in the availability of visas caused by changes in the demand by the largest industry recipient of visas. The motivation is as follows. In any given year, the share of all H-1B visas granted to the largest employer – IT and Management Consultants (NAICS 5415-6)— is substantial. The share fluctuates greatly during the 2000-2009 period. Since the US government allocates visas on a first-come-first-served basis, and visas are in limited supply, firms compete for available visas. In essence, an increase in the demand of IT Consultants drastically and arguably exogenously (to any given state) reduces the aggregate number of visas granted to other sectors. Given this, we can construct an instrument for the inflows into a state, for all H-1Bs *not* employed by IT Consultants. Consequently, when using this strategy we look for evidence of displacement of the native population *not* employed by IT Consultants. Both instruments can explain a significant portion of the within-state change in H-1B visas granted. The second instrument, for example, can explain over 80 percent of the within-state change in visas in the 2000-2009 period.

My analysis employs microdata on workers in 50 states drawn from the 2000 Census and the 2001-2009 American Community Survey. Consistent with previous findings, there is little evidence that H-1B workers lower *total* college-educated employment. Though the estimates are always slightly negative, they are almost always imprecisely estimated. The effects for young natives, however, are always negative and significant. My estimates suggest that increasing the growth rate of H-1B workers by one percentage point of total employment decreases the growth rate of young college-educated native employment by 2-4 percentage points of total employment. These results are consistent with a scenario in which young skilled workers are more substitutable with H-1B workers than older natives. To my knowledge, this is the first empirical paper that finds a negative effect of skilled foreigners on the employment of skilled young natives. It is also one of the very few that finds negative employment effects on any group of workers[2].

This article contributes to a larger literature on the effects of skilled immigrants on other variables such as patents and productivity (Kerr and Lincoln 2010, Hunt and Gauthier-Loiselle 2010, and Moser, Voena and Waldinger 2012, Borjas and Doran 2012)[3]. More broadly, this paper fits in the literature the impacts of general immigration on the host country[4]. My identification strategy, for example, is related

[2]A notable exception is a firm-level study by Doran, Isen, and Gelber 2014 that finds that hiring an H-1B worker increase employment at the firm by less than 1 worker, which is taken as evidence of displacement. Borjas (2009) finds that foreign doctoral students lower the wages of native-born doctorates.

[3]See surveys by Nathan(2013), Kerr (2013) and Chapter 8 in Borjas(2014)

[4]With respect to the impact of immigration on the labor market, the seminal contributions are Card (2001) and Borjas(2003). See also surveys by Hanson (2009) and Chapters 3-6 in Borjas(2014).

to the approach in Kato and Sparber (2013) who study how the decrease in the cap in 2004 impacted the quality of international student applicants to US universities. This study is also related to Smith (2012) who finds that low-skill immigrants hurt the employment prospects of teens in the US, an effect missed in city-level studies that estimate the same effect for all age groups.

The paper is organized as follows. Section II provides background on the H-1B program and summarizes the data sources used. Section III discusses the empirical strategy, the identification problem, and the instrumental variable approach. Section IV presents the results and various robustness exercises. Section V concludes.

2.2 H-1B Visa Background and Data

2.2.1 Background

A novel feature of this study is its usage of MSA-specific data on approved H-1B visas. I first provide a brief description of the H-1B program to describe the data better. This summary also highlights aspects of the program relevant in the empirics.

The H-1B visa grants temporary working rights to high-skill foreign workers, with most H-1B recipients having at least a bachelor's degree.[5] The H-1B program came into effect under the Immigration Act of 1990. Congress set a quota (commonly referred to as the "cap") of 65,000 on the number of visas to be issued each year. By the middle of the decade, the cap became binding and was increased to over 100,000 workers for fiscal years 1999 and 2000.[6] The cap was further raised to 195,000 for fiscal years 2001, 2002 and 2003 but because of falling H-1B demand that followed the 2001-recession, it was lowered in 2004 to its current level of 65,000.[7][8] Since 2004, the cap has been exhausted every year. These large policy-driven changes in the

[5]In general, more than half of successful applicants are in Science and Engineering or computer related professions (Kerr and Lincoln, 2010).

[6]This took place under the American Competitiveness and Workforce Improvement act of 1998

[7]For the most part, growth in the H-1B population mirrors changes in the level of the cap with differences arising in years where the cap does not bind.

[8]Under the American Competitiveness in the Twenty-First Century Act of 2000, government and some nonprofit research organizations, as well as universities, were exempt so that the number of

availability of visas will be at the core of the identification strategy I use in this paper.

The application process requires a potential recipient to be sponsored by her prospective employer and thus the firm finds the worker in advance[9]. First, the employer must file a Labor Condition Application (LCA) with the Department of Labor to ensure that the employment arrangement will comply with US labor laws. The firm specifies the location, salary, length, and type of employment. With the LCA in hand, the employer files a form I-129, "Petition for a Nonimmigrant Worker", with the U.S. Citizenship and Immigration Service (USCIS). If the applicant meets the admission criteria and the cap is not yet reached, the USCIS approves the petition (GAO 2011).[10] Petitions are approved on a first-come-first-served basis, irrespective of firm or worker characteristics such as location, industry, or occupation. The window to submit petitions to the USCIS for a given fiscal year opens on April 1^{st} of the previous fiscal year, six months before the employment arrangement is set to begin. If the cap is close to being reached, the USCIS stops receiving applications and runs a lottery to allocate the remaining visas.

The USCIS issues visas for three-year at a time after which the employer can apply for a three-year extension. As well, the worker can switch employers at any point in time. Extensions and changes of employer require the filing of a new LCA and Form I-129 though they do not count towards the cap. The H-1B is a "dual intent" visa: the recipient can legally pursue immigrant status while holding a temporary visa. At any point during the worker's employment arrangement, the firm can choose to file for permanent residency for the worker in which case the worker can stay in the US indefinitely.

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new visas issues always exceeds the cap. As well, in FY 2005, 20,000 additional visas were reserved for workers with graduate degrees.

[9]This can be done in a multitude of ways. For instance, firms can recruit foreigners already in the US as students or from abroad through foreign affiliates and other sources.

[10]If the worker is already in the U.S., the USCIS changes their previous visa status to H-1B and the worker may begin working immediately. Otherwise, the worker takes the approved I-129 to a consular office of the Department of State which reviews the entire package and issues the visa.

2.2.2 H-1B Data and Summaries

The empirical analysis will require data on H-1B inflows at the state-level. Unfortunately, government agencies do not keep track of the number of H-1B workers that are in the U.S. at a given point in time (GAO 2011).[11] Instead, I approximate inflows to a state in a given period from microdata on all newly approved visas, taken from the form I-129. I obtained the data from the USCIS under a Freedom of Information Act request. Aside from employer characteristics such as name, address and 4-digit NAICS industry, each I-129 record contains data on worker occupation, annual wages, age and country of origin. The data span the fiscal years 1998 to 2011.

To help us classify workers into useful age categories let us consider the age distribution of H-1B workers. Table 2.1 reports the age profile of workers who obtained a visa for the first time in the year 2000, the initial year of the sample period. The largest group –with almost 40 percent of the total– is that of workers in the 26-30 range. The second largest age group consists of workers in the 21-25 range (27.6%) so that about two-thirds of H-1B visas are granted to workers under 30 years of age. Only around 7 percent of H-1Bs are over the age of 40. Motivated by these summaries, I define young workers as being 30 years old or younger.

2.3 Methodology

2.3.1 Specification

We want to estimate how hiring skilled immigrants affect the employment opportunities of US natives. To this purpose, I exploit differences in H-1B hiring across states and over time. I take to the data the following specifications:

[11]Estimating the population requires combining H-1B gross inflow data with assumptions about the rates at which the stock is depleted.

$$\Delta y_{it} = \gamma_i + \delta_{rt} + \beta \Delta H_{it} + \alpha C_{it} + \varepsilon_{it} \tag{2.1}$$

where Δy_{it} stands for the annual employment change for the demographic group of interest for state i. As mentioned above, we are interested in testing for displacement effects and thus we want to focus on native groups with similar characteristics to H-1B workers as we would expect these groups to experience stronger competition from H-1Bs. To this purpose, I focus on natives with a college degree or better. Given that H-1Bs are young, I also explore the impact for natives with 30 years of age or less.

The change in the H-1B population for the given period is given by ΔH_{it}. In most specifications, I normalize employment changes by initial employment in the state, as is conventional in the literature (see Card 2001, Peri et al. 2014 etc.). In unreported regressions, I perform the entire analysis without normalizing the changes in our variables and find nearly identical results.

Note that since our specification is in first differences, we have already controlled for permanent differences across states, which may simultaneously drive H-1B and native hiring (e.g. initial state size). The state-specific fixed effects γ_i control for differential (linear) time trends across states. Region-year fixed effects δ_{rt} account for non-linear employment shocks to 9-Census regions[12]. Thus the beta coefficients are identified using variation in H-1B growth rates within states over time while accounting for regional shocks common to all states in a given time period. The error term is given by ε_{it}.

The variable C_{it} is an additional vector of controls. In this vector, I first include a variable meant to capture possibly confounding shocks to labor demand arising from the changing industrial structure of the US economy. The idea is to essentially predict what the change in demand for a given labor type would be in state if the

[12]The 9 Census regions are New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific.

industries in the state expanded at the same rate than their national counterparts. These variables are commonly referred to as Bartik demand instruments –inspired by Bartik (1991) –and are frequently accounted for in literature on immigration that takes the metropolitan area as the unit of observation (see Peri et al. 2014 and Wozniak and Murray 2012).

A second control takes accounts for flows of other immigrant types that may affect native employment but also correlate with H-1B hiring. These variables are the commonly referred to as "shift-share" or "supply-push" instruments developed by Card (2001). The main idea is to approximate what the inflow of immigrants into a state would be, based solely on national trends in immigration and the fact that immigrants tend to cluster together geographically. Finally, I account for changes in the *national* skill composition of US workers that may affect subsequent changes in skilled and STEM employment across states. Below, I give a more detailed explanation of how I construct these variables.

Data on employment counts and characteristics of US natives are drawn from the 5% 1990 and 2000 US Censuses and the 1% American Community Surveys for 2001-2009. The data are publicly available from the Minnesota Population Center website. My panel consists of 50 US states. I restrict the sample to non-institutionalized workers over 17 years of age but less than 65, which are not currently in school. See the appendix for detailed instructions on how I construct the variables used in this study.

2.4 Identification and Instrumental Variables Strategy

While specification (2.1) includes an extensive set of controls, it may still be the case that other unobserved time-varying shocks to native labor demand also influence the demand for skilled foreign workers– in which case we fail to capture the causal relationship of interest. For example, it may be the case that latent shocks to productivity in a state increase labor demand for all labor types, drive up wages and induce H-1B workers to apply for positions in the state. Thus, these latent shocks will induce a positive correlation between the H-1B flows that we observe and native labor demand. As noted by Kerr and Lincoln (2010), however, the direction of the bias in the estimates is ambiguous. States experiencing negative productivity shocks may increase H-1B hiring to compensate for native outflows.

To mitigate endogeneity concerns, I introduce two variations of the empirical strategy of Kerr and Lincoln (2010)[13]. Kerr and Lincoln use the changes in the cap mentioned above to identify the effect of the H-1B program on the rate of patenting and employment. To get variation across cities, the authors use the fact that there are large differences in the intensity in which cities use H-1B labor. In a reduced-form framework, they test whether increases in the H-1B population – induced by changes in the cap – had a stronger effect on cities that were initially more "dependent" on the program[14]. Some cities are more exposed to H-1Bs than others because their production technology requires more intensive use of H-1B inputs. For example, since the H-1B visa grants working rights to college-educated workers, we would expect cities intensive in college-educated labor always to request more workers. As well, cities with a large presence of firms with ties to foreign countries or with large pre-existing ethnic enclaves may find less costly to find and recruit foreign workers.

The instruments I develop in this paper generate variation in H-1Bs across states and over time in a similar fashion. The instruments combine differences across states in their initial dependence on the program and changes in the nationwide supply of visas which is likely exogenous to labor demand conditions in any given state.

The first instrument, which most closely resembles the Kerr-Lincoln approach, exploits the decline in the aggregate supply of visas available induced by the lowering

[13]This approach is a variant of the "supply-push" instrument of Card (2001), which is the standard instrumental variables strategy in the literature.

[14]The Kerr-Lincoln reduced-form regression is given by:

$$y_{it} = \alpha_i + \mu_t + \beta D_i \times \log(H_t) + \epsilon_{it}$$

where y_{it} is the log of the outcome variable, H_t is an estimate of the size of the national H-1B population and D_i is a proxy for the employment share of H-1Bs in a city. D_i is measured as the ratio of yearly-mean of LCAs filed in 2001-2002 to employment.

of the cap in 2004 from 195,000 to 65,000. I measure dependency for state i, D_i, as the ratio of total visas granted from 2000 to 2002, h_{i0}, to employment in the year 2000, E_{2000}. The first instrument is given by

$$\frac{\widehat{\Delta H_{it}}}{E_{2000}} = IV_{it}^{1} = D_i \times D_t = \frac{h_{i0}}{E_{2000}} \times D_t \tag{2.2}$$

Where D_t is a dummy that equals 0 for the 2000-2003 period and 1 for the 2003-2009 period.

As shown below, the first instrument is an excellent predictor of the within-state change in H-1B visas in our period of study. It is possible, however, to improve its predictive power by leveraging an additional source of variation in the national component of the instrument. For the second instrument, which is unique to this paper, I use changes in the availability of visas caused by changes in visa demand by the largest industry employer of H-1Bs[15]. As I document in more detail below, the share of visas granted to the largest H-1B employer – Computers Systems Design and Management, Scientific and Technical Consulting Services ("IT firms" or "IT")—is substantial, and it fluctuates greatly during the timeframe of this study.[16] Given that the USCIS grants visas on a first-come-first-served basis and visas are in limited supply, firms compete with one another for available visas. An increase in demand by IT firms disproportionately reduces the total number of visas available to other sectors ("non-IT firms"), and this increase is arguably exogenous to any particular industry. The reduction in visas is larger for more dependent industries within the non-IT sector. With this in mind, I construct an instrument for H-1B employment in non-IT sectors within a state. Consequently, we now test for employment effects on the non-IT native labor force. [17]

[15]The second instrument considers changes in the availability of visas to a set of firms that occurs even when the level of the cap remains fixed.
[16]IT and Management Consultants are classified as NAICS 5415 and 5416.
[17]A concern in using this approach is that our results may not be sufficiently general because we constrain our sample to non-IT workers. As I report below, the employment estimates obtained by

As before, the instrument combines an industry's dependence on the program with a variable measured at the national level. The latter variable captures changes in the supply of visas determined by the degree of competitiveness in the market for visas stemming from the level of IT demand.

The second instrument is given by

$$\frac{\overline{\Delta H^{noIT}_{i2000}}}{E_{2000}} = IV^2_{it} = \frac{h^{noIT}_{i0}}{E_{2000}} \times s^{IT}_t \tag{2.3}$$

where s^{IT}_t is the IT share of total H-1B visas granted nationally in a given sub-period. The superscript in a states' dependency to the H-1B program, $\frac{h^{noIT}_{i0}}{E_{2000}}$, denotes that we construct the variable with data on H-1B employment in non-IT sectors.

I now provide some descriptive evidence motivating the second instrumental variable approach. Figure 2.1 describes the percentage of H-1B petitions subject to the cap for the top 25 4-digit NAICS sectors, using data on all initial H-1B visas from 1998 to 2011, which amount to over 2.5 million petitions.[18] The figure reveals that H-1Bs are highly concentrated in a few sectors with business services sectors employing almost 80 percent of all applicants[19]. More importantly, Figure 2.1 underscores the central role played by IT firms in the H-1B program. IT firms take about half of all petitions filed in the period with over 400,000 initial petitions and close to 1 million total petitions. Highlighting the importance of the IT sector in the H-1B program is that it receives eight times more visas than the second largest recipient, Architectural and Engineering Services.

Figure 2.2 documents the evolution of visas granted to IT and non-IT firms from 1998 to 2011. When the cap is increased in the late 1990's, visas for both groups also increased. At the onset of the dot-com recession, we see a large fall in visas granted

focusing only on non-IT workers within a state are strikingly similar –in both sign and magnitude—to the estimates obtained when using the full sample.

[18]The figure excludes Healthcare and Education which became fully or partially exempt from the cap through the American Competitiveness in the Twenty-First Century Act of 2000.

[19]As well, we see that many H-1Bs are employed by IT capital producers with about 6 percent of petitions accruing to the computer and communications manufacturing 3-digit NAICS subsector.

to both groups. The decrease for IT firms was much larger with visas granted falling in a single year from close to 100,000 to around 30,000. This large fall in demand is mostly responsible for the large gap in 2002 and 2003 between visas granted and the cap. During this time in which the cap is not binding, demand by non-IT sectors is stable at around 58,000. When IT demand bounces back in 2004, it is met with a lower supply of visas as the cap reverts to 65,000 visas per year. As a result, the cap becomes binding once again. From 2004 to 2008 we see a monotonic decrease in visas granted to other sectors from around 53,000 to just below 30,000. As IT demand plummets at the onset of the Great Recession, however, we see an immediate jump in visas granted to other sectors likely as a result of the increase in the residual supply of visas.

It is possible that a decline in non-IT labor demand, and not the increase in competition for visas by IT firms, led to fewer visas granted to non-IT. Figure 2.4 presents evidence against this possible scenario. The figure shows trends in Labor Condition Applications, a prerequisite in the application process, submitted by IT Consultants and other sectors from 2003 to 2011. Unlike the form I-129, the LCA is recorded irrespective of whether the applicant receives the-the visa or not. We see that demand for both groups always move in the same direction and are both increasing from 2004 to 2008. Relative demand, though, falls monotonically. It appears visas granted to non-IT decreased during this time because demand by IT firms increased more rapidly. When the Great Recession begins, demand drops across the board, but as shown in Figure 2.2, the actual number of visas granted to non-IT sectors increases. This behavior is indicative of a scenario in which non-IT firms are highly constrained before the recession. Although their total demand falls, demand after the recession is still larger than the number of visas they had obtained in the past and thus the number of visas granted to non-IT increase from the previous year.

2.5 First Stage

I now test the predictive power of my set of instruments. For both instruments, I report first stage estimates for each instrument separately and then estimates obtained from including both instruments in the first stage simultaneously. Initially, I present estimates of our first stage where our only control is the state-specific fixed effects. I then include a stricter set of controls and test for sample selection to reduce concerns that the instruments are correlated with the error term in (2.1).

To compare the performance of the IV employed in the literature (the "first instrument") with that of the IV introduced in this paper (the "second instrument"), I test the predictive power of the first instrument on the sample of non-IT workers. In unreported regressions, I show that the first instrument behaves nearly identically when we use the full sample of workers.

Accordingly, our first stage regression is the following:

$$\frac{h_{it}^{noIT}}{E_{i,2000}} = \gamma_i + \pi_1 \frac{h_{i0}^{noIT}}{E_{i,2000}} \times D_t + \pi_2 \frac{h_{i0}^{noIT}}{E_{i,2000}} \times s_t^{IT} + \rho C_{it} + \epsilon_{it} \tag{2.4}$$

where the variables are as previously defined for 50 states over the 2000-2009 interval. To gauge the relative importance of each instrument, I scale all variables by their sample standard deviation. We expect that as the cap tightens and as IT consulting demand increases, states that are initially more exposed will suffer relatively larger losses in H-1Bs. I find support for this hypothesis if both $\pi_1 < 0$ and $\pi_2 < 0$.

Columns 1 and 2 in Table 2.2 present the first stage estimates for the first and second instruments, respectively. Each row reports the results of a difference specification varying in the set of controls and the sample of state we include in the regressions. The last column reports the number of states in each specification. I cluster standard errors at the state-level.

Row A presents the results controlling only for the state fixed effects. For both instruments, the coefficient estimates are negative, as posited above. Reflecting a strong relationship between our instruments and H-1B flows to a state is that, in both cases, the estimated coefficients are economically meaningful, and the standard errors are very small. This result is consistent with the scenario described above in which the availability of visas by non-IT firms first decreases as the cap is lowered and then once more as IT demand picks up. Because of this, compared to IT firms, non-IT firms have an even harder time obtaining visas in the 2003-2010 period.

In Row B, I introduce the region-year fixed effects and the Bartik control for college-educated workers. Point estimates remain nearly identical for both instruments. The remaining rows all include the Bartik controls. The standard errors in Row B are somewhat larger than in Row A but remain very small in magnitude.

In Column 3, I present the first stage coefficients from models that include both instruments simultaneously. In this exercise, I find that the coefficients remain the correct sign for both instruments, and the standard errors are small and of similar magnitude as before. Importantly, the explanatory power of both instruments combined –reflected in our r-squared coefficient– is larger than in models that include each instrument separately.

In addition to increasing explanatory power, making use of the second instrument has an additional advantage over the identification approach followed in the literature. Recall that the second instrumental variables strategy differs from the literature in that the aggregate component of the instrument reflects the degree of competitiveness in the market for visas. One advantage of this approach is that, because the degree of competitiveness varies from year to year, we can identify the labor market effects of H-1Bs during time intervals when the cap remains fixed (e.g. after 2004)—and this would not be possible in first-differenced models that also include state-specific fixed effects because of collinearity concerns.

In Column 4, I report first stage coefficients for the second instrument estimated from models using only the subperiods where the cap is fixed at 65,000 visas per year (i.e. the years in the 2004-2009 interval). The coefficients remain of similar sign and magnitude as the estimates from models that include the 2000-2003 period. The coefficients in this exercise are also precisely estimated as before.

Before proceeding with the sensitivity checks, I outline the construction of the Bartik demand controls. These controls are meant to capture shifts in local labor demand that arise from changes in the *nationa*l demand for the goods produced in that area, and may be correlated with H-1B inflows. Using similar notation and terminology as in Peri et al. 2014, I define the sector driven employment growth for group x in state i at period t as

$$S_{it}^{x} = \sum_{m} s_{im,1990} * \frac{\Delta y_{mt}^{x}}{y_{mt}} \tag{2.5}$$

where $s_{im,1990}$ is the 1990 share of total employment in state i in sector m, and $\frac{\Delta y_{mt}^{x}}{y_{mt}}$ is the normalized change of *national* native employment for group of workers x, in period t. In computing the measure, I use the 223 industries that I can consistently track over the 1990- 2009 period. Industries are categorized under the 1990 Census classification.

To construct the low-skill immigration shift-share control for state i, we assign a portion of the *national* (net) flow of low-skill immigrants from source country k between t and t - 1, m_{kt} to state i based on the share of immigrants living in that state in 1990, λ_{ik}. The shift-share control is given by $\sum_g \lambda_{cg} m_{gt}$. I construct the shift-share for college-educated natives in an analogous fashion. The college-educated native shift share is $\lambda_i c_{it}$, where λ_i is the share of college-educated workers living in i in 1990 and c_{it} is the change in the college-educated population between t and t - 1. I normalize both variables by employment in the year 2000.

Row C checks the robustness of the results to sample selection by excluding the top 5 largest states in the year 2000. Row D includes the control for the growth in the national stock of college-educated workers. Finally, Row E includes the "supply-push" component for low-skill immigrants. The results in Rows C-E show that the estimated coefficients for our baseline models are robust. These results are strongly supportive of the IV mechanism posited: the lowering of the cap led to a significant decline in the availability of visas, and this had a differential effect on states based their initial exposure to the H-1B program. For non-IT firms, the decline in available visas was even larger as competition from the IT sector intensified in 2003-2010 period compared to 2000-2003.

2.6 Results

In this section, I explore whether wages and employment outcomes respond to the H-1B program based on worker characteristics. In particular, I focus on the effect on the opportunities college workers. I then explore whether the effects on these two subgroups of natives differ based on their age profile.

The latter exercise, though interesting on its own, is also useful because of several other reasons. Thus far, in the literature that examines this question by exploiting geographic variation in outcomes, finds insignificant effects on the employment of college and STEM workers (Kerr and Lincoln 2010, Peri et al. 2014). This finding suggests that, even in the absence of wage gains, U.S. workers are no worse off by changes in the H-1B policy. This conclusion may be inaccurate if the displacement of workers takes place within these groups but the effects are masked within averages. For instance, if young, college-educated workers are closer substitutes for H-1B labor inputs –but perhaps complementary with those of older workers– firms may substitute away from young natives, leading to lower employment for young workers. This result is obscured if we simply examine total college employment.

The employment data used in this section comes from the Census for the year 2000, and the ACS for 2001-2009. The sample consists of 50 states. College workers are those with a college degree or better. I define young workers as those less than

30 years of age. All specifications include the state-specific fixed effects and cluster standard errors at the state level.

Table 2.3 presents the instrumental variables results for different specifications using our first instrument– where we include the full sample of workers when constructing our variables (i.e. we include IT workers in our state-level measures of native employment). Column captions denote the dependent variable Δy_{it} for different demographic subgroups. Specifically, Column 1 shows the estimate for total college employment and Column 2 the estimate for college employment of young workers (those with less than 30 years of age).

The first rows of Table 2.3 present the baseline results which controls for state-specific fixed effects, the Bartik controls, and the region-year fixed effects for our nine Census regions. First, let us focus on the result for total employment in Column 1. The coefficient is negative but not estimated precisely. These results are similar to those found in the literature which finds no employment effects of high-skilled immigrants by comparing local labor markets (Kerr and Lincoln 2010, Peri et al. 2014). Column 2, however, now shows a negative estimate for the effects on employment of young college natives. The coefficient of -2.39 is economically meaningful and is estimated precisely (the standard error is .66).

To test whether our results are driven primarily by outliers, Row C removes the five largest state. Rows D and E include the low-skill immigrant shift-share and the native college-educated shift-share, respectively. Neither of these choices changes the magnitude or precision of the estimates by much.

Table 2.4 mirrors Table 2.3, but now we now we also instrument our regressor with the second instrument. Thus, our analysis excludes IT consultants when we construct both our dependent and explanatory variables, as well as our instruments. In Columns 1 and 2, I report the results for the first instrument. The estimates in shown in these columns are qualitatively identical as those in Table 2.3. As before, we do not see an effect for total college employment but find a negative impact on employment of the young. The results differ in that now the coefficient estimates are slightly smaller. The coefficient for young college natives is now in the neighborhood of -3. In Columns 3 and 4, I report the results for the first instrument. The point estimates are qualitatively the same as those found in Columns 1 and 3, respectively, although the magnitude of the coefficients differs in some cases. The main difference lies in how precisely the coefficients are estimated. While the coefficient is significant in the baseline model, once we include the set of controls the standard errors become a bit larger. Though there are many reasons why these effects are sometimes imprecisely estimated, and in some cases may be smaller in magnitude (e.g. the effect varies at the sector level) it is reassuring to find the same qualitative results when we focus on the non-IT population.

2.7 Conclusion

In this paper, I argued that because younger skilled natives and H-1B workers are close in the education-experience space, they are most likely to experience negative effects from increases in H-1B inflows. I identify the effects by using differences in outcome growth across 50 states over the 2000-2009 period. To deal with the endogeneity of immigrant inflows, I have used an instrumental variable strategy that takes advantage of the fact that (1) H-1B visas became more difficult to obtain in 2003-2010 than in 2000-2003 and (2) states differ in how intensively they use H-1Bs in production.

Consistent with previous work, I find no evidence of employment effects on college-educated workers when considering all workers irrespective of their age. I find, however, that young natives are affected negatively by H-1Bs. My estimates imply that increasing the growth rate of H-1B workers by one percentage point of total employment point decreases the growth rate of college-educated native employment by 2-4 percentage points of total employment. These results suggest that young skilled workers are more substitutable with H-1B workers than older natives.

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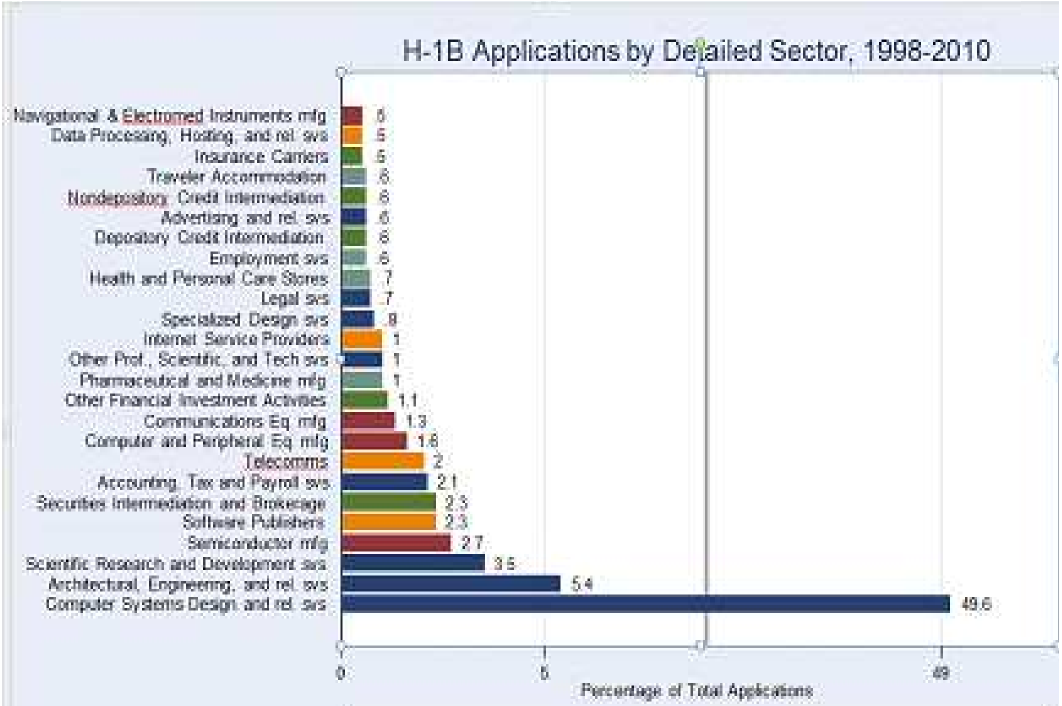

Fig. 2.1.. H-1B Applications by Detailed Sector, 1998-2010

Notes: The figure reports the percentage of total H-1B petitions for the top 25 minor sectors (4-digit NAICS) for over 2.5 million approved H-1B applications for 1998-2010. The data used includes initial approved H-1Bs as well as those for continuing employment. The figure excludes Healthcare and Education which became fully or partially exempt from the cap through the American Competitiveness in the Twenty-First Century Act of 2000. The vertical gray bar denotes a break in the x-axis created to save space. Computer Systems Design includes Computer Systems Design (NAICS 5415) and Management, Scientific and Technical Consulting Services (NAICS 5416).
Source: Form I-129 from the U.S. Citizenship and Immigration Service

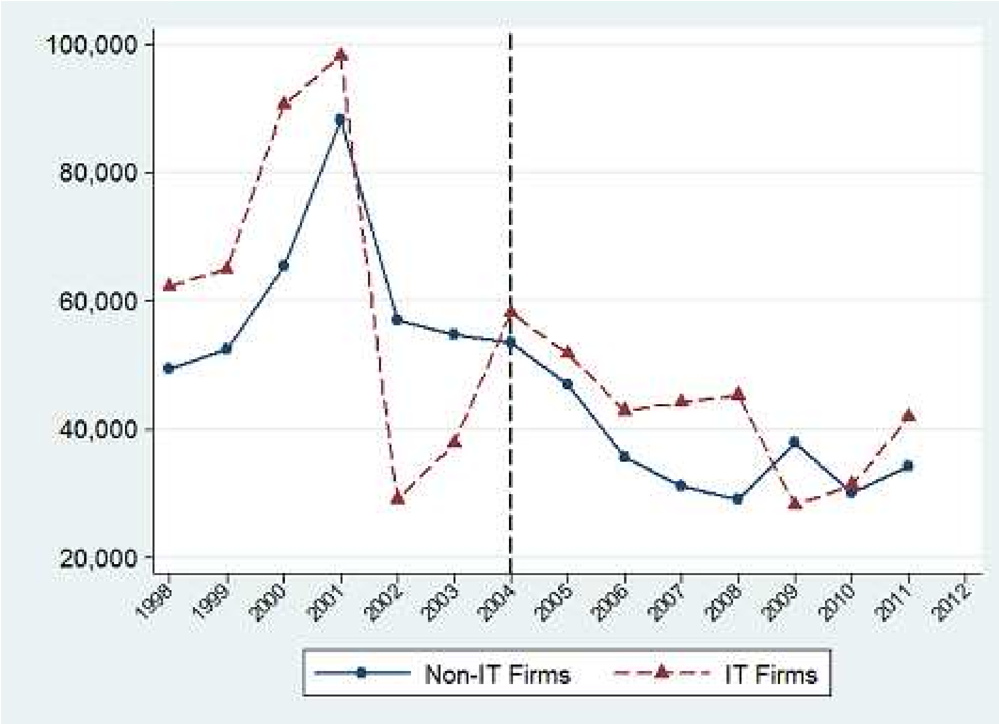

Fig. 2.2.. IT and Non-IT H-1B visas granted for initial employment, 1998-2011

Notes: Figure 2.2 reports the evolution in initial H-1B visas granted to IT and Management Consulting firms ("IT Firms") and for all other firms for the 1998-2011 period. The figure excludes the Healthcare and Education sectors which became fully or partially exempt from the cap through the American Competitiveness in the Twenty-First Century Act of 2000. The vertical line highlights the year in which the cap was lowered from 195,000 visas to 65,000.

Source: Form I-129 from the U.S. Citizenship and Immigration Service

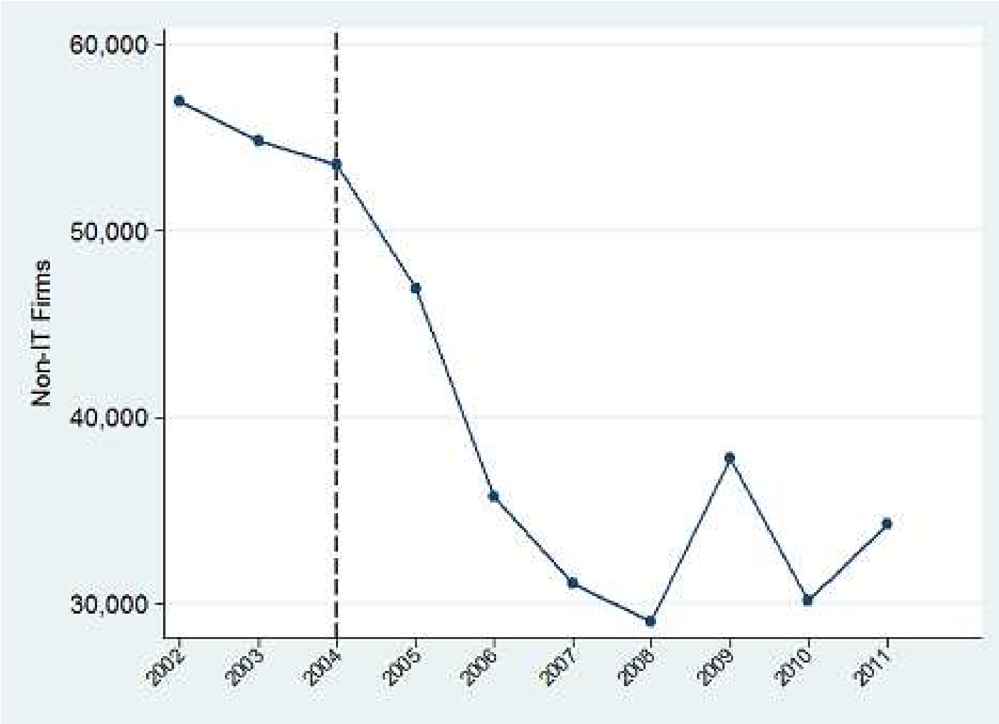

Fig. 2.3.. Non-IT H-1B visas granted for initial employment, 2002-2011

Notes: Figure 2.3 reports the evolution in initial H-1B visas granted to firms other than IT Consultants for the 2002-2011 period. The figure excludes the Healthcare and Education sectors which became fully or partially exempt from the cap through the American Competitiveness in the Twenty-First Century Act of 2000. The vertical line highlights the year in which the cap was lowered from 195,000 visas to 65,000.
Source: Form I-129 from the U.S. Citizenship and Immigration Service

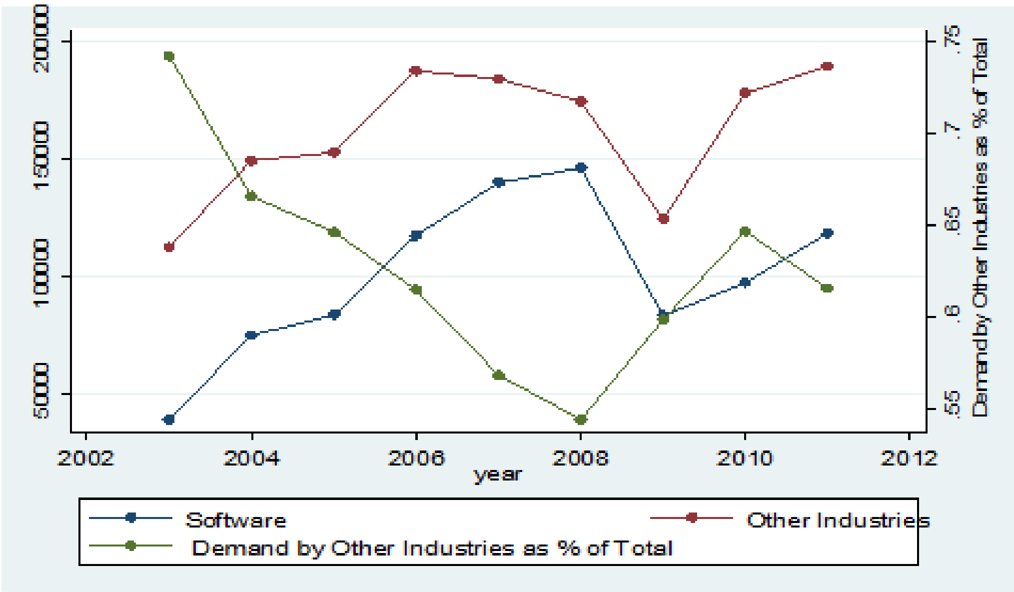

Fig. 2.4.. IT and Non-IT Labor Condition Applications, 2003-2011

Notes: Figure 2.4 reports the evolution in Labor Condition Applications (LCA) submitted to IT and Management Consulting firms ("IT Firms") and for all other firms for the 2003-2011 period. The table also presents the ratio of Non-IT to IT LCAs.

Table 2.1.. Age Profile of H-1B workers in 2000

Initial Petitions in FY 2000		
Age	Total	%
<=20	514	0.4
21-25	37713	27.6
26-30	52070	38.1
31-35	25169	18.4
36-40	11840	8.7
41-45	5129	3.8
46-50	2332	1.7
51-55	1060	0.8
56-60	432	0.3
61-65	123	0.1
>=65	380	0.3

Notes: The table reports the age composition of initial H-1B petitions in FY 2000.

Source: Form I-129 from the U.S. Citizenship and Immigration Service

Table 2.2.. First Stage Estimates

	IV1	IV2	IV1	IV2	IV2 (post-2004)	N
	(1)	(2)	(3)		(4)	(5)
(A) State fixed effects only	-0.53***	-1.40***	-0.26***	-0.88***	-1.10***	500
	(0.03)	(0.07)	(0.02)	(0.08)	(0.11)	
R-Squared	0.753	0.811	0.886		0.700	
(B) Full model (Including region-year FE + Bartik Controls)	-0.55***	-1.42***	-0.30***	-0.83***	-1.02***	500
	(0.03)	(0.08)	(0.02)	(0.07)	(0.10	
R-Squared	0.845	0.854	0.915		0.771	
(C) drop top 5 state	-0.37***	-1.12***	-0.07	-0.98***	-1.23**	450
	(0.09)	(0.13)	(0.15)	(0.20)	(0.28)	
R-Squared	0.640	0.698	0.70		0.520	
(D) College Native Control	-0.56***	-1.41***	-0.30***	-0.83***	-1.03***	500
	(0.03)	(0.08)	(0.02)	(0.07)	(0.10)	
R-Squared	0.846	0.858	0.916		0.771	
(E) Non-College Immigrant Controls	-0.56***	-1.41***	-0.30***	-0.83***	-1.03***	500
	(0.03)	(0.44)	(0.04)	(0.33)	(0.10)	
R-Squared	0.846	0.858	0.916		0.771	

Notes: Columns 1-2 in Table 2.2 present the first stage coefficients for the first and second instruments, respectively. Each row represents a different specification. The dependent variable is the number of initial H-1Bs granted for the appropriate subperiod. In Column 3, I present the first stage coefficients from models that include both instruments simultaneously. Column 4 shows estimates for the second instrument for the subperiods after 2004– where the H-1B cap binds and is fixed at 65,000 visas per year. Row B shows the baseline specification which includes state and region-year fixed effects, and the Bartik for the appropriate groupwhich is included in all subsequent rows. Row C drops the top 5 largest states in 2000. Row D controls for the national growth in the supply of college-educated workers. Row E controls for the shift-share of immigrants without a college degree. All specifications are unweighted. Standard errors are clustered at the state level.

Table 2.3.. Change in Initial H-1B visas granted between 2000-2010: First Instrument

	IV1		N
	Employment: College Educated		
	Total	Young	
	(1)	(2)	(3)
(A) State fixed effects only	0.77	-2.39***	500
	(1.90)	(0.66)	
(B) Full model (Including region-year FE + Bartik Controls)	-4.72	-3.04**	500
	(3.45)	(1.23)	
(C) drop top 5 states	-8.71**	-4.46***	450
	(4.39)	(2.03)	
(D) College Native Control	-4.87	-3.01**	500
	(3.49)	(1.24)	
(E) Non-College Immigrant Controls	-4.87	-3.01**	500
	(3.49)	(1.24)	

Notes: Columns 1 and 2 in Table 2.3 present the instrumental variable results for the first instrument using as the dependent variable the employment of total and young college-educated workers as described on the column heading. The last column reports the number of state-year observations in each specification. Employment data are from the 2000 Census and the ACS for 2001-2009. Row A shows the baseline specification which includes state fixed effects. Row B includes region-year fixed effects and includes the Bartik for the appropriate groupwhich is included in all subsequent rows. Row C drops the top 5 largest states in 2000. Row D controls for the national growth in the supply of college-educated workers. Row E controls for the shift-share of immigrants without a college degree. All specifications are unweighted. Standard errors are clustered at the state level.

Table 2.4.. Change in Initial H-1B visas granted between 2000-2010: First and Second Instruments

	IV1		IV2		N
	Employment: College Educated		Employment: College Educated		
	Total	Young	Total	Young	
	(1)	(2)	(3)	(4)	(5)
(A) State fixed effects only	4.19*	-2.27***	1.02	-5.63***	500
	(2.38)	(0.70)	(5.44)	(2.27)	
(B) Full model (Including region-year FE + Bartik Controls)	-2.02	-3.15**	3.57	-3.14	500
	(3.21)	(1.24)	(10.33)	(4.52)	
(C) drop top 5 states	-4.44	-3.22*	1.89	-0.44	450
	(4.49)	(1.91)	(16.04)	(6.44)	
(D) College Native Control	-2.15	-3.13**	3.46	-3.07	500
	(3.18)	(1.26)	(10.38)	(4.59)	
(E) Non-College Immigrant Controls	-1.90	-3.40**	3.39	-3.04	500
	(3.28)	(1.22)	(10.36)	(4.57)	

Notes: Columns 1 and 2 in Table 2.3 present the instrumental variable results for the first instrument using as the dependent variable the employment of total and young college-educated workers as described on the column heading. Columns 3 and 4 present the estimates for the second instrument. In all columns, results are presented for models where I exclude IT and Management Consultants in the construction of all variables. The last column reports the number of state-year observations in each specification. Employment data are from the 2000 Census and from the ACS for 2001-2009. Row A shows the baseline specification which includes state fixed effects. Row B includes region-year fixed effects and includes the Bartik for the appropriate groupwhich is included in all subsequent rows. Row C drops the top 5 largest states in 2000. Row D controls for the national growth in the supply of college educated workers. Row E controls for the shift-share of immigrants without a college degree. All specifications are unweighted. Standard errors are clustered at the state level.

3. SKILLED IMMIGRANTS AND SERVICE OFFSHORING IN US INDUSTRIES

3.1 Introduction

In recent decades, technological change in information and communications technology (ICT) has made increasingly feasible for businesses to offshore service activities (Freud and Weinhold 2002). As a consequence, US service trade has increased dramatically and has greatly outpaced growth in manufacturing trade (Amiti and Wei 2009). Alongside the rapid increase in service offshoring, there has been a large increase in the employment of skilled immigrants by US businesses. From 1998 to 2006, the number of H-1B visa holders – a key source of skilled immigration to the US—nearly doubled increasing from 261,000 to 500,000 (Borjas 2014).

How has the rising popularity of these two business practices affected the labor market prospects of US workers? The answer to this question is strongly debated by the public and has been addressed extensively in the literature. Instead, this study focuses on a related question that has received much less attention: how has the rise of skilled immigration affected service offshoring? Note that hiring skilled immigrants may lead to higher or lower offshoring so that the direction of overall effect is unclear. As noted by critics of globalization, in some industries such as information technology, cost savings from offshoring and from hiring H-1Bs are similar in magnitude, and thus, firms can use both types of labor somewhat interchangeably (Matloff 2004). In this case, higher immigration leads to lower offshoring by the firm. However, there is also evidence that, in some industries, immigration may facilitate offshoring as H-1Bs assist as liaisons to offshore workers or are themselves offshore workers provisionally in the US for training purposes (Matloff 2004).

In this paper, I empirically evaluate how hiring skilled immigrants by an industry affects service offshoring. Establishing this causal relationship is difficult because variation in input choice across industries –whether from domestic or foreign sources– likely depends on the relative economic conditions industries are experiencing. For instance, a shock to productivity in an industry likely raises demand for all inputs rendering immigrant hiring endogenous to offshoring. To deal with this issue, I exploit variation in H-1B hiring caused by policy changes that took place during 1995-2007. During this time, H-1B hiring increased dramatically as the limit on the number of visas issued each year was raised from 65,000 to 195,000 and then lowered to the original 65,000. These national changes had differential effects on industries because some industries were initially more exposed to the H-1B program.

My analysis requires yearly data on H-1B hiring by industry. Unfortunately, these data are not available to the public. I obtain administrative data on approved H-1B visas from the US Citizenship and Immigration Services (USCIS) under a Freedom of Information Act Request. From these data, I generate industry-level summaries of H-1B employment and link them to a variant of the metric of industry offshoring first developed by Feenstra and Hanson (1999). The service offshoring measure combines data on service imports at the economy-wide level with data on intermediate use from input-output accounts. This metric has been used by Amiti and Wei (2005) and Crino (2009) in papers that examine the impacts of service offshoring on US productivity and labor markets.

My empirical approach consists of regressing service offshoring by industry on a measure of industry exposure to skilled immigration. The analysis employs data on 205 4-digit NAICS US industries for the period from 1995-2007. I find a positive and statistically significant relationship between skilled immigration and service offshoring. My 2SLS estimates suggest that a one standard deviation increase in industry exposure to skilled immigration leads to a .35 standard deviation increase in service offshoring. In the 2000-2001 period, my estimates imply that service offshoring growth is close to 1 percentage point higher for an industry in the 90^{th} percentile of exposure than for an industry in the 10^{th} percentile. These findings are robust to different variable definitions and to controlling for industry output and industry-specific time trends. These findings are in agreement with a setting in which higher high-skill immigration decreases service offshoring costs and thus increases service offshoring by US firms.

This paper is most closely related to a small line of research that considers how immigration affects offshoring (Ottaviano, Peri, and Wright 2010; Barba Navaretti, Bertola, and Sambenelli 2008). I contribute to this literature by focusing on skilled immigration as opposed to immigration in general and by considering service offshoring instead of merchandise offshoring. This paper is also related to a literature that studies the effects of skilled immigration on economic outcomes in the US (Pekkala Kerr, Kerr and Lincoln 2014; Peri, Shih, and Sparber 2014, 2015; Kerr and Lincoln 2010; Hunt and Gauthier-Loiselle 2010; Moser, Voena and Waldinger 2012; Borjas and Doran 2012). Lastly, this paper also relates to a literature that examines how foreign workers –while still in their home country– impact the labor market opportunities of US workers through service offshoring (Amiti and Wei 2009; Crino 2009).

The paper proceeds as follows. Section II provides background on the H-1B program and describes the data used in the study. Sections III and IV discuss measurement, sections V and VI the empirical strategy and identification issues. Section VII presents the results and various robustness exercises. Section VIII concludes.

3.2 Background and H-1B data

As described below, I will measure offshoring at the industry level, and thus we will need industry-level data on H-1B workers. The following section provides relevant background information on the H-1B program to understand better the data and the institutional details that underpin my identification strategy. Finally, I document the industry composition of H-1B employment.

3.2.1 General Background

The H-1B visa is a temporary visa that reserved for skilled foreign workers in professions that "require theoretical or technical expertise in specialized fields". Scientists and engineers fall into this category as well as accountants and medical doctors. With few exceptions, most H-1B recipients have at least a bachelor's degree and are concentrated in just a few occupations. As is well documented, H-1B workers are concentrated in STEM occupations with the lion's share being in computer-related occupations (Kerr and Lincoln 2010). In my data, roughly 70 percent of H-1B applicants work in STEM fields, with 55 percent in computer-related occupations.

3.2.2 The Cap

In 1990, the US Congress set a numerical limit of 65,000 on the number of visas that can be issued in a given year. This limit –usually referred to as the "cap"—has changed over time. Figure 3.1 shows the evolution of the numerical cap from 1990 to 2008, as well as the actual number of cap-bound visas granted during the period. By the middle of the decade, the cap became binding and was provisionally increased to over 100,000 workers for fiscal years 1999 and 2000[1][2]. The cap was further raised to 195,000 for the 2001-2003 period. During this time, the cap did not bind as visa demand fell, which led to the cap being lowered back to 65,000 in 2004. Ever since 2004, the cap has been reached every year, even though an extra 20,000 visas were allocated to foreign workers with graduate degrees from universities in the United States.[3][4]

[1]Knowing this also tells you that creating the measure in 1998 is before the cap ws lifted

[2]Under the American Competitiveness and Workforce Improvement act of 1998

[3]Under the American Competitiveness in the Twenty-First Century Act of 2000, government and some nonprofit research organizations, as well as universities, became exempt from the cap so that the number of visas issued exceeds the cap in many years. In my data, I cannot distinguish which visas are cap-exempt. In Figure 3.1, I report an approximate number of cap-bound visas issued by excluding firms in Healthcare and Education from the computation.

[4]For FY 2006, however, an additional 20,000 additional visas were reserved for workers with graduate degrees from US universities.

3.2.3 Application Process and Data

The application process requires a potential recipient to be sponsored by her prospective employer, and thus the firm and the H-1B worker meet in advance.[5] Once the employer-employee match occurs, the firm must file a form I-129, "Petition for a Nonimmigrant Worker" with the U.S. Citizenship and Immigration Service (USCIS). The USCIS approves the petition if admission conditions are met and the cap has not been reached (GAO 2011).[6] Petitions are approved on a first-come-first-served basis, irrespective of firm or worker characteristics such as industry or occupation. Visas are issued for three years after which the employer can apply for a three-year extension, and this requires filing for a new I-129, though extensions are not subject to the cap.

As previously mentioned, my empirical approach requires data on H-1B employment/wages by industry. Unfortunately, industry employment counts are not known because the government agencies tasked with administering the program do not keep track of H-1B stock, whether at the national level or the industry level (GAO 2011).[7] Instead, I use microdata on all newly cap-bound visas to approximate yearly changes in H-1B employment for a given industry, and thus I estimate my empirical models in first differences. Data on newly issued visas are taken from the form I-129. Because these records are not readily available to the public, I obtain the data from the USCIS under a Freedom of Information Act request. Each I-129 record contains information on the name, 4-digit NAICS industry and location of the sponsoring firm. Moreover, the records contain information on wages, age, country of origin, and occupation of the H-1B recipient. The data span the 1998 to 2012 period.

[5]This can be done in a multitude of ways. For instance, firms can recruit foreigners already in the US as students or from abroad through foreign affiliates and other sources.

[6]If the worker is already in the U.S., the USCIS changes their previous visa status to H-1B and the worker may begin working immediately. Otherwise, the worker takes the approved I-129 to a consular office of the Department of State which reviews the entire package and issues the visa.

[7]There are national estimates of the H-1B population, however. Influential work by Kerr and Lincoln (2010) uses an estimate of the population developed by Lowell (2000). Estimating the population requires combining H-1B gross inflow data with assumptions about the rates at which the stock is depleted.

3.2.4 Sectoral Composition

Figure 3.2 describes the sector composition of H-1B workers subject to the cap. To construct the figure, I use the I-129 data on over 2.5 million petitions approved H-1B visas from 1998 to 2010.[8] The figure underscores why hiring H-1B workers has the potential to have an immediate impact on service offshoring in the US. Around 80 percent of H-1B workers are employed by firms in the professional and business services (PBS), financial, and information sectors. These services can be performed remotely and thus are tradable. Figure 3.3 shows the percentage of H-1B petitions for the top 25 4-digit NAICS employer industries. The pattern outlined in Figure 3.3 further documents that the H-1B program is primarily used by firms in tradable services industries. On this list, 20 industries fall under the tradeable service industry category.

3.3 Measuring Offshoring Shocks

Ideally, we would want to measure offshoring at the industry level using data on imports of intermediate inputs by industry. These data, however, are not readily available because the value of imported intermediates consumed by any given US industry is not known. To deal with this issue, I obtain its proxy (off_{it}) by combining data on intermediate use from input-output accounts –which unfortunately do not distinguish between domestic and foreign supply sources – with data on economy-wide imports. The idea is then to distribute economy-wide imports across domestic industries based the industry's exposure to inputs of a given type, irrespective of the location of the supplier. This approach to measuring offshoring was pioneered by Feenstra and Hanson (1999).

I construct my measure of offshoring by industry, off_{it}, as follows: I first estimate the value of imported intermediates bought at time t by national industry i from

[8]The figure does not include visas granted to Healthcare and Education because these sectors became fully or partially exempt from the cap through the American Competitiveness in the Twenty-First Century Act of 2000

foreign industry j ($\tilde{M}_{ijt}$). I do this by scaling the national value of imports from foreign industry j (IN_{jt}) –from all country sources–by the pre-sample share of output from industry j that is consumed by industry i, $\alpha_{ij0} = \frac{N_{ij0}}{Y_{j0}}$, where Y_{j0} is output in industry j, and N_{ij0} is the value of intermediates consumed by i from j, from both domestic and foreign suppliers. Then, $\tilde{M}_{ijt} = \alpha_{ij0} IN_{jt}$. The share α_{ij0} is measured in the pre-sample to mitigate endogeneity concerns as in Crino (2009).

The second step is to obtain the total value of imported intermediates for each industry i, $\tilde{M}_{it}$, by summing over all service industries j that supply to i. Specifically,

$$\tilde{M}_{it} = \sum_j \tilde{M}_{ijt} = \sum_j \alpha_{ij0} IN_{jt} \tag{3.1}$$

As mentioned in the previous section, we will measure H-1B shocks in first differences due to data constraints. Accordingly, we will also measure offshoring in first differences. The final step in assembling our offshoring metric is to first difference $\tilde{M}_{it}$ and then normalize it by total intermediate input usage in i, N_{it}, so that $\Delta off_{it} = \frac{\Delta \tilde{M}_{it}}{N_{it}}$. This choice of normalization follows Crino (2010).[9] Data on the value of intermediates purchased (N_{ij0} and N_{it}) and output (Y_{i0}) are taken from the annual input-output (IO) use tables from the Bureau of Labor Statistics (BLS), where, N_{ij0}, is the *use* value in 1995, and Y_{i0} is output in 1995 . Data on IN_{jt} are taken from the US International Services tables from the Bureau of Economic Analysis (BEA) for 19 four-digit NAICS industries. [10] In the appendix, I document some summary statis-

[9] In some cases, the normalizing variable is industry output instead of total intermediate usage. The results do not change significantly based on this choice of normalization.

[10] The 19 industries are the following: Software publishers; Telecommunications; Data processing, hosting, related services, and other information services; Securities, commodity contracts, and other financial investments and related activities; Insurance carriers; Agencies, brokerages, and other insurance related activities; Funds, trusts, and other financial vehicles; Automotive equipment rental and leasing; Consumer goods rental and general rental centers; Commercial and industrial machinery and equipment rental and leasing; Lessors of nonfinancial intangible assets (except copyrighted works);Legal services; Accounting, tax preparation, bookkeeping, and payroll services; Architectural, engineering, and related services; Specialized design services; Computer systems design and related services; Management, scientific, and technical consulting services; Scientific research and development services; Advertising and related services.

tics of the offshoring variable. In my sample of industries, the mean yearly change in service offshoring is 0.1 percentage points, with a standard deviation of 0.5 percentage points.

3.4 Measuring Immigration Shocks

To explain the approach I follow to measure an industry's exposure to skilled immigration, let us first recall that our goal is to test whether skilled immigration has an effect on service offshoring in the US. We could carry out such test by regressing the estimated value of offshoring carried out by a given industry –as described in (3.1)– on the number of immigrants hired by that industry. The previous exercise, however, encounters the following two issues. First, as mentioned above, H-1B employment is highly concentrated in a handful of sectors. We thus will only have a handful of treated units, and therefore our results will be strongly contingent on the industry sample that we include in the regressions. Nonetheless, in the regression models described below, I include measures of the direct hiring of H-1Bs by industry as controls.

More importantly, our measure of offshoring distributes national imports of a given commodity across industries based on an industry's consumption share irrespective of whether the supply source of that commodity is foreign or domestic. This imputation approach seems particularly problematic given that the largest H-1B industries are input suppliers to other domestic industries (e.g. IT services). Because of this, if as a result of higher immigration a domestic industry outsources a task to an H-1B industry, and the latter industry offshores this task to its foreign counterpart, a fraction of the task is recorded as being offshored by the domestic industry.

To see more clearly why this issue may be problematic, consider the following scenario. Suppose that firms in the IT services sector in the US always offshore a portion of the work they do for their clients, perhaps because they have affiliated parties in India where IT labor is much cheaper than in the US. Now, a relaxation in immigration policy allows IT firms to hire more immigrants from India and, as a consequence, allows them to offer lower prices to their customers in the US.[11] In response to lower IT prices, an insurance firm now decides to outsource domestically some IT tasks previously performed in-house. The domestic IT sector then offshores some of these tasks to the foreign IT sector.

In this scenario, higher immigrant employment in the IT sector leads to higher within-industry input trade in IT, and thus national imports of IT services rise. Now, our measure of offshoring distributes national IT imports across all industries that use IT services as inputs. Thus, as imports of IT services rise so does measured offshoring in the insurance sector, and also in all other sectors downstream in the supply chain from IT. Because of this, regressing measured offshoring by industry on immigrant employment counts may return biased estimates of the true effect of immigration on offshoring.

It is worth pausing briefly to note that hiring H-1B workers by the domestic IT sector need not lead to higher offshoring, as in the previous example, and thus the effect of skilled immigration on service offshoring is theoretically unclear. For instance, it may be the case that our insurance company does not source IT inputs strictly from domestic firms but also from foreign firms unaffiliated to domestic IT firms. In this situation, as domestic IT prices fall in response to an increase in H-1B hiring by IT firms, the insurance company substitutes away from foreign IT into domestic IT, which leads to lower offshoring.

A simple way to account for the measurement issue just described is to assume that part of the measured offshoring in an industry depends on how many H-1Bs it hires directly but also on how many H-1Bs are hired by that industry's input suppliers. To account for the relative importance of different suppliers for a given industry, we can construct our measure of an industry's exposure to immigration by taking a similar approach to the one we followed to construct (3.1) above. The idea is to distribute a sector's H-1B employment across industries based on an industry's consumption share of inputs from that sector.

[11]This is perhaps because IT offshoring costs depend on the size of foreign employment in the IT sector.

I construct my measure of immigrant exposure by industry i, ID_{it} as follows: I first estimate the number of H-1Bs employed in industry j that are *indirectly* employed by industry i (IDH_{ijt}). Since we are measuring our variables in changes, I do this by scaling the annual *change* in H-1B employment in industry j between t and *t-1* (ΔH_{jt}) by the pre-sample share of output from industry j that is consumed by industry i, $\alpha_{ij0} = \frac{N_{ij0}}{Y_{j0}}$, where Y_{j0} is output in industry j in 1995, and N_{ij0} is the value of intermediates consumed by i from j in 1995, as previously defined. Then, $IDH_{ijt} = \alpha_{ij0}\Delta H_{jt}$.

The second step is to sum over all service industries j that supply to i. Specifically,

$$IDH_{it} = \sum_j IDH_{ijt} = \sum_j \alpha_{ij0}\Delta H_{jt} \tag{3.2}$$

Finally, as before, we normalize by total intermediate inputs by i, N_{it}, so that $\Delta ID_{it} = \frac{IDH_{it}}{N_{it}}$. I proxy for ΔH_{jt} using the number of cap-bound visas for initial employment that are granted to sector j at time t. The data come from the sources previously noted.

3.5 Instrumental Variables Approach

My empirical methodology regresses our measure service offshoring on the measure of immigration exposure just described. Unfortunately, the OLS estimates of such regression may be biased because, for example, it may be the case that latent (possibly time-varying) factors that affect an industry's decision to offshore also affect H-1B employment by that industry's suppliers. To fix ideas, consider the following scenario. Assume that technical change takes place in the financial services industry. In response, the industry offshores more IT services but also decides to outsource some of these services domestically, which induces the domestic IT industry to hire more H-1B workers to meet higher demand.

To deal with this potential issue, I construct instruments that leverage variation in H-1B flows that depend on (1) the level of admissions set by the government and (2) macroeconomic conditions that are arguably exogenous to offshoring shocks to any given industry. These national shocks have a different impact on industries because some industries are always more exposed to the H-1B program than others. The intuition for the instrument is as follows. For some reason, some industries always want to hire more H-1Bs than others. For example, because of differences in production technology some industries always use more STEM labor than others so that their quantity of H-1Bs demanded is always higher: IT consulting firms always demand more H-1B workers than firms in finance.[12] When national shocks to the supply or the demand for visas hit the market, these firms are more affected by the common shock.

To help us describe the construction of the instruments, and its identification assumptions, let us first consider the following simplified model of H-1B industry employment in a setting where the national demand for visas exceeds supply and thus the cap binds in a given year. Abstracting away from the timing of the application, and because visas are granted independently of the industry of the applicant, we can approximate the number of newly hired H-1Bs by industry i in year, h_{it}, with the following quantity

$$h_{it} = \frac{app_{it}}{\sum_j app_{jt}} \times cap_t = app_{it} \times \frac{cap_t}{\sum_j app_{jt}} \tag{3.3}$$

where app_{it} stands for visa demand (i.e. the number of applications industry i submits in year t). The level of the cap is given by the term cap_t, and $\sum_j app_{jt}$ is national demand. From the previous expression we see that H-1B hiring by an industry depends on how competitive the application process is in that given year,

[12]Other industry characteristics may also generate these differences. For example, some industries have stronger ties to foreign countries perhaps because firms in the industry have affiliated partners in those countries. For firms in these industries it is less costly to find and recruit foreign workers and thus hire relatively more of them.

which is represented by the ratio, $\frac{cap_t}{\sum_j app_{jt}}$. An increase in national demand, or a decrease in the level of the cap, makes it more difficult to obtain visas in a given year. As well, from (3.3) we see that industries that demand a larger number of visas will tend to hire more workers.

I model industry i's visa demand at time t as

$$app_{it} = c_{i0} + \epsilon_{it} \tag{3.4}$$

where c_{i0} is a fixed term which captures stable differences in H-1B demand across industries. The second term in (3.4) is a time-varying component that captures shocks to labor demand and is possibly correlated with offshoring shocks.
Substituting the previous expression into (3.3) yields

$$h_{it} = app_{it} \times \frac{cap_t}{\sum_j app_{jt}} = c_{i0} \times \frac{cap_t}{\sum_j app_{jt}} + \epsilon_{it} \times \frac{cap_t}{\sum_j app_{jt}} \tag{3.5}$$

Note that $c_{io} \times \frac{cap_t}{\sum_j app_{jt}}$ is independent of time-varying industry-specific labor demand shocks ϵ_{it} and can be used as an instrumental variable for h_{it}. Since c_{io} is unobservable, I proxy for it using h_{i0}, the number of applications in the first year available in my data, so that my instrument for h_{i0}, h_{it}^{IV} is given by $h_{it}^{IV} = h_{i0} \times \frac{cap_t}{\sum_j app_{jt}}$.

Now, because h_{i0} also depends on ϵ_{i0}, our instrument is only valid if our errors are not correlated over time, as would be the case if for example, these same group of industries are always more likely to experience positive shocks to offshoring. In the next section, I try to account for this possibility by accounting for differential trends in offshoring across industries.

With instruments for industry H-1B inflows in hand, I use a similar procedure as above to construct the instruments for the indirect shocks, namely

$$ID_{it}^{IV} = \sum_j \alpha_{ij0} \frac{h_{it}^{IV}}{N_{it}} \tag{3.6}$$

As discussed in section II, the H-1B cap binds in most years. Because of this, the expression in (3.3) is a reasonable approximation of the true development of the H-1B inflows for most years in my data. The quantity in (3.3), however, poorly approximates inflows for years where the cap does not bind (i.e. when the cap does not bind the number of visas granted equals the quantity demanded, $h_{it} = app_{it}$), as with fiscal years 2002 and 2003 – where the cap was at its highest point.

To deal with this issue, I use the fact that during economic expansions, the most exposed sectors increase H-1B demand at a higher rate than others. Conversely, they also contract a higher rate. Keeping with the notation used above (i.e. $app_{it} = c_{i0} + \epsilon_{it}$), we now assume that $\epsilon_{it} = b_{i0} \times GDP_t + v_{it}$, where b_{i0} is an industry-specific scaling factor, GDP_t is GDP at time t, v_{it} is our error term which is potentially correlated with offshoring shocks, and where $b_{i0}GDP_t$ and v_{it} are uncorrelated. Thus we have that H-1B demand is given by

$$app_{it} = c_{i0} + b_{i0} \times GDP_t + v_{it} \tag{3.7}$$

The idea is now to use $b_{i0}GDP_t$ as a second instrument for h_{it} to account for the years where the cap does not bind. As before, we proxy for b_{i0} with h_{i0}.

The scatterplot in Figure 3.4 relates the explanatory variable ΔID_{it} with the instrumental variable in (3.6). Each dot stands for one of 2460 industry-year observations. The scatterplot shows a strong relationship between the two variables and thus underscores the predictive power of the instrument. The slope of the regression line is .48 and is estimated precisely with a robust t-statistic of 10.47. The corresponding r-squared is .68.

3.6 Empirical Section

I take to the data the following specifications:

$$\Delta off_{it} = \mu_t + \beta \Delta ID_{it} + \alpha Trends_{it} + \varepsilon_{it} \tag{3.8}$$

where Δoff_{it} is the annual change in offshoring for industry i as described in (3.3) . Period fixed effects μ_t control for shocks common to all industries in a given time interval. As well, since (3.8) is expressed in first differences, we have already accounted for permanent differences across industries that may be correlated with our main variable but also with an industry's level of offshoring. The error term is given by ε_{it}. We estimate our β coefficient using 2SLS where our instruments are as previously described. I cluster standard errors at the level of the industry.

Recall that we want to use the fact that because of fixed differences in production technology, some industries will always be more exposed to immigration shocks than others, and this happens independently of other factors that affect offshoring. A concern, however, is that these fixed differences may nonetheless be correlated with other factors that independently create the offshoring patterns that we observe. For example, industries experiencing rapid technological change, in the years before the increase in the H-1B cap, may have simultaneously increased their demand for foreign inputs alongside their demand for outsourced domestic inputs, and thus H-1B demand by their suppliers. If these positive shocks are correlated over time (i.e. if these same set of industries continued to experience these positive technology shocks) our tests will return upwardly biased estimates of the effect of interest.

To address this concern, I include in my regressions the vector $Trends_{it}$, which stands for a vector of controls designed to capture trends that may correlate with our instrument. The first element in the vector is the mean annual log change in offshoring, from 1990 to 1995. The second element in our vector of pre-trend controls is an industry-specific fixed effect. Since my models are estimated in first-differences, this latter exercise controls for linear trends in our outcomes of interest possibly correlated with our instruments.

3.7 Results

In this section, I report the estimates of the effect of high-skilled immigration on service offshoring in the US. I collect these estimates in Tables 3.1 and 3.2. Each column of the tables reports the estimates from a different specification of the model in Equation (3.8) above. In all specifications, the dependent variable is the yearly change in our offshoring measure. As well, all specifications include period fixed effects. Specifications vary based on the mode of estimation (OLS vs. IV), on variable construction (e.g. alternate normalization choices), and on the inclusion of additional control (e.g. output, industry fixed effects). All specifications cluster standard errors at the industry level. The sample spans the 1995-2007 period for 205 BLS industries where industries are for the most part defined at the 4-digit NAICS. All variables are normalized by their sample standard deviation to aid with the interpretation of my estimates.

The first column of Table 3.1 shows the OLS estimates. I find that a positive correlation between skilled immigration and service offshoring. This correlation is consistent with a scenario in which greater skilled immigration lowers service offshoring costs and thus leads to greater offshoring by US firms. Interpreting this correlation as causal is difficult since skilled immigration is likely dependent on other factors that independently affect offshoring. To make progress on this front, we estimate our models using 2SLS. In Column 2, I show the baseline 2SLS estimates that include only period fixed-effects as controls. The results remain qualitatively the same, but now the point estimates are larger. My 2SLS estimates suggest that a one standard deviation increase in industry exposure to skilled immigration leads to a .53 standard deviation increase in service offshoring. In the 2000-2001 period, my estimates imply that service offshoring growth is close to 1 percentage point higher for an industry in the 90^{th} percentile of exposure than for an industry in the 10^{th} percentile. In both the OLS and IV estimates, the estimates are significant at the 10 percent level. Not surprisingly given the strong relationship between the instrument and my dependent variable described in Figure 3.4, the instruments are very strong with F-statistics being always larger than 100.

In columns 3 and 4 of Table 3.1, I test the robustness of the results to changes in variable definitions and sample selection. In column 3, I normalize the offshoring and immigration variables by industry output instead of by total intermediate usage. The point estimates are slightly smaller in magnitude where the coefficient is now .37. The estimates are still significant at the 10 percent level. Finding that these results are similar is perhaps not surprising given that other studies using similar offshoring measures have found that normalization choice seems to be of second order importance (Crino 2010). In column 4, I test the robustness of the results to allowing the shares α_{ij0} to vary over time. The results are robust to this variable construction choice with point estimates remaining of similar magnitude although the coefficients are somewhat less precisely estimated. Column 5 drops the top most dependent sectors regarding their exposure to skilled immigration. Column 6 includes output as a control. In both cases, results remain qualitatively the same.

Table 3.2 presents estimates from additional robustness exercises as well as estimates of the *direct* effects of skilled immigration on offshoring. I obtain these direct estimates by regressing our measure of offshoring on the normalized H-1B employment change in an industry. In Column 1 we see that our indirect effect estimates are robust to the inclusion of the direct shock variable, as well as to estimating the model without the 1995-1999 time interval. The direct estimates in Column 1 and Column 2, however, suggests a negative direct effect of skilled immigration on offshoring.

Though the point estimates fall in magnitude, the indirect coefficients survive the inclusion of industry-fixed effects in Column 3, and the inclusion of output and industry-fixed effects in Column 4. This is not the case for the direct estimates which become insignificant once we include industry-fixed effects. The last column includes as a control the measure of expected offshoring growth discussed above. The inclusion of the expected offshoring control in Column 5, however, brings my estimated indirect effect to 0, and thus our claims that skilled immigration has a causal effect on service offshoring should be interpreted with some caution.

3.8 Conclusion

Using new microdata on approved H-1B visas for the 1995 to 2007 period, I have documented that the large increase in skilled immigrant employment in the US during this period was undertaken by firms in tradeable service sectors such professional and business services. I have then estimated the effect of this increase in immigrant employment on service offshoring by US industries. I instrument immigrant flows with variables that leverage changes the national level of H-1B admissions and on macroeconomic conditions that are exogenous to any particular industry. I find evidence that hiring skilled immigrants leads to higher offshoring at the industry level.

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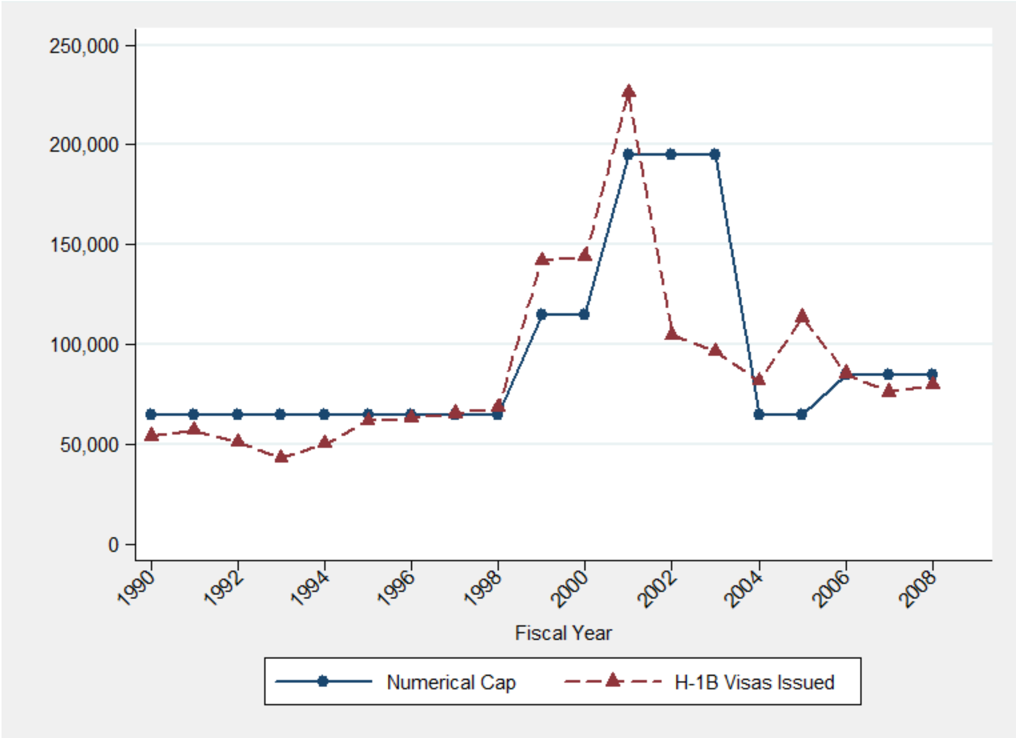

Fig. 3.1.. The H-1B numerical cap and number of approved visas subject to the cap, 1990-2008

Notes: Figure 3.1 shows the evolution of the H-1B numerical cap and the actual number of visas issued subject to the cap for 1990-2008. The figure excludes visas issued to Healthcare and Education because these sectors became fully or partially exempt from the cap through the American Competitiveness in the Twenty-First Century Act of 2000. Data on aggregate visa issuances from 1990 to 1997 are taken from Kerr and Lincoln (2010). Data on aggregate visa issuances from 1998 to 2008 are computed using data from the Form I-129

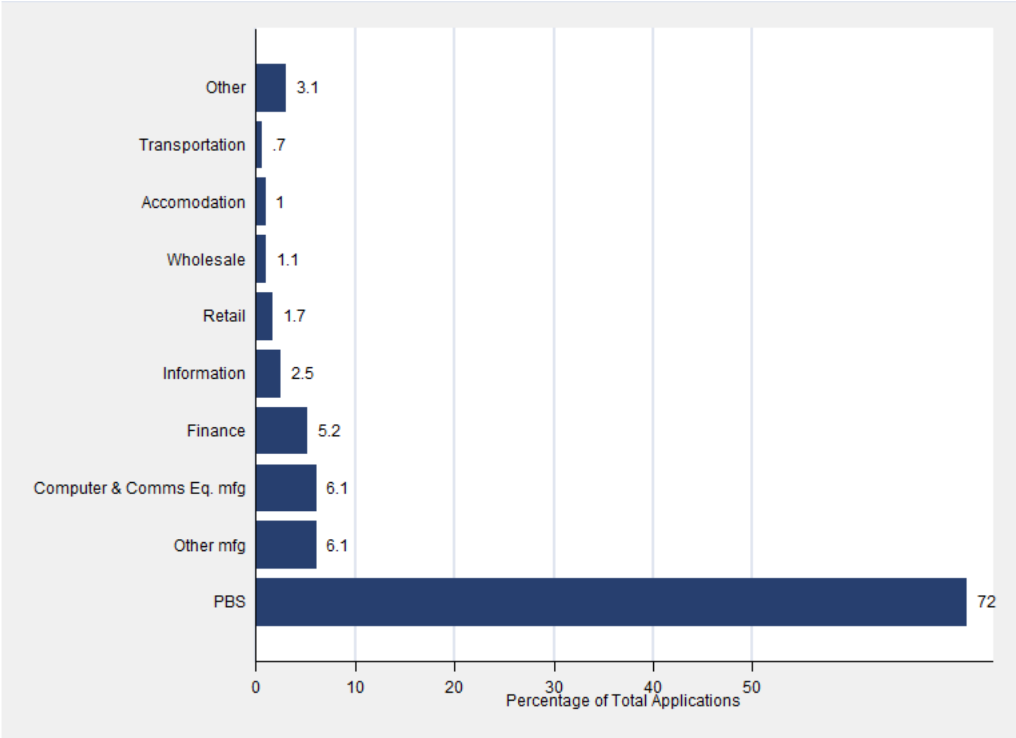

Fig. 3.2.. H-1B Applications by Major Sector, 1998-2010

Notes: Figure 3.2 reports the major sector (two-digit NAICS) distribution of over 2.5 million approved H-1B applications for 1998-2010. The data used includes new approved H-1Bs as well as those for continuing employment. The figure excludes Healthcare and Education, which became fully or partially exempt from the cap through the American Competitiveness in the Twenty-First Century Act of 2000. PBS stands for Professional and Business Services. Source: Form I-129 from the U.S. Citizenship and Immigration Service

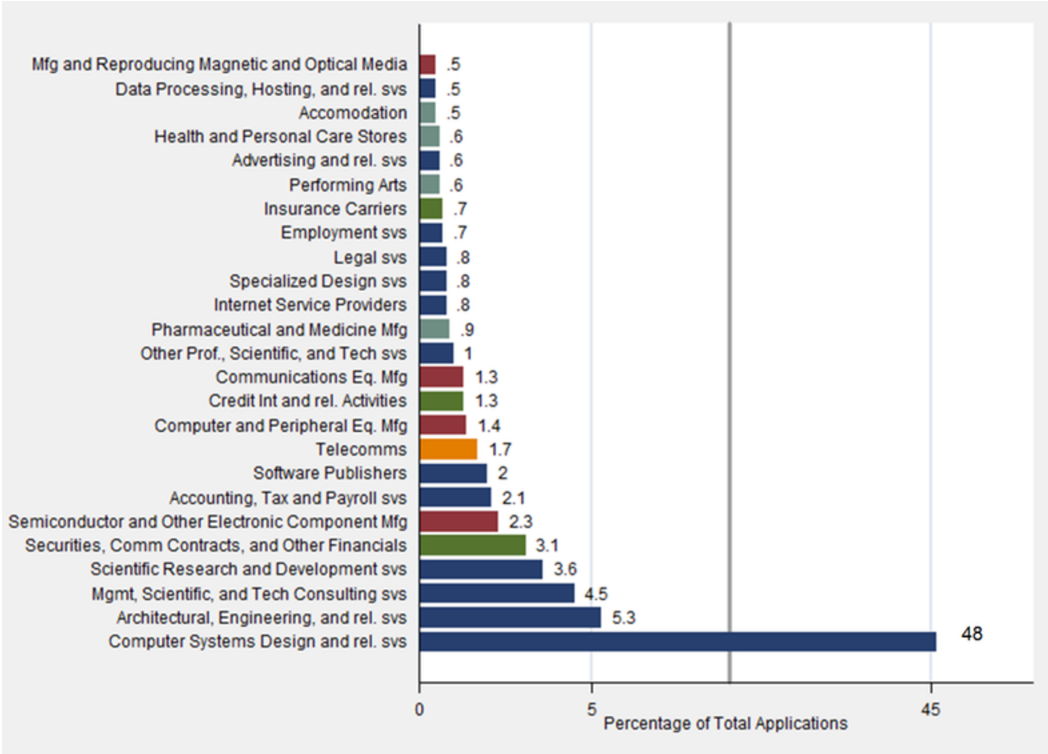

Fig. 3.3.. H-1B Applications by Detailed Sector, 1998-2010

Notes: Figure 3.3 reports the percentage of total H-1B petitions for the top 25 minor sectors (4-digit NAICS) for over 2.5 million approved H-1B applications for 1998-2010. The data used includes new approved H-1Bs as well as those for continuing employment. The figure excludes Healthcare and Education which became fully or partially exempt from the cap through the American Competitiveness in the Twenty-First Century Act of 2000. The vertical gray bar denotes a break in the x-axis created to save space. Each bar representing a minor sector is colored according to the major sector to which it belongs.
Source: Form I-129 from the U.S. Citizenship and Immigration Service

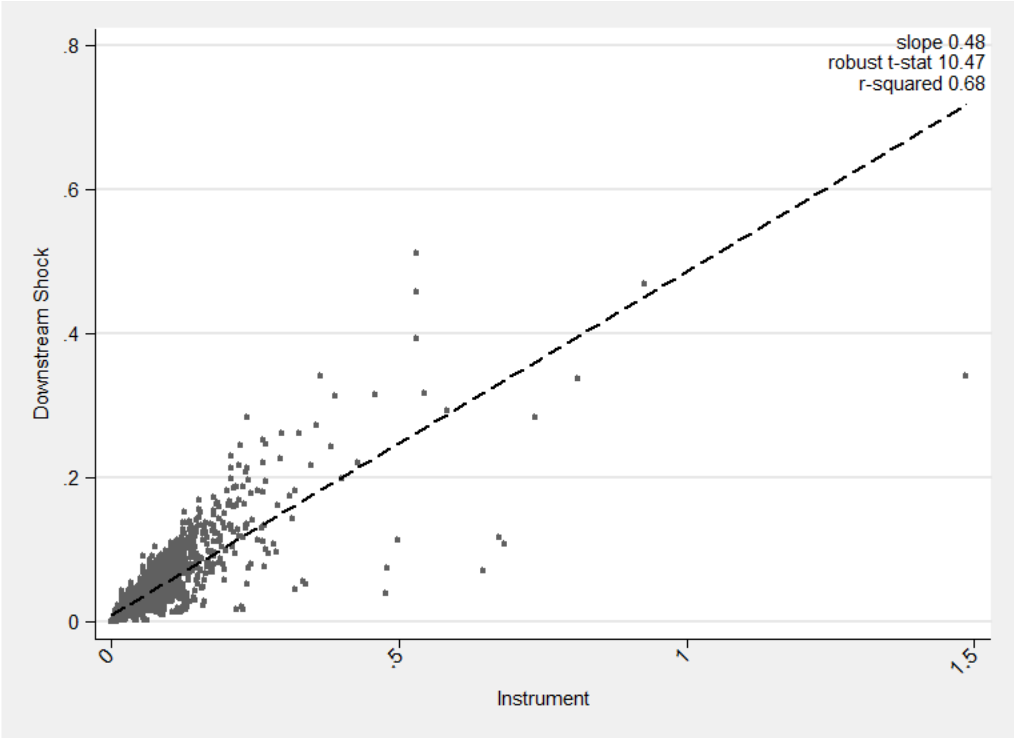

Fig. 3.4.. Downstream shock and Instrumental Variable

Notes: The scatter plot shows the relationship between the measure of industry downstream shocks and the instrumental variable. Each point in the scatterplot represents an industry-year pair for 185 industries for 1995-2007, excluding the years when the cap does not bind (i.e. 2002 and 2003). The downstream shock is scaled by 100 to improve readability. The t-statistics are computed using robust standard errors.
Source: Form I-129 from the U.S. Citizenship and Immigration Service

Table 3.1.. Industry-Level Offshoring Regressions

	Dependent variable: ΔOffshoring					
	(1)	(2)	(3)	(4)	(5)	(6)
H-1B Indirect Exposure	0.35**	0.53**	0.37**	0.48*	0.36***	0.53**
	(2.30)	(2.21)	(2.06)	(1.91)	(5.56)	(2.20)
ΔLog Output						-0.08**
						(-2.38)
Industry Fixed Effects	No	No	No	No	No	No
Number of observations	2665	2665	2665	2460	2600	2665
Number of industries	205.00	205.00	205.00	205.00	200.00	205.00
F-Statistic	X	488.18	111.73	1024.43	442.52	511.34

Notes: Each column in Table 3.1 shows the results from industry-year regressions where the dependent variable is the change in offshoring from 1995 to 2007. To construct the H-1B indirect exposure measure, I first multiply the direct shocks to the industrys suppliers with their share in total intermediate input costs, and then sum across all suppliers. Direct shocks are defined as the change in the H-1B wage bill normalized by industry output. The first instrumental variable for downstream shocks interacts the indirect dependency measure with the cap. The second instrument interacts indirect dependency with a dummy that equals 1 for the 2001-2002 and 2002-2003 intervals. Indirect dependencies are constructed using data on H-1B visas issued in 1998-1999 and data from the 1997 Benchmark IO tables. Column 1 shows the OLS estimate. Column the baseline 2SLS estimate. Column 3 normalizes variables by industry output instead of by total intermediate use. Column 4 lets the shares α_{ij0} vary over time when constructing the variables. Column 5 drops the top most dependent sectors regarding their exposure to skilled immigration. The specification in column 6 includes output as a control. All specifications are unweighted and include period and industry fixed effects. Standard errors are clustered at the industry level.

Table 3.2.. Industry-Level Offshoring Regressions

	Dependent variable: ΔOffshoring				
	(1)	(2)	(3)	(4)	(5)
H-1B Indirect Exposure	0.57**	0.67**	0.31*	0.31*	0.05
	(2.21)	(2.46)	(1.68)	(1.68)	(0.84)
Direct Exposure	-0.26**	-0.25**	0.16	0.15	-0.06*
	(-2.06)	(-2.48)	(0.89)	(0.88)	(-1.78)
ΔLog Output				0.01	
				(1.26)	
Mean Change in Offshoring (1993-1995)					562.34***
					(29.13)
Industry Fixed Effects	No	No	Yes	Yes	No
Number of observations	2478	1521	2478	2478	2665
Number of industries	192.00	192.00	192.00	192	192
F-Statistic	126.51	122.59	281.12	254.09	189.61

Notes: See Table 3.1. Column 1 shows the baseline 2SLS estimates for direct and indirect shocks. The specification in Column 2 includes industry-fixed effects as controls, and Column 3 includes output and industry fixed effects. Column 4 includes as a control the measure of expected offshoring growth discussed above. The last Column estimates the models without the 1995-1999 period. All specifications are unweighted and include period and industry fixed effects. Standard errors are clustered at the industry level.

3.10 Appendix

Table 3.3.. Summary Statistics

	N	Mean	Std. Dev.	Min	Max
Change in Offshoring	2665	0.001834	0.005786	-0.0035	0.116419
Indirect Shock	2665	0.00039	0.000429	0	0.005107
Direct Shock	2478	0.000303	0.001448	0	0.037175

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