Understanding the Economic Impact of the H-1B Program on the U.S.*

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Abstract

Over the 1990s, the share of foreigners entering the US high-skill workforce grew rapidly. This migration potentially had a significant effect on US workers, consumers and firms. To study these effects, we construct a general equilibrium model of the US economy and calibrate it using data from 1994 to 2001. Built into the model are positive effects high skilled immigrants have on innovation. Counterfactual simulations based on our model suggest that immigration increased the overall welfare of US natives, and raised workers' incomes by 0.2% to 0.3%. High-skill immigration did, however, have significant distributional consequences. In the absence of immigration, wages for US computer scientists would have been 2.6% to 5.1% higher in 2001. US workers switch to other occupations, reducing the number of US born computer scientists by 6.1% to 10.8%. On the other hand, complements in production benefited substantially from immigration, and immigration also lowered prices and raised the output of IT goods by between 1.9% and 2.5%, thus benefiting consumers. Finally, firms in the IT sector earned substantially higher profits due to immigration.

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An increasingly high proportion of the scientists and engineers in the US were born abroad. At a very general level, the issues that come up in the discussion of high-skill immigration mirror the discussion of low-skill immigration. The most basic economic arguments suggest that both high-skill and low-skill immigrants: (1) impart benefits to employers, to owners of other inputs used in production such as capital, and to consumers, and (2) potentially, impose some costs on workers who are close substitutes (Borjas, 1999). Evidence suggests, however, that the magnitude of these costs may be substantially mitigated if US high-skill workers have good alternatives to working in sectors most impacted by immigrants (Peri et al., 2013; Peri and Sparber, 2011). Additionally, unlike low-skill immigrants, high-skill immigrants contribute to the generation of knowledge and productivity through patenting and innovation, both of which serve to shift out the production possibility frontier in the US and may also slow the erosion of the US comparative advantage in high tech (Freeman, 2006; Krugman, 1979).

In this paper we study the impact that the recruitment of foreign computer scientists on H-1B visas had on the US economy during the Internet boom of the 1990s. An H-1B is a non-immigrant visa allowing US companies to temporarily employ foreign workers in specialized occupations. The number issued annually is capped by the federal government. During the 1990s, we observe a substantial increase in the number of H-1B visas awarded to high-skill workers, with those in computer-related occupations becoming the largest share of all H-1B visa holders (U.S. General Accounting Office, 2000). Given these circumstances, it is of considerable interest to investigate how the influx of H-1B visa holders during this period might have affected labor market outcomes for US computer scientists and other US workers, and overall productivity in the economy.

We focus on the period 1994 to 2001 for a number of reasons. During the latter half of the 1990s, the US economy experienced a productivity growth attributable, at least in part, to the IT boom, facilitated by the influx of foreign talent (Jorgenson et al., 2015). At the same time, the recruitment of H-1B labor by US firms was at or close to the H-1B cap during this period, enabling us to treat foreign supply as determined by the cap. Finally, more recent growth of the IT sector in India and changes in the law authorizing the H-1B have complicated the picture since 2001.[1] Nonetheless, in an appendix we show that our model does a reasonable job of predicting employment and wages all the way till 2015.

In earlier work evaluating the impact of immigration on Computer Science (CS) domestic workers, we constructed a dynamic model that characterizes the labor supply and demand for CS workers during this period (Bound et al., 2015). We built into the model the possibility that labor demand shocks, such as the one created by the Internet boom, could be accommodated by three sources of CS workers: recent college graduates with CS degrees, US residents in different occupations who switch to CS jobs, and high-skill foreigners. Furthermore, our model assumed firms faced a trade-off when deciding to employ immigrants: foreigners were potentially

[1] See Khanna and Morales (2015) for a long-run extension of this work that also models the Indian IT sector.

either more productive or less costly than US workers, but incurred extra recruitment/hiring costs.

The approach we took in that analysis was distinctly partial equilibrium in nature – that is, we focused on the market for computer scientists and ignored any wider impacts that high-skill immigration might have on the US economy (Nathan, 2013). While we believe that approach could be used to understand the impact that the availability of high-skill foreign labor might have had for this market, it precludes any analysis of the overall welfare impact of the H-1B program in particular, or of high-skill immigration more generally.

The implications of the model regarding the impact of immigration on the employment and wages of native workers depended on the elasticity of labor demand for computer scientists. As long as the demand curve sloped downwards, the increased availability of foreign computer scientists would put downward pressure on the wages for computer scientists in the US. However, in the case of computer scientists, other factors may affect this relationship. First, even in a closed economy, the contribution of computer scientists to innovation reduces the negative effects foreign computer scientists might have on the labor market opportunities for native high-skill workers. In addition, in an increasingly global world, US restrictions on the hiring of foreign high-skill workers are likely to result in greater foreign outsourcing work by US employers. Indeed, if computer scientists are a sufficient spur to innovation, or if domestic employers can readily offshore CS work, any negative effects that an increase in the number of foreign CS workers might have on the domestic high-skill workforce would be offset by increases in the domestic demand for computer scientists.

In Bound et al. (2015), we used data on wages, domestic and foreign employment, and undergraduate degree completions by major, during the late 1990s and early 2000s to calibrate the parameters of our model to reproduce the stylized facts of the CS market during the analytic period (1994 to 2001). Next, we used the calibrated model to simulate counterfactuals on how the economy would have behaved if firms had been restricted in the number of foreign CS workers they could hire to the 1994 level. Conditional on our assumptions about the elasticity of the demand curve for computer scientists, our simulation suggests that had US firms faced this restriction, CS wages and the number of Americans working in CS and the enrollment levels in US computer science programs would have been higher, but the total number of CS workers in the US would have been lower.

The predictions of our model did not depend on the specific choice we made for non-calibrated parameters, with one important exception: crowd out in the market for computer scientists depended crucially on the elasticity of demand for their services. Ideally, we would have been able to use exogenous supply shifts to identify the slope of the demand curve for computer scientists, as we use exogenous shifts in demand to identify supply curves. In other contexts, researchers have treated the increase in foreign born workers in the US economy as exogenous.

However, in the current context, immigration law in the US implies that most of the foreign born and trained individuals who migrate to the US to work as computer scientists do so because they are sponsored by US based firms. Thus, it seems implausible to treat the number of foreign born computer scientists in the US as an exogenous increase in supply. In the end, without credible sources of identifying information, we resorted to parametrically varying the elasticity of the demand for computer scientists.

In the current analysis, we take a different track. We interpret the arguments about the potential productivity effects of high-skill immigrants in terms of models of endogenous technical change. Within the context of a simple general equilibrium model of the US economy, we link productivity increases in the U.S. economy during the 1990s to increases in the utilization of computer scientists in the economy. This allows us to derive the demand curve for computer scientists.

Within the context of our model, it is possible to understand the effect that the availability of high-skill foreign workers has on the earnings of both high and low-skill workers, the goods available in the economy, and profits in the high-tech sector of the economy. However, our conclusions are dependent both on our modeling choices and on values of our calibrated parameters. For this reason, we do extensive sensitivity analyses to determine which of our conclusions are robust.

A key feature of high-skill immigrants is that they contribute to innovation. While this point is well understood, we know of no earlier work that has tried to quantify the magnitude of this effect within the context of an explicit model of the US economy. The magnitude of this effect is important because it speaks to the magnitude of any first-order gains to US residents of high-skill immigration, and because it has a direct influence on the slope of the labor demand curve for close substitutes for high-skill immigrants.

Our model is limited in a number of important respects. While we allow for endogenous technical change, we incorporate trade in a very stylized manner and do not allow explicitly for outsourcing.[2] As such, we think our model captures relatively short-run effects of H-1B immigration. Although in this sense our model is different from models incorporated in recent work by, for example, Grossman and Rossi-Hansberg (2008) or di Giovanni et al. (2015), we believe that it captures important elements of the current debate about the H-1B program.

We review this literature in detail, and describe the market for CS workers in section 1. Section 2 presents the model we build to characterize the market for CS workers when firms can recruit foreigners. In section 3, we describe how we calibrate the parameters of the model and in section 4 we run counterfactual simulations where firms have restrictions on the number of foreigners they can hire. Section 5 talks about welfare changes under this counterfactual scenario. We

[2] Available evidence suggests that outsourcing options were somewhat limited during the 1990s (Liu and Trefler, 2008), though it is not clear that this is still true.

conclude with section 6, which presents a discussion based on the results of the analysis.

1 The Market for Computer Scientists in the 1990s

1.1 The Information Technology Boom of the Late 1990s

The mid 1990s marks the beginning of the use of the Internet for commercial purposes in the United States, and a concomitant jump in the number of Internet users. One indicator of a contemporaneous increase in demand for IT workers is the rise of R&D expenditures among firms providing computer programming services, and computer-related equipment. Specifically, the share of total private R&D expenditures for firms in these sectors increased from 19.5% to 22.1% between 1991 and 1998.[3] The entry and then extraordinary appreciation of tech firms like Yahoo, Amazon, and eBay provide a further testament to the boom in the IT sector prior to 2001.

These changes had a dramatic effect on the labor market for computer scientists. According to the Census, the number of employed individuals working either as computer scientists or computer software developers increased by 161% between the years 1990 and 2000. In comparison, during the same period, the number of employed workers with at least a bachelor degree increased by 27% and the number of workers in other science, technology, engineering, and math (STEM) occupations increased by 14%.[4] Table 1 shows that computer scientists as a share of the college-educated workforce and the college-educated STEM workforce was rising before 1990, but increased dramatically during the 1990s. Indeed, by 2000 more than half of all STEM workers were computer scientists. In Figure 1a, we use CPS data to show a similar pattern, additionally showing that the growth of CS employment started in the second half of the decade - a period corresponding to the dissemination of the Internet.

The Internet innovation affected educational choices as well as employment decisions. We show in Figure 1b that the CS share of both all bachelor's degrees and of STEM major degrees increased dramatically during this period, in both cases rising from about 2% of all Bachelor degrees granted in 1994 to almost than 3.5% in 2001.

The behavioral response would be different if the boom was only a temporary response to the Y2K bug. The employment and educational evidence, however, suggests that many expected this boom, as a response to technological innovations, to be permanent. Indeed, in 1997, the Bureau of Labor Statistics (BLS) projected a steady increase in CS employment after the turn

[3] Bound et al. (2015) calculation using Compustat data

[4] Here and elsewhere, our tabulations restrict the analysis to workers with at least a bachelor degree and use the IPUMS suggested occupational cross walk. Other STEM occupations are defined as engineers, mathematicians and computer scientists. For more details see Appendix A.2.

of the century. More specifically, the BLS predicted that between 1996 and 2006 "Database administrators, computer support specialists, and all other computer scientists" would be the fastest growing occupation and "Computer engineers" would be the second fastest in terms of jobs. Furthermore, they predicted that "Computer and data processing services" would grow by 108% – the fastest growing industry in the country.[5]

In addition to affecting employment and enrollment decisions, there is also empirical evidence that CS wages responded to expanding Internet use. From the Census, we observe an 18% increase in the median real weekly wages of CS workers between 1990 and 2000. The CPS presents similar patterns: starting in the year 1994 we observe in Figure 1c that wages of computer scientists increased considerably when compared to both workers with other STEM occupations and all workers with a bachelor degree. In fact, while during the beginning of the 1990s, the earnings of CS workers were systematically lower than other STEM occupations, the wage differential tends to disappear after 1998.

1.2 Contribution of Immigration to the Growth of the High Tech Workforce

Employment adjustments in the market for computer scientists occurred disproportionately among foreigners during the Internet boom. Evidence for this claim is found in Table 1 and Figure 1d, where we use Census and CPS data to compare the share of foreign computer scientists to the share of foreign workers in other occupations.[6] In the second half of the 1990s, the foreign fraction of CS workers increased considerably more than both the foreign fraction of all workers with a bachelor degree and the foreign fraction of all workers in a STEM occupation. In particular, in 1994 the share of foreigners working in CS was about the same as the share working in other STEM occupations, but later in the decade, during the boom in Internet use, the share of foreigners among all CS workers rose steeply, comprising about 30% of the increase in all CS workers during this period.

The growth in the representation of the foreigners among the US CS workforce was fueled by two supply-side developments in this period. First, the foreign pool of men and women with college educations in science and engineering fields increased dramatically (Freeman, 2009). In India, an important source of CS workers in the US, the number of first degrees conferred in science and engineering rose from 176,000 in 1990 to 455,000 in 2000. Second, the Immigration Act of 1990 established the H-1B visa program for temporary workers with at least a bachelor's degree working in "specialty occupations" including engineering, mathematics, physical sciences, and business among others.

[5] Source: BLS Employment Projections *http://www.bls.gov/news.release/history/ecopro_082498.txt*

[6] Here and elsewhere, we define foreigners as those who immigrated to the US after the age of 18. We believe that this definition is reasonable proxy for workers who arrived to the US on non immigrant visas.

Firms wanting to hire foreigners on H-1B visas must first file a Labor Condition Application (LCA) in which they attest that the firm will pay the visa holder the greater of the actual compensation paid to other employees in the same job or the prevailing compensation for that occupation, and the firm will provide working conditions for the visa holder that do not adversely affect the working conditions of the other employees. At that point, prospective H-1B non-immigrants must demonstrate to the US Citizenship and Immigration Services Bureau (USCIS) in the Department of Homeland Security (DHS) that they have the requisite education and work experience for the posted positions. The USCIS may approve the petition for the H-1B holder for a period of up to three years, with the possibility of a three-year extension. Thus foreign workers can stay a maximum of six years on an H-1B visa, though firms can sponsor these workers for a permanent resident visa. Because H-1B visas are approved for solely the applying firm, H-1B foreign workers are effectively tied to their sponsoring company.

Since 1990, when the visa was initiated, the number of H-1B visas issued annually has been capped. The initial cap was of 65,000 visas per year was not reached until the mid-1990s, when demand began to exceed the cap. However, the allocation tended to fill each year on a first come, first served basis, resulting in frequent denials or delays on H-1Bs because the annual cap had been reached. After lobbying by the industry, Congress raised the cap first to 115,000 for FY1999 and then to 195,000 for FY2000-2003, after which the cap reverted to 65,000. Figure 1e shows the growth in the number of H-1 visas (the H-1 was the precursor to the H-1B) issued 1976-2008, estimates of the stock of H-1 visas in the economy each year, and the changes in the H-1B visa cap.[7]

Through the decade of the 1990s, foreign workers with H-1B visas became an important source of labor for the technology sector. The National Survey of College Graduates shows that 55% of foreigners working in CS fields in 2003 arrived in the US on an H-1B or a student-type visa (F-1, J-1). Furthermore, institutional information indicates a significant increase in the number of visas awarded to workers in computer-related occupations during the 1990s. A 1992 U.S. General Accounting Office report shows that "computers, programming, and related occupations" corresponded to 11% of the total number of H-1 visas in 1989, while a report from the U.S. Immigration and Naturalization Service (2000) finds that computer-related occupations accounted for close to two-thirds of the H-1B visas awarded in 1999. More specifically, the U.S. Department of Commerce (2000) estimated that during the late 1990s, 28% of all US programmer jobs went to H-1B visa holders.

While H-1B visa holders represent an important source of computer scientists, they do not

[7]The Immigration and Nationality Act of 1952 established the precursor to the H-1B visa, the H-1. The H-1 non-immigrant visa was targeted at aliens of "distinguished merit and ability" who were filling positions that were temporary. Non-immigrants on H-1 visas had to maintain a foreign residence. The Immigration Act of 1990 established the main features of H-1B visa as it is known today, replacing "distinguished merit and ability" with the "specialty occupation" definition. It also dropped the foreign residence requirement and added a dual intent provision, allowing workers to potentially transfer from an H-1B visa to immigrant status.

represent all foreigners in the country working as computer scientists. A significant number of such foreigners are permanent immigrants, some of whom may have come either as children or as students. Other foreigners enter the US to work as computer scientists in the US on L-1B visas, which permit companies with offices both in the US and overseas to move skilled employees from overseas to the US. While we know of no data showing the fraction of computer scientists working in the US on L-1B visas, substantially fewer L-1(A&B) visas are issued than are H-1Bs.[8]

1.3 Impact of Immigrants on the High Tech Workforce in the US

Critics of the H-1B program (Matloff, 2003) argue that firms are using cheap foreign labor to undercut and replace skilled US workers, although even the fiercest critics do not claim that employers are technically evading the law (Kirkegaard, 2005). Rather, they argue that firms skirt the requirement to pay H-1B visa holders prevailing wages by hiring over-qualified foreigners into positions with low stated qualifications and concomitant low "prevailing wages." These critics claim that the excess supply of highly qualified foreigners willing to take the jobs in the US plus the lack of portability of the H-1B visa limit the capacity of H-1B workers to negotiate fair market wages.

One way to get a handle on the extent to which H-1B visa holders are being under-paid relative to their US counterparts is to compare foreigners on H-1B visas to those with green cards – an immigrant authorization allowing the holder to live and work in the US permanently, with no restrictions on occupation. Using difference-in-difference propensity score matching and data from the 2003 New Immigrant Survey, Mukhopadhyay and Oxborrow (2012) find that green card holders earn 25.4 percent more than observably comparable temporary foreign workers. Using log earnings regressions and data from an internet survey, Mithas and Lucas (2010) find that IT professionals with green cards earn roughly 5 percent more than observationally equivalent H-1B visa holders. Comparisons between green card and H-1B holders are far from perfect. Since many green card holders begin as H-1B visa holders who are eventually sponsored by their employers for permanent residence status, it is reasonable to assume that green card holders are positively selected on job skills. Given this consideration, it is somewhat surprising that the observed green card premium is not larger than this 5%.

Perhaps the most compelling work concerning productivity differences between H-1B visa holders and their US resident counterparts comes from a recent paper by Doran et al. (2015) who analyze H-1B lotteries used in FY 2006 and 2007 to identify the productivity effects on firms of hiring an additional H-1B worker. During these two years, firms that submitted an LCA during the day the H-1B quota was hit would enter a lottery to determine whether they were permitted to hire the additional H-1B worker. Doran et al. (2015) find that winning the lottery

[8] See Yeaple (2017) for a discussion on L-1 and H-1B visas.

had no effect on subsequent patenting or employment in the affected firm, consistent with the notion that a firm unable to hire a H-1B worker would end up hiring an alternative, equally productive worker.[9]

While there may be no incontrovertible estimate of the productivity (conditional on earnings) advantage of foreign high-skill labor, simple economic reasons suggest this advantage must exist. US employers face both pecuniary and non-pecuniary costs associated with hiring foreigners. A small GAO survey (U.S. General Accounting Office, 2011) estimated the legal and administrative costs associated with each H-1B hire to range from $2,300 to $7,500 dollars. Assuming that these workers earn $60,000 per year in total compensation, which would seem to be conservative, this amounts to no more than 2% of compensation spread over 6 years. It seems reasonable to assume that employers must expect some cost or productivity advantage when hiring foreigners, however modest. If not, why would they incur the associated effort and expense?

Whatever the perceived cost or productivity advantages, H-1B critics argue that US employers' use of foreign labor in high-skill jobs either "crowds out" native workers from these jobs or puts downward pressure on their wages. Although, as far as we know, critics of the H-1B program have not yet estimated the magnitude of either of these effects, recent work by economists has started to fill this void. Kerr and Lincoln (2010) and Hunt and Gauthier-Loiselle (2010) provide original empirical evidence on the link between variation in immigrant flows and innovation measured by patenting, finding evidence that the net impact of immigration is positive rather than simply substituting for native employment. Kerr and Lincoln (2010) also show that variation in immigrant flows at the local level related to changes in H-1B flows do not appear to adversely impact native employment and have a small, statistically insignificant, effect on their wages. More recently, Peri et al. (2014) found positive effects of high-skill immigrant workers on the employment and wages of college-educated domestic workers.

A potential issue with the analyses of Kerr and Lincoln (2010) and Peri et al. (2014) is that the observed, reduced-form outcomes may capture concurrent changes in area specific demand for computer scientists. To circumvent the problem, each paper constructed a variable that interacts an estimate for the total number of individuals working on H-1B visas in a city with local area dependencies on H-1Bs.[10] However, given the nature of the H-1B visa, the location of immigrants depends, in large part, on the location of employers hiring them. If because of

[9] Doran et al. (2015) point estimates suggest that replacing a US resident with a H-1B holder might raise patenting at small firms by 0.26% (95% CI -0.42 0.47%), implying that the H-1Bs visa holders are no more than 4.7% more productive than are US resident workers.

[10] Kerr and Lincoln (2010) and Peri et al. (2014) hope that the variation in this variable is driven largely by changes in the cap on new H-1B visas that occurred over the last 20 years. That said, it is unclear the extent to which the variation they use is being driven by variation in the visa cap. Because of the dot com bubble bust in 2000 and 2001, the variation in the H-1B cap is only loosely related to actual number of H-1Bs issued. What is more, the cap will have different effects across areas, and one can worry about the exogeneity of this variation. In addition, it is hard to imagine that the cap was exogenous to the demand for IT workers.

local agglomeration effects, the IT boom was concentrated in areas of the country that were already IT intensive (such as Silicon Valley), then the measure of local dependency would be endogenous, an issue that Kerr and Lincoln (2010) and Peri et al. (2014) understand.

Ghosh et al. (2014) take a different approach. They match all LCAs, with firm-level data on publicly traded US companies, comparing changes in labor productivity, firm size, and profits between 2001 and 2006, for firms that were highly dependent on H-1B labor with firms that were not. They argue that the H-1B-dependent firms would feel more effects than their counterparts from the dramatic drop in the H-1B cap from 195,000 to 65,000 in 2004. And, indeed, they find that, over this period, labor productivity, firm size, and profits all declined more for the H-1B-dependent firms, which they attribute to the loss of the H-1B labor. The concern here is that the firms more dependent in H-1B labor in 2001 would have been systematically different from those less so dependent in ways correlated with the change in performance between 2001 and 2006.

In another paper, Peri et al. (2015) use data on the number of LCAs filed by firms in local (metro) areas during 2007 and 2008 as a measure of potential demand for H-1B workers, and the number of H-1B applications filed by foreigners as their measure of H-1Bs hired. In 2007 and 2008, the number of H-1B applications exceeded the annual quotas, and lotteries were used in awarding visas. The large gap between these two measures represent the unmet demand for skilled foreign workers. Cross-metro-area variation in this variable is due to at least two sources: (1) cross-metro-area demand for foreign high-skill labor, and (2) truly random fluctuations in the fraction of LCAs picked in the lotteries. While this second source of variation should be truly random, Peri et al. (2015) find too little of such variation to reliably identify the net effects of high-skill labor immigration.

Previous researchers studying the impact of H-1B workers on the US economy have focused on identifying exogenous variation in the number of H-1B workers, typically finding that H-1B workers tend to raise productivity and act as complements to, rather than crowd-out, college-educated native workers. However, as these researchers have acknowledged, it is easy to question the validity of the instruments used in these analyses. Rather than using a natural experiment to identify effects, we derive effects from a calibrated model. The model allows us to connect endogenous productivity advances in the IT sector during the 1990s to changes in the demand for CS labor. While the validity of the conclusions that Kerr and Lincoln (2010), Peri et al. (2014), Peri et al. (2015), and Ghosh et al. (2014) depend on the validity of the natural experiments they use to identify effects, our conclusions depend on our model accurately reflecting key features of the US economy. As such, the credibility of our results hinges on the plausibility of our assumptions and/or the robustness of our conclusions to variations in the specific modeling choices we made.

2 A Model of the Product and Labor Markets

Our model consists of two major sections. The first is the product market where goods are produced by firms and sold to consumers. The second is the labor market for college graduates, where US workers decide whether to work as computer scientists or in other occupations. Our product market, has two sectors: the IT sector and the 'Other' sector. The IT sector is monopolistically competitive, wherein firms produce different varieties of the same IT good. Firms in the IT sector are heterogeneous in terms of their level of productivity, which is exogenously drawn. Importantly, we include the possibility of endogenous technological change, whereby CS workers' innovation causes the production function to be increasing returns to scale at the aggregate level. All other goods in the economy are produced in the residual 'Other' sector, which is a perfectly competitive sector with homogeneous firms.

Every period a firm chooses its inputs to maximize profits. Since firms in the IT sector are monopolistically competitive, they have some market power when making these choices. Firms use intermediate inputs from the Other sector and labor to produce their output. The labor inputs consist of three types of workers: computer scientists, college-educated non-computer scientists, and non-college-educated workers. In our model, all foreign immigrants are hired as computer scientists. IT sector firms are also able to export their products to foreign markets, whereas the US economy imports only non-IT goods. Consumers, on the other hand, choose how much of each good to consume in order to maximize their utility subject to their labor income. Like firms, they make these choices every period, and have no savings.

Building on this setup, we include the labor supply decisions of college graduates. Since human capital investments and career choices have long term payoffs, US workers in our model are allowed to choose their fields of study and occupations based on the information they have today and their expected payoffs in the future. They are then allowed to switch occupations, by paying a switching cost, when a change occurs in the current or expected payoffs associated with any occupation. Given the labor supply decisions of US workers, the labor supply of immigrants, and the labor demand from firms in each sector, the market clears to determine the equilibrium wages for each type of worker. Equilibrium prices are determined in the product market, where the demand for the two types of goods from consumers meets the supply of these goods from firms.

2.1 Product Market

2.1.1 Household problem

There are X number of consumers in the economy who supply one unit of labor each. Each consumer has the same preferences over the two goods: C_d produced by the IT sector and Y_d,

the good produced by the residual sector in the economy. Their preferences can be represented by the Constant Elasticity of Substitution (CES) utility function in equation 1.

$$U(C_d, Y_d) = \left[\gamma C_d^{\frac{\sigma-1}{\sigma}} + (1-\gamma) Y_d^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

Y_d is assumed to be homogeneous, whereas the IT good C_d is composed of a continuum of varieties (indexed by ν) in the framework introduced by Dixit and Stiglitz (1977) [11]:

$$C_d = \left(\int_{\nu \in \Omega} c_{di}^{\frac{\epsilon-1}{\epsilon}} d\nu\right)^{\frac{\epsilon}{\epsilon-1}} , \tag{2}$$

where Ω is the set of varieties and ϵ is the elasticity of substitution between the varieties of IT goods. In our analysis, we set the consumption bundle to be the numeraire.[12] In Appendix A.1.1 we solve for the demand for each good.

Consumers/workers have identical consumption preferences but do not receive the same labor income as they work in different occupations. Furthermore, workers can either be native workers (denoted by a subscript n) or foreign workers (denoted by a subscript F).

We outline the details of the labor-supply decisions in Section 2.3, where we discuss how workers choose their field of college-majors and occupations over time. The decision of whether to attend college or not is made outside this model. This means that the supply of non college graduates $\bar{H}$ is exogenous, and so is the total supply of native college graduates $(\overline{L_n + G})$. Those who do get a college degree can choose whether to work as a computer scientists L_n, or in some other occupation that requires a college degree G.

High skilled immigrants who come in on H-1B visas can do so only if they meet the skill requirements of the visa and only if firms recruit them. As we have mentioned before, over the 1990s immigrants coming in as H-1Bs were increasingly being recruited as computer scientists. For simplicity, we will assume that all recruited H-1Bs are computer scientists L_F.

The size of the labor force in the economy is $X = \bar{H} + \overline{L_n + G} + L_F$ and total income m can be written as the sum of the labor income for the different types of workers plus profits earned by firms in the IT sector (Π) as in equation 3:

$$m = w(L_n + L_F) + sG + r\bar{H} + \Pi , \tag{3}$$

[11] This setting with one composite and one homogeneous good follows recent papers such as Melitz and Ottaviano (2008), Demidova (2008) and Pfluger and Russek (2013)

[12] This means that the ideal price index is normalized to 1: $\frac{\left(\gamma + (1-\gamma)\left(\frac{P_c}{P_Y}\frac{\gamma}{1-\gamma}\right)^{\sigma}\right)^{\frac{\sigma}{\sigma-1}}}{P_c + P_Y\left(\frac{P_c}{P_Y}\frac{\gamma}{1-\gamma}\right)^{\sigma}} = 1$

where w is the wage paid to computer scientists, s the wage earned by college graduate non computer scientists and r is the wage paid to non college graduates.

We assume that foreign computer scientists are willing to come and work in the US at any available wage and are marginally more productive than native computer scientists. Each year the number of immigrants in the economy is capped at a given level $\bar{L}_F$ and because of this small productivity premium the cap always gets exhausted. Native computer scientists face a residual demand curve after all available foreigners have been hired.

One way to think about this assumption in our model is that any extra productivity is almost entirely offset by the recruitment costs of hiring foreigners. Also, due to H-1B restrictions, immigrants get paid the same wage as native computer scientists. In what remains of subsection 2.1 we will refer to foreign and native computer scientists as a single group, since from a firm's point of view they are indifferent between hiring the two at the going wage.[13]

2.1.2 Production in the IT sector

The IT sector produces an aggregate IT good C. There are N monopolistically competitive heterogeneous firms that produce a different variety of this good as shown in equation 2. Following the framework introduced by Hopenhayn (1992) and Melitz (2003), each of these firms will have a different level of productivity. Each firm j has a Cobb Douglas technology in the labor aggregate and intermediate inputs from the other sector as in equation 4:

$$c_j = \phi_j L_c^{\beta} y_{cj}^{\psi_1} x_{cj}^{1-\psi_1} \ , \tag{4}$$

where y_{cj} is the amount of intermediate goods from sector Y and x_{cj} is the labor aggregate. Firm technology, $A(\ell_j) = \phi_j L_c^{\beta}$, has an endogenous component L_c^{β} and an exogenous component ϕ_j which is a productivity draw that varies across firms. The term L_c^{β} captures a technological spillover in the IT sector which depends on the total number of computer scientists employed. Since computer scientists are innovators, their innovations create spillovers that increase the productivity of all firms in the sector, and this is captured by the β term.

The firm employs all three types of labor available in the economy in a nested Constant Elasticity of Substitution (CES) structure.

$$x_j = \left[\alpha^c h_j^{\frac{\tau-1}{\tau}} + (1-\alpha^c) q_j^{\frac{\tau-1}{\tau}}\right]^{\frac{\tau}{\tau-1}} \ , \tag{5}$$

where h_j is the number of non college graduates and q_j is the labor aggregate for college

[13] In the data, we see that H-1Bs are almost entirely hired by larger firms. While this is an interesting and suggestive feature of the data, we leave it for future researchers to explore.

graduates. Here τ is the elasticity of substitution between college graduates and non-college graduates. Due to the nested nature of the CES function, we know that q_j is:

$$q_j = \left[(\delta + \Delta)\ell_j^{\frac{\lambda-1}{\lambda}} + (1 - \delta - \Delta)g_j^{\frac{\lambda-1}{\lambda}}\right]^{\frac{\lambda}{\lambda-1}} , \tag{6}$$

where ℓ_j is the number of CS workers and g_j the non-CS college graduates employed by firm j. Here λ is the elasticity of substitution between the CS workers and non-CS college graduates.

In equation 4 it is clear that the IT sector firms have two drivers of technological change. The exogenous component of technology ϕ_j, has been modeled similar to the setup in the trade and the industrial-organization literature (Chaney (2008); Hopenhayn (1992); Melitz (2003)). The endogenous component of technology, captured by β, depends on the total number of computer scientists hired by the IT sector. These computer scientists innovate and create new technologies, increasing overall firm productivity. Here, we modify the set-up used in the literature on economic growth (Acemoglu (1998); Arrow (1962); Grossman and Helpman (1991); Romer (1990)).[14]

In the IT sector, the number of potential entrepreneurs is assumed to be fixed and their productivities have a known distribution $\Psi(\phi_j)$ with a positive support over $(0, \infty)$ and an associated density function $\psi(\phi)$. There is a productivity cutoff $\phi = \phi^*$, that captures the productivity level of the firm that breaks even. Therefore, the marginal producing firm earns no profits ($\pi(\phi^*) = 0$). Since profits are an increasing function of the productivity level, the equilibrium ϕ^* determines which firms produce ($\phi_j > \phi^*$) and which ones do not ($\phi_j < \phi^*$). The conditional distribution of $\psi(\phi)$ on $[\phi*, \infty)$ can therefore be written as:

$$\mu(\phi) = \begin{cases} \frac{\psi(\phi)}{1-\Psi(\phi^*)}, & \text{if } \phi \geq \phi^* \\ 0, & \text{otherwise} \end{cases}$$

The productivity distribution $\Psi(\phi_j)$ of entrepreneurs is assumed to be a Pareto distribution, with parameters k and ϕ_{min} such that $\Psi(\phi_j) = 1 - \left(\frac{\phi_{min}}{\phi_j}\right)^k$.

The intuition behind this modeling choice is that whenever economic conditions change, the firms that get pushed into/out of production are the marginal firms (those with ϕ_j closer to ϕ^*) while the larger more productive firms produce regardless. We expect such behavior in the IT sector when we allow more immigrants into the economy. As immigration allows firms to pay lower wages, the marginal firms are the ones that enter into production and large firms capture

[14]Since we do not model economic growth, there are some clear departures from this literature. While many papers assume that the *rate of change* of technology depends on the quantity of a type of labor, we assume the *level* of technology depends on labor. Furthermore, a lot of this literature models a separate R&D sector that sells patents for these technologies – whereas in our model technology is assumed to be non-excludable.

most of the increase in profits. For a given mass of potential producers, N_e, the total number of firms that produce can be written as in equation 7:[15]

$$N = (1 - \Psi(\phi^*))N_e \tag{7}$$

Such a model follows an approach to market entry closer to Chaney (2008) rather than the original Melitz (2003) model where the potential pool of entrants is not fixed.[16]

The firm's problem therefore boils down to maximizing profits by choosing the amount of labor inputs. If they choose to produce, they pay an upfront fixed cost of production f which is in terms of the cost of the non IT good P_Y (equation 8). Each firm is a monopolist for their own variety and faces a demand curve as in equation 30.

$$\max_{\ell_j, g_j, h_j, y_{cj}} \pi_j = \phi_j P_c C^{\frac{1}{\epsilon}} c_j^{\frac{\epsilon-1}{\epsilon}} - w\ell_j - sg_j - rh_j - P_Y y_{cj} - P_Y f \tag{8}$$

The first order conditions from this exercise, determine the labor demand from the IT sector for each type of labor. Total labor hired by this sector is denoted by the subscript c, and aggregate employment of each type of worker can be expressed as L_c, G_c and H_c.

2.1.3 Production in the Non IT sector

The non IT sector produces good Y and is assumed to be perfectly competitive. The representative firm in this sector has a Cobb Douglas constant returns to scale technology over intermediate inputs from the other sector and the labor aggregate.

$$Y = C_y^{\psi_2} X_y^{1-\psi_2} \ , \tag{9}$$

where again C_y represents intermediate inputs from the IT sector and X_y the labor aggregate. This sector also employs the three types of labor denoted by subscript Y. Therefore, X_y can be written as:

$$X_y = \left[\alpha^y H_y^{\frac{\tau-1}{\tau}} + (1-\alpha^y) Q_y^{\frac{\tau-1}{\tau}}\right]^{\frac{\tau}{\tau-1}} \tag{10}$$

[15] While our model of firm entry does not have dynamic implications, Waugh (2017) provides a more extensive treatment of the potential effects of skilled immigration on firm entry and exit dynamics.

[16] In the original Melitz setting there are a number of potential entrants who have to pay an additional fixed cost f_e to get a productivity draw, and once they know their productivity they produce if $\phi_j > \phi^*$. New entrants in this model can be both high and low productivity and end up driving expected net profits to zero. di Giovanni et al. (2015) think of the case with a fixed pool of potential producers as the short run, where the number of varieties available only changes through the entry and exit of marginal firms, having small effects on aggregate welfare.

Again, using the nested CES format, Q_y can be represented by:

$$Q_y = \left[\delta L_y^{\frac{\lambda-1}{\lambda}} + (1-\delta) G_y^{\frac{\lambda-1}{\lambda}}\right]^{\frac{\lambda}{\lambda-1}} \tag{11}$$

This sector is less intensive in computer scientists than the IT sector. To capture this, we model the intensity of CS workers to be higher in the IT sector (captured by Δ), and allow the computer scientists in the IT sector to have an additional impact on the technology in the firm (captured by β). Both sectors have the same elasticity of substitution between college and non college graduates (τ) and between computer scientists and college graduates non CS (λ).

The representative firm in the non-IT sector has to therefore solve the following maximization problem:

$$\max_{L_y, G_y, H_y, C_y} \Pi_y = P_y C_y^{\psi_2} X_y^{1-\psi_2} - wL_y - sG_y - rH_y - P_c C_y \tag{12}$$

The first order conditions determine the demand for the intermediate inputs and the different types of labor in this sector. Together with the demand for labor from the IT sector, we can then derive the aggregate labor demand for each worker. Section 2.3 describes the supply of the different types of workers, and Section 2.4 describes the equilibrium, where we also detail how the labor demand curve shifts over time given the technological boom in the 1990s.

2.2 Trade with the Rest of the World

The US economy trades both IT goods and the other good with the rest of the world (W). IT firms export final goods to consumers in other countries, whereas US consumers import the other good from the rest of the world.[17]

Consumers in the rest of the world (W) have the same utility function as US consumers:

$$U_W(C_W, Y_W) = \left[\gamma_W C_W^{\frac{\sigma-1}{\sigma}} + (1-\gamma_W) Y_W^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{13}$$

Since the US is the only producer of IT goods, foreign consumption is equivalent to US exports of IT goods. Imports into the US from the rest of the world are represented by Y_{IM}. For convenience we assume trade is balanced implying that the value of imports must equal the value of exports:

$$P_c C_W = P_y Y_{IM} \tag{14}$$

[17] While we do not explicitly model outsourcing decisions, we do allow for the fact that imported goods in the other sector can be used as intermediate goods in production for the IT sector.

Here we assume that the US is the only producer of IT. Even though Freeman (2006) stresses how high-skill immigration may help the US maintain its comparative advantage in IT, we may, expect that immigration policy affects IT production elsewhere in the world, especially via the diffusion of knowledge. Khanna and Morales (2015) draw up a general equilibrium model of both the US and India – the other major producer of IT – to study how the H1B program affects production, human capital accumulation and labor market welfare for agents in both countries. The possibility of migrating to the US induces students and workers in other countries to accumulate CS-specific human capital, and return migrants help facilitate the diffusion of technology. Over time, in the latter half of the 2000s, India becomes the major exporter of IT, eroding the US's comparative advantage. Khanna and Morales (2015) can be thought of as a long-run extension of our current work, with consistent implications for the period of study here – the 1990s.

2.3 Labor Supply of U.S. Computer Scientists

The firms' decision problem determines not only the product market equilibrium but also the demand curves for the different types of labor. To describe the workers' decisions we develop a dynamic model of labor supply that captures the choices made in deciding a field of study in college, and occupational choices later in life. The model builds on previous work by Freeman (1975, 1976); Ryoo and Rosen (2004) and closely follows the set-up of Bound et al. (2015). While Bound et al. (2015) was a partial equilibrium model that studied the decisions made between CS and STEM occupations for a given labor demand elasticity, we extend it to a general equilibrium framework which includes all types of labor and rigorously model the firm's decision to derive the labor demand curve that the workers face as well.

While we model the decisions to choose a field of study for US workers who attend college, we do not explicitly model the decision to attend college in the first place. This is because we assume that changes in wages for computer-science related occupations do not greatly affect the college-going decision for students. The supply of workers who have only a high school degree $\bar{H}$ is therefore assumed to be the same whether or not there were changes in the number of foreign computer scientists in the labor market. Therefore the total supply of US workers with a college degree ($\overline{L_n + G}$) is also assumed to be fixed. However, we do model the decisions of these college-educated workers as they make choices between majoring in CS degrees or other degrees and then their occupation-choices in each year of their life till retirement.

In our model, there are three potential sources of CS workers. First, there are those who earn computer science bachelor's degrees from US institutions and join the workforce only after they finish college. Second, there are college-educated US residents working in other occupations who can switch into computer science, but must pay costs to switch occupations. Third, there are foreigners who are being recruited on temporary work visas.

Given that most foreign workers that come on H-1Bs are computer scientists, we model CS as the only profession that they get hired into. There are therefore two sources of non-CS college-educated workers – those that graduate with any degree that is not computer-science and those that switch from CS work to non-CS work by paying the switching cost.

We model US college graduates as maximizing their life-time utility by making two types of decisions. When they are 20 years old, they choose their field of study in college which influences their initial occupation at graduation. From ages 22 to 65, they choose between working as a computer scientist or in another occupation. All individuals have rational, forward looking behavior and make studying and working decisions based on the information available in each period.

The labor demand curve derived from the firms' decision problem discussed in the previous sections, shifts out yearly due to productivity shocks. These shifts help identify the labor-supply parameters and trace out the labor supply curve.

2.3.1 Field of Study Decision

In our model students choose their field of study when they are undergraduate juniors. Equation 15 captures this decision. At age 20, a student i draws idiosyncratic taste shocks for studying computer science or another field: η_i^{cs} and η_i^o,respectively. This student has expectations about the prospects of starting a career in each occupation after graduation (age 22), which have values V_{22}^{cs} and V_{22}^o respectively. Given this information, an individual chooses between pursuing computer science or a different choice of major at the undergraduate level.[18]

Worker utility is a linear function of their tastes and their career prospects in each sector and they discount their future with an annual discount factor ρ. Additionally, there is an attractiveness parameter θ_o for studying in a field that is not computer science, that all students experience. This parameter may be negative if, on average, students prefer studying computer science.

$$max\{\rho^2\mathbb{E}_t V_{22}^{cs} + \eta_i^{cs}, \quad \rho^2\mathbb{E}_t V_{22}^o + \theta_o + \eta_i^o\} \tag{15}$$

We assume that the individual taste parameters η_i^{cs} and η_i^o are independently and identically distributed and for $d = \{cs, o\}$, can be defined as $\eta_i^d = \sigma_0 v_i^d$, where σ_0 is a scale parameter and v_i^d is distributed as a standard Type I Extreme Value distribution. This assumption allows the decisions of agents to be formulated in aggregate probabilities, and is therefore commonly used in dynamic discrete choice models (Rust (1987), Kline (2008)). We describe the probability of

[18]We are assuming that students decide their major after the end of their second year in school. Bound et al. (2015) experiment with a four-year time horizon and doing so made little qualitative difference.

enrollment in degrees in Appendix A.1.2.

One crucial parameter for how studying choices are sensitive to different career prospects is the standard deviation of taste shocks. Small values of σ_0 imply that small changes in career prospects can produce big variations in the number of students graduating with a computer science degree.

2.3.2 Occupational Choice

The field of study decisions determine if an individual enters the labor market at age 22, as either a computer scientist or in a different occupation. However, individuals can choose to switch occupations between the ages of 22 and 65. At the start of each period, individuals use the information at hand and choose their occupation in order to maximize the expected present value of their lifetime utility.

Switching occupations, however, is costly for the worker, and these costs vary with age. This is because workers have occupational-specific human capital that cannot easily be transferred across occupations (Kambourov and Manovskii, 2009). The occupational switchings costs are modeled as a quadratic function of a worker's age, allowing for the fact that it becomes increasingly harder to switch occupations as workers get older.[19]

Like in the college major decision, we assume that workers have linear utility from wages, taste shocks and career prospects.[20] The value functions of worker i at age a between 22 and 64 at time t if she starts the period as a computer scientist or other occupation are therefore going to be:

$$V^{cs}_{t,a} = max\{w_t + \rho\mathbb{E}_t V^{cs}_{t+1,a+1} + \varepsilon^{cs}_{it}, \quad s_t - \zeta(a) + \rho\mathbb{E}_t V^{o}_{t+1,a+1} + \varepsilon^{o}_{it} + \theta_1\} \tag{16}$$

$$V^{o}_{t,a} = max\{w_t - \zeta(a) + \rho\mathbb{E}_t V^{cs}_{t+1,a+1} + \varepsilon^{cs}_{it}, \quad s_t + \rho\mathbb{E}_t V^{o}_{t+1,a+1} + \varepsilon^{o}_{it} + \theta_1\} \tag{17}$$

where $\zeta(a) = \zeta_0 + \zeta_1 a + \zeta_2 a^2$, is the monetary cost of switching occupations at age a, and θ_1 is the taste attractiveness parameter for not working as a computer scientist, experienced by all workers. Finally, all workers retire at age 65 and their retirement benefits do not depend on their career choices. Therefore, at age 65 workers face the same decision problem without consideration for the future.

[19] While our model has no general human capital accumulation and wages do not vary with the age of a worker, the implications of the model would still hold if individuals expect similar wage growth profiles in each occupation.

[20] Wages must be totally consumed in that same year and workers cannot save or borrow.

As in the college-major decision problem, we will assume that taste shocks are independently and identically distributed and for $d = \{cs, o\}$ can be defined as $\varepsilon_{it}^d = \sigma_1 v_{it}^d$ where σ_1 is a scale parameter and v_i^d is distributed as a standard Type I Extreme Value distribution.

The standard deviation of the taste shocks, the sector attractiveness parameter and the cost of switching occupations will affect the sensitivity of occupational switching to changes in relative career prospects. Since individuals are forward looking, the working decisions depend upon the equilibrium distribution of their career prospects. We describe the probabilities of employment, occupational switching and the expected value of future prospects in Appendix A.1.2.

2.3.3 Labor Supply of Foreign Computer Scientists

We model high skilled foreign workers as only being hired as computer scientists, since during the 1990s a majority of H-1Bs were hired into this occupation. By 2001, more than 21% of all computer scientists were born abroad and immigrated after the age of 18 (March CPS). We assume that high skilled foreigners have a perfectly elastic labor supply curve to the US, since the wage that a computer scientist could obtain in countries like India or China, for instance, is substantially lower than it is in the US (Clemens, 2013). This wage premium creates a large queue of foreigners ready to take jobs in the US. There is, however, an institutionally imposed cap on the total number of H-1Bs that restricts the number of foreign computer scientists each year.

Institutional requirements also force firms to pay foreigners the prevailing US wage. We assume that the additional costs of recruiting foreigners offsets the productivity advantage that foreigners may have over their US counterparts. During the 1990s, a large fraction of the CS workers coming from abroad were on H-1B visas. Given that this was a period when the H-1B cap was usually binding, and given our assumption that foreign and domestic CS workers are effectively identical, we treat the quantity of foreign CS coming to the US as exogenous.

2.4 Equilibrium

Equilibrium in each period can be defined as a set of prices and wages (P_{ct}, P_{Yt}, w_t, s_t, r_t), quantities of output and labor (C_t^*, Y_t^*, C_{dt}^*, C_{yt}^*, C_{Wt}^*, Y_{dt}^*, Y_{ct}^*, Y_{IMt}^*, L_{nt}^*, L_{Ft}^*, G_t^*, H_t^*), number of firms (N_t) and the productivity cutoff (ϕ_t^*) such that:[21]

- Consumers in the US and the rest of the world, maximize utility by choosing C_t and Y_t taking prices as given, and choose their college major and occupations taking wages as given

[21] Note that we've introduced a t subscript to each of the variables to denote that there is a different equilibrium for each time period

- Firms in both sectors maximize profits taking wages and aggregate prices as given
- In the IT sector, the firm with productivity ϕ_t^* gets zero profits. All firms with $\phi_{jt} > \phi_t^*$ produce while those with $\phi_{jt} < \phi_t^*$ do not.
- Output and labor markets clear. The equations for the market clearing conditions are in Appendix A.1.3

Native college graduates face the decision of whether to work as computer scientists or in some other occupation that requires a college degree. This decision is no longer static, but has an inter-temporal dimension which requires the definition of the dynamic equilibrium in the labor market for college graduates. As in Bound et al. (2015), this equilibrium is characterized by the system of equations (15 - 17) and a stochastic process Z_t. In Appendix A.1.2 we characterize further equations, including future expectations, and the dynamic supply of colleges and workers.

A unique equilibrium is pinned down each period by an aggregate labor demand curve for US computer scientists relative to other college graduates that comes from the product market model.

Even though this labor demand curve from the two sectors has no closed form solution we will express it as in equation 18, a setup that will prove to be useful for the calculations in the following sections.

$$\frac{L_{nt}}{G_t} = Z_t + \Upsilon\left(\frac{w_t}{s_t}\right) \tag{18}$$

where $\Upsilon(\frac{w_t}{s_t})$ is a baseline relative demand curve that depends on the relative wage. Z_t is a shifter that can be thought of as a combination of the productivity shocks from the IT boom, that shifts out the relative demand for computer scientists every year and the cap of foreign computer scientists $\bar{L}_F$ that shifts in the relative demand curve every period. Z_t is assumed to follow a random walk process with high persistence such that:

$$Z_t = 0.999 Z_{t-1} + 0.001\bar{Z} + \xi_t \tag{19}$$

where $\bar{Z}$ is the steady state value of Z_t and ξ_t is an i.i.d. shock.[22]

The equilibrium in the labor market can be expressed by a mapping from the state variables: $s = \{\mathrm{R_t}, L^{22}_{n,t-1}, ..., L^{64}_{n,t-1}, G^{22}_{t-1}, ..., G^{64}_{t-1}, Z_{t-1}\}$ and exogenous productivity shock ξ_t to the values of L_{nt}, w_t, G_t, s_t and $\mathbf{V_t}$, the vector of career prospects at different occupations for different

[22] We assume workers consider both the technological progress from the IT boom as well as the increase in immigrants to be a series of highly persistent shocks.

ages, that satisfies the system of equations for labor supply as well as each period's relative demand curve.

3 Calibration

We calibrate the parameters of our model in order to determine how welfare changes due to immigration. We have a total of 25 parameters: σ, ϵ, γ, γ_W, ψ_1. ψ_2, β, α_c, α_y, τ, λ, δ, Δ, k, ϕ_{min}, N_e and f from the product market and σ_0, σ_1, θ_0, θ_1, ζ_0, ζ_1, ζ_2 and ρ from the US college graduates labor market. We focus on the period 1994-2001 that corresponds to the IT boom and when the H-1B cap was mostly binding.

In order to calibrate the different parts of the model we follow a sequential approach. First, we calibrate the parameters in the product market assuming total labor supply of L_t, G_t and H_t are fixed (i.e. ignoring the choice of native workers between L_t and G_t). What makes this possible in our model is that fact that adjustment costs imply that the stock of the different types of labor are fixed in the very short run. This approach is akin to the approaches taken by Freeman (1975, 1976) and Ryoo and Rosen (2004) in their modeling of adjustments on the labor market for scientists.

In the next step we use the calibrated parameters to derive the aggregate labor demand curve for computer scientists relative to other college graduates for every year. As a third step, we use the predicted shifts in labor demand to calibrate the parameters of the labor supply curve of different types of college graduates. Finally, we use the calibrated labor supply curve, labor demand curve and product demand parameters to calculate welfare under the economy where immigration is encouraged via the H-1B program and the counterfactual scenario where immigration is restricted.

3.1 Product Market Calibration

We calibrate the parameters of the product market to match different features of the data as explained in sections 3.1.1 - 3.1.5. The details of the data we use, including sources and definitions of the different sectors and occupations can be found in Appendix A.2.

The model is calibrated separately for each year between 1994 and 2001. While some parameters are assumed to be constant over time, others change in order to capture structural changes in the economy. Particularly, the production function parameters (α_{ct}, α_{yt}, δ_t, Δ_t, ψ_{1t} and ψ_{2t}) will be re-calibrated every year to capture the technological change that affects the two sectors during this period. This can be thought of as describing the skill-biased technological change over this period, since the share of labor cost that these sectors spend in computer scientists is

increasing over time. The utility parameters γ_t and γ_{Wt} are also allowed to shift over time to capture changes in local and foreign consumer preferences towards the IT sector. A summary of all calibrated parameters in the product market can be found in Table 2.

3.1.1 Domestic utility function parameters

The three parameters in the consumer utility function are σ, ϵ and γ_t. σ is the elasticity of substitution between the composite IT good C and the good Y. We calibrate this parameter using the ratio of first order conditions of goods Y and C from the consumer's utility maximization problem: $\frac{\gamma}{1-\gamma}\left(\frac{C}{Y}\right)^{-\frac{1}{\sigma}} = \frac{P_c}{P_Y}$.

This relationship can be reformulated as:

$$\log\left(\frac{C}{Y}\right) = -\sigma \log\left(\frac{1-\gamma}{\gamma}\right) - \sigma \log\left(\frac{P_c}{P_Y}\right) \tag{20}$$

We estimate σ using a regression of the relative quantity-index on the relative price-index. We use data from the Bureau of Economic Analysis' (BEA) industry-specific price and quantity indices.[23] The BEA data allows us to distinguish prices and quantities in the IT sector, and all the other sectors in the economy. The coefficient of this regression is statistically indistinguishable from $\sigma = 1$. Given the plausibly exogenous technological change during the period which drives down prices, we use this estimate as our main specification and proceed using a Cobb Douglas utility specification. We also run a series of robustness checks running the results for different values of σ that are summarized in Appendix A.4.

ϵ, the elasticity across IT varieties, is calibrated using the markup condition that comes from the IT firms' profit maximization condition (equation 21). We follow an approach similar to Gaubert (2015) and match average value added to cost ratios for the IT sector. The data for this is again taken from the BEA's annual industry accounts that report value added as well as costs like compensation to employees and taxes. For a marginal cost $MC(c_i)$, the price-markup can be used to determine the value of ϵ:

$$p_i = \frac{\epsilon}{\epsilon - 1} MC(c_i) \tag{21}$$

We calibrate $\epsilon = 3.26$. Bernard et al. (2003) calculate a value of 3.8 for all US plants, whereas Broda and Weinstein (2006) find a value of 2.2 for varieties of 'automatic data processing

[23] The BEA price indices methodology can be found here http://www.bea.gov/national/pdf/chapter4.pdf and at http://www.bls.gov/opub/hom/pdf/homch17.pdf. The specific methodology for personal computers and peripheral equipment are detailed at http://www.bls.gov/cpi/cpifaccomp.htm, where they discuss adjusting for quality as well. While they do adjust for quality differences, we may still underestimate quality changes in IT (Gordon, 1990), which would affect our estimate of β. We do a rigorous sensitivity analysis for different values of β.

machines and units.' Since our estimates lie within this region, we believe them to be reasonable. We show that our results are robust to other reasonable values of this parameter in Appendix A.4.

We calibrate the distribution parameter γ_t to match the share of expenditures in the IT good (using equation 22). Again we use data from the BEA on industry specific GDP of IT as a share of total GDP.[24]

$$\frac{P_c C}{m} = \frac{P_c}{P_c + \left(\frac{1-\gamma}{\gamma} P_c\right)^{\sigma}} \tag{22}$$

We calibrate γ_t conditional on the equilibrium prices, the share of consumption of the IT good and the calibrated value of σ. For the Cobb Douglas specification we just use the share of IT industry GDP to total domestic GDP. As already discussed, γ_t is time-varying in order to capture potential changes in consumer preferences over time for the IT good relative to the rest of the goods in the economy. Table 2 shows how γ_t steadily rises from 0.042 at the start of the period to 0.052 by the year 2001.

3.1.2 Foreign utility function

Consumers from the rest of the world are assumed to have the same utility function as consumers in the US. While we assume the elasticity of substitution σ is the same for both countries ($\sigma = 1$), the distributional parameter γ_{tW} is selected to match the share of consumption of the rest of the world for US IT products. We use the share of exports in IT to US GDP and the relative size of the US economy to the rest of the world to pin down this parameter. Again, we allow this parameter to change over time to capture potential changes in preferences for consumers abroad.

3.1.3 Production Function Parameters

The elasticity of substitution between high school and college grads (τ) and between computer scientists and other college graduates (λ) are assumed to be time invariant and equal across sectors. To calibrate τ we follow several influential papers that provide estimates for this parameter such as Katz and Murphy (1992), Card and Lemieux (2001) and Goldin and Katz (2007) and set $\tau = 1.7$ which is an average of their estimates.[25] We present our results for a

[24] For all time varying parameters that are matched to shares observed in the data we run a regression of the raw share on a linear and quadratic time trend to recover the time invariant parameters. We then predict the share using those coefficients and calibrate the parameters to match the predicted shares.

[25] Katz and Murphy (1992) find 1.41, Card and Lemieux (2001) find estimates between 2-2.5 and Goldin and Katz (2007) find 1.64. Strictly speaking, these numbers refer to the elasticity of substitution between college and non college educated labor in the US economy, while our parameter is sector specific. The aggregate elasticity

range of values of λ (1, 2 and 4) which correspond to aggregate relative labor demand elasticities of 1.02, 1.99 and 3.98. Ryoo and Rosen (2004) estimate aggregate relative demand elasticities that lie between 1.2 and 2.2 for engineers which are included in the range of values we use.

To calibrate the value of β, the technological spillover from total CS in the IT sector, we look at the relationship between the price decline in IT and the increase in total CS working in the sector. We use the aggregate CS in IT equilibrium condition that gives us a relationship between prices of IT and total labor in CS as in equation 23:

$$logP_c = \mho(w_t, s_t, r_t) - \frac{1}{\epsilon}logC_t - \psi_1\frac{\epsilon - 1}{\epsilon}logP_y + \frac{(1 - \beta(\epsilon - 1))}{\epsilon}logL_c \tag{23}$$

We run the regression of $log(P_c)$ on a linear and quadratic time trend, the log of quantity of IT good, the log price of the other good and the log of total computer scientists in IT. The time trend aims to capture fluctuations in the wages of the different types of workers over time. The calibrated value of β is 0.233. Effectively, this procedure attributes all of the TFP change to the increase in computer scientists working for the IT sector while in reality there are several other factors that also affect technical progress in IT. As a result, our estimates will tend to over estimate the impact of computer scientists on technological change. Our estimate is quite close to the Peri et al. (2014) estimates of changes in TFP attributable to the total number of STEM workers. In Appendix A.4 we explore the sensitivity of our results to our estimate of β.

The production function parameters α_{ct}, α_{yt}, δ_t, Δ_t, ψ_{1t} and ψ_{2t} are calibrated separately every year to reflect the skill-biased technological change the two sectors face during the period. This allows us to capture that increasingly, firms in both sectors spend a higher share of their expenditures on college graduates.

The share of expenditures on non college graduates in both sectors are matched to the observed share of labor income for each year in the March Current Population Survey (CPS). Here we define the shares observed in the data as $\vartheta_{t,C,H}$ and $\vartheta_{t,Y,H}$, such that:

$$\vartheta_{t,C,H} = \frac{\alpha_{ct}\bar{H}_{ct}^{\frac{\tau-1}{\tau}}}{\alpha_{ct}\bar{H}_{ct}^{\frac{\tau-1}{\tau}} + (1 - \alpha_{ct})\bar{Q}_{ct}^{\frac{\tau-1}{\tau}}} \tag{24}$$

Where $\bar{H}_{ct}$ and $\bar{H}_{ct}$ are the quantities observed in the CPS for each sector. We analogously calibrate α_{yt} using the shares observed in the data ($\vartheta_{t,Y,H}$, $\bar{H}_{yt}$ and $\bar{Q}_{ct}$)

In both sectors we have the parameter δ_t that is the distributional parameter associated with computer scientists. We calibrate this parameter to match the relative wage of CS to other

involves both within and between sector components. However, our simulations suggest that setting $\tau = 1.7$ produces an aggregate elasticity indistinguishable from 1.7 to the first digit.

college grads $\left(\frac{w_t}{s_t}\right)$. The IT sector has a higher share of CS than the Other sector, so we calibrate the parameter Δ to match the share of total labor expenditure spent in CS by the IT sector in a manner similar to our approach for calibrating α_{yt} and α_{ct}.

In Table 2 we can see how skill-biased technological change in the economy changes these parameters over time. δ_t steadily increases over this period as both sectors want to hire more computer scientists. The values of α_{yt} and α_{ct} steadily decrease for both sectors showing that they spend more of their income on college graduates than on high school graduates. Parameters associated with the intermediate inputs from another sector (ψ_{1t}, ψ_{2t}) are calibrated using the share of intermediate inputs from other sectors relative to the GDP which we obtain from the Bureau of Labor Statistics' (BLS) input-output tables.

3.1.4 Entry into Production in the IT sector

There are four parameters related to the entry-decision and productivity distribution in the IT sector. The number of firms in the sector depend on f, the fixed cost of production, and N_e, the mass of potential producers. The Pareto distribution parameters k and ϕ_{min}, determine the productivity levels of these firms. All these parameters are assumed to be time-invariant.

We calibrate f to match the average firm size in the IT sector observed in the data for the steady state year 1994. In order to do this we use information on the number of firms and total employment in the IT sector from the Census' Statistics of U.S. Businesses (SUSB).[26] In 1994 we calibrate f to match the ratio of total employees and number of firms in the data for the IT sector. The calibrated values for f are 1.24, 1.14 and 1.07 (for λ values of 1, 2 or 4 respectively). For the rest of the years we allow the number of firms N_t to adjust endogenously as the profits from production change over time.

N_e is calibrated using information on establishment entry entry and exit.[27] We look at the total number of establishments over 500 employees in 2001 and calibrate the ratio of $\frac{N_t}{N_e} = \frac{N_{94}}{N_{01}}$. Given that N_t in 1994 is used to calibrate f we get the rescaled $N_e = 0.25$.[28]

The Pareto distribution parameter k is set to match the standard deviation of logarithm of US domestic plant revenues. Following Demidova (2008), we use the simulation reported by Bernard et al. (2003) of 0.84. In our model the standard deviation of $Ln(p_i c_i)$ is $\frac{\epsilon-1}{k}$ so given our value of $\epsilon = 3.2$ we get a value of $k = 2.62$. The scale parameter ϕ_{min} is related to the

[26] This information comes from the 1992 Statistics of U.S. Businesses (SUSB). Since the information was only available for 1992 and 1997-2012, so we use the figures for 1992 as a proxy for 1994

[27] We get information on entry and exit of establishments in the IT sector by year from the Business Dynamics Statistics. Entry and exit was only available for establishments, not firms when looking at specific industries.

[28] Other papers such as Demidova (2008) and Melitz and Redding (2015) use the exit rate to calibrate parameters related to fixed cost of production and entry but unlike us calibrate the slightly different Melitz (2003) model. The strategy we use is somewhat different as we have a fixed pool of potential entrants.

choice of units in which to measure productivity so we follow the convention in the literature and normalize it to 1.

3.1.5 Total Quantity of Labor

To calibrate the product market parameters, we use the total quantities observed in the data for each occupation type $\bar{L}_t$, $\bar{G}_t$ and $\bar{H}_t$ as if they were exogenously given. We normalize the US working population from the March CPS in 1994 to 100, and then allow for the population in our model to grow at the same rate as the growth in the US population. The shares of each type of worker are set equal to those observed in the data each year which allows us to know the total number of college and non-college graduate workers, as can be seen in Table 3.

3.2 Deriving the Labor Demand Curve

Once we calibrate the product market parameters we are able to derive a labor demand curve for computer scientists relative to other college graduates. Such a demand curve does not have a closed form solution that comes directly from the model so we derive it by first changing the relative values of $\frac{\bar{L}_t}{\bar{G}_t}$ that we feed into the model and then calculating the predicted value of $\frac{w_t}{s_t}$. We run this exercise only for the steady-state year, 1994, and calculate $\frac{w_t}{s_t}$ for different values of $\frac{\bar{L}_t}{\bar{G}_t}$ that ranges between 0.04 and 0.07.[29] We then fit a second order polynomial to get a closed form solution of the relative labor demand curve.[30]

The elasticity of labor relative demand for computer scientists to other college graduates depends crucially on the parameter λ. We derive the labor demand for our three values of λ and get what we call the baseline labor demand curve as in equation 25, calculated using the calibrated model for the steady state year 1994:[31]

$$\frac{\hat{L}_t}{G_t} = \hat{\Upsilon}\left(\frac{w_t}{s_t}, \lambda\right) \tag{25}$$

For the remaining years we allow the demand curve to shift for two reasons. First, to capture the innovation taking place in the economy. This exogenous technological change is captured by the time-varying parameters of the production functions. Second, the demand curve shifts to capture the relative changes in the stock of college grads to non college grads which is determined outside of the model.

[29] Relative total CS to other college graduates in the data is 0.0406 in 1994 and goes up to 0.0466 in 2001. We therefore capture more than the range of possible values in the data.

[30] The second order polynomial perfectly predicts the model with a $R^2 = 1$. We experiment with higher order polynomials to fit the labor demand curve and our results do not change.

[31] The elasticity of the derived labor demand curve is very close to the value of λ, more specifically 1.015, 1.99 and 3.98 for λ equal to 1, 2 and 4 respectively.

We can calculate the labor demand shifter Λ_t as in equation 26. This shifter applies to the total demand of computer scientists relative to other college graduates, including both native and foreign computer scientists.

$$\hat{\Lambda}_t = \frac{L_t}{G_t} - \hat{\Upsilon}\left(\frac{w_t}{s_t}\right) \tag{26}$$

As a last step, in order to use the variation in the demand curve to trace out the relative supply curve for *native* computer scientists only, we subtract the relative number of foreign computer scientists each year to derive to the total demand shifter Z_t as presented in equation 18. As a reminder, we treat the quantity of foreign CS workers coming to the US as exogenous since the H-1B cap was binding throughout this period. Given that we assume foreign CS workers are willing to work at any wage and are slightly more productive than natives, they get hired first until they exhaust the H-1B cap while native workers face a residual labor demand curve. The total shifter $Z_t = \hat{\Lambda}_t - \frac{\bar{L}_{tF}}{G_t}$ allows us to write the labor demand for native CS relative to other college graduates as in equation 27:

$$\frac{L_{nt}}{G_t} = Z_t + \hat{\Upsilon}\left(\frac{w_t}{s_t}\right) \tag{27}$$

In the steady state, $\hat{\Lambda} = 0$ and $\bar{Z} = -\frac{\bar{L}_{94,F}}{\bar{G}_{94}}$

3.3 Calibrating Labor Supply

On the labor supply side of the model, we have eight parameters that need to be calibrated - $\{\sigma_0, \theta_0, \sigma_1, \theta_1, \zeta_0, \zeta_1, \zeta_2, \rho\}$. Of these, we pick the annual discount rate to be $\rho = 0.9$, and calibrate the other parameters to match the data. In our model we assume the total quantities of non college graduates $\bar{H}_t$, native college graduates $\overline{(L_n + G)}_t$ and foreign computer scientists $\bar{L}_{tF}$ are determined outside the model.

In the way we set-up the model, changes in lagged degree attainment, employment and wages are driven by the exogenous technology shocks that shift out the demand curve for the different types of labor over this decade. As the demand curve shifts, it traces out the labor supply curve for workers. The technological developments that drive these shifts in the labor demand are assumed to not affect the parameters of the workers' labor supply decisions.

We use data on relative wages, employment, lagged degree attainment and age shares to calibrate the remaining seven parameters. The first three series compare computer scientists to non-CS college graduate workers. For example, relative wages compare the wages for CS workers with wages for non-CS college graduates. To do this, we use the March Current Population

Survey (CPS). Details of the sample used in the data and specific variable definitions can be found in Appendix A.2.[32]

We simultaneously match wages, employment and the share of US computer science workers that are young (between 22 and 40) in 1994 and 2001.[33] We also match relative degrees in computer science for 1994, 1997 and 2001. The series we use from the data are as follows:[34]

1. $\frac{L_{n,t}}{G_t} = \frac{\text{US computer scientists}}{\text{Non-CS college educated US workers}}$ for $t = \{1994, 2001\}$
2. $\frac{w_t}{s_t} = \frac{\text{Median weekly wages for computer scientists}}{\text{Median weekly wages for non-CS college educated}}$ for $t = \{1994, 2001\}$
3. $\frac{q^{cs}_{t+2}}{q^{o}_{t+2}} = \frac{\text{US computer science college degrees awarded (lagged 2 years)}}{\text{US non-CS college degrees awarded (lagged 2 years)}}$ for $t = \{1994, 1997, 2001\}$
4. $age^{22,40}_t = \frac{\text{US computer scientists with age between 22 and 40}}{\text{US CS}^{22,40}+\text{US CS}^{41,65}}$ for $t = \{1994, 2001\}$

To simultaneously find parameter values which solve the model under these data restrictions, we use a Nelder-Mead simplex method. While the system uses all the data at the same time, there is strong intuition behind the identification of each parameter. For example, the relative degree attainment data should help identify the taste parameters for field of major decisions (σ_0 and θ_0) as well as the fixed cost of switching occupations (ζ_0), whereas the relative employment data should help pin down the occupation specific tastes (σ_1 and θ_1). The age shares in computer science employment help identify the occupation switching cost parameters that depend on age (ζ_1 and ζ_2).

3.3.1 Labor Supply Calibration results

Figure 2 shows the data used and the model fit from this exercise. The figures report both the path of the variables of interest predicted by the model, and the CPS data we use for these series. We match two extreme years (1994 and 2001) for employment and wages and three years (1994, 1997 and 2001) for lagged degree attainment, and the remaining years plotted are an out of sample test of our method. The years in between (1995 to 2000) include years where there were observed changes to immigration laws, and other potentially structural changes that may make it difficult for the data to fit perfectly.

[32] We exclude imputed wages, and multiply top-coded values by 1.4. Bollinger and Hirsch (2007) show that including imputations can lead to biased results. Whereas the top-coding adjustment is standard in the literature (Lemieux, 2006). We smooth the raw data over three-year moving averages as follows: $X_{t,smooth} = \frac{1}{3}(X_{t-1,raw} + X_{t,raw} + X_{t+1,raw})$

[33] Given that in our labor supply model we impose all cohorts are the same size, we normalize the number of computer scientists of a given age group dividing by the total number of college graduates in that age group before calculating the age shares.

[34] We have an exactly identified system as we use nine data moments to recover ten parameters - $\{\sigma_0, \theta_0, \sigma_1, \theta_1, \zeta_0, \zeta_1, \zeta_2\}$ and two implied values of technology in the years we match the wage/employment data $\{A_{94}, A_{01}\}$

The employment series in Figure 2a and the wage series shown in Figure 2b fit well at the start and end of the period, but it misses some years in between, particularly because it can't match the dip in wages that occur after 1994 and the simultaneous spike in employment in that same period. Lastly, the lagged degree attainment series can be seen in Figure 2c, and matches the data relatively well.

In Appendix Figure A.1 we extend this exercise to later years,and study how well our calibrated parameters match the data in the 2000s. We do a good job of matching wages and employment in this out-of-sample exercise, but over-predict enrollment in computer science for the years post-2004.

Table 4 presents the values of the calibrated parameters for the different values of λ. On average, we can see that there is a mean taste for not working in CS occupations, which is consistent with the wage differential seen across CS and non-CS work.

These calibrated parameters allow us to trace out the labor supply curve for computer-scientists relative to non-CS college educated workers. In order to do this, we use the model set-up and the parameters, and vary the relative wage to measure the response in relative quantities of labor. This derives the relative supply curve which we then use in the labor market to find the equilibrium wage.[35]

3.4 Endogenous Variables During the IT Boom

The calibration exercise so far helps us identify the parameters in the model that govern the trends in the endogenous variables over time. We can study these trends to understand how our model predicts what is happening at the time of the IT boom and the influx of foreign computer scientists. Given the solution of the model in each period, we study how prices and wages, employment by occupation and sector, and quantities produced change over time.

While US workers were more likely to work in CS occupations over time, the fraction of foreigners in CS work was increasing at a yet faster rate. Also consistent with the trends seen in the data for this period, the wage for computer scientists increases faster than the wages in other occupations. This IT boom overall leads to an increase in consumption of the IT good and a fall in prices of the IT good which benefits consumers.

Figure 3a shows how the ratio of US computer-scientists to non-CS college graduates $\left(\frac{L_{US}}{G}\right)$ evolves over this period according to our model for the different values of λ. During the time of the boom this ratio increases from about 0.040 to 0.047 for $\lambda = 2$, as more and more US workers shifted into CS work. At the same time, there was an increasing share of foreigners in CS occupations – the ratio of foreign to US computer scientists $\left(\frac{L_{Foreign}}{L_{US}}\right)$ more than doubled

[35] Our estimated relative labor-supply elasticities lie between 1.96 and 2.48.

from about 0.13 in 1994 to about 0.29 in 2001.

Our model predicts that over this period IT sector employment grew faster than employment in the other sector, and most of this was driven by hiring in computer science occupations (Figure 3b). The ratio of employment in IT to non-IT sectors over time $\left(\frac{L_C+G_C+H_C}{L_Y+G_Y+H_Y}\right)$ increases over this period, highlighting the importance of the IT boom in employing more workers. At the same time, with the influx of foreign computer scientists, the intensity of CS workers in the IT sector eventually increases. This can be seen in the series that plots the ratio of CS to non-CS workers in the IT sector $\left(\frac{L_C}{G_C+H_C}\right)$ in Figure 3b. The overall growth in the IT sector employment, therefore, was skewed towards CS employment.

While employment for CS workers, and the IT sector workers as a whole was increasing over this period, we can also study how the relative wages for these types of workers change. Figure 3c plots the CS wage relative to non-CS college graduate workers wages $\left(\frac{w}{s}\right)$ and relative to non-college graduate workers wages $\left(\frac{w}{r}\right)$. Consistent with the data, the model predicts that wages for computer scientists increase at a faster rate than wages for the other types of workers.

The boom in the IT sector increased overall production and consumption for IT goods. Figure 3d shows how relative consumption $\left(\frac{C}{Y}\right)$ increases and relative prices $\left(\frac{P_c}{P_y}\right)$ fall over this period as the supply of IT goods from firms increases. The reduction in the price of IT goods will affect overall consumer utility as laid out by the model, and the following section will discuss how we calculate utility for the different types of workers and the owners of firms.

4 Counterfactuals

In order to isolate the impacts of high-skilled immigration on the various endogenous variables and on worker welfare, we conduct a counterfactual exercise. In the exercise we restrict the stock of immigrants to be constant at the 1994 level, and subject the economy to the same innovation shocks that were experienced during this period. Using the identified parameters, we can then trace out what happens to all the endogenous variables over this period in a situation where the stock of immigrants is fixed.

We use the notation 'open' to refer to the real scenario under the H-1B regime, and 'closed' to the counterfactual of restricted immigration. We can then define any endogenous variable x_s, under the two scenarios $s = \{open, closed\}$. For example, L^{US}_{open} is the number of US computer scientists in the 'real' scenario under which high-skilled immigration is encouraged via the H-1B program, and all CS workers earn a wage w_{open}. In contrast, L^{US}_{closed} and w_{closed} are the employment of US computer scientists and wages for all computer scientists in the counterfactual scenario where the stock of foreigners is restricted to its 1994 level.

4.1 Employment and College Degrees in CS

Figure 4a describes the restriction under the counterfactual exercise. It shows how, under the real scenario where the economy is open to H-1B immigration, there is an increase in the stock of foreign computer scientists, whereas under the counterfactual scenario where the economy is 'closed,' the stock of foreign computer scientists is restricted to the 1994 level.

How this restriction affects the stock of US computer scientists in our model can be seen in Figures 4b-4c. Over this period there is an increase in the total number of computer scientists when we allow for immigration, but the number of US computer scientists actually decreases with respect to the closed economy every year as the number of immigrants increases. In 2001, the number of US computer scientists was between 6.1%-10.8% lower under the open than in the closed economy (Table 5). These numbers imply that for every 100 foreign CS workers that enter the US, between 33 to 61 native CS workers are crowded out from computer science to other college graduate occupations.

When the economy is open to immigration under the H-1B program, some US computer scientists switch over to non-CS occupations, shifting out the supply of these workers. This can be seen in Figure 4d. While over time there has been a rapid increase in the number of non-CS college educated workers, this increase would have been lower if the number of foreign CS workers were restricted. In fact, the growth rate between the open and closed economies plotted in Figure 4d mirrors the decrease in Figure 4c as US workers switch from CS to non-CS occupations.

Since students in our model choose their college major in their junior year, a change in the wages for computer scientists will affect these choices. Under the open economy scenario the fraction of CS degrees in 2001 would be between 1.3 - 2.6 percentage points lower than in the closed economy as can be seen in Figure 4e.

4.2 Wages

Over the period of study, wages grew for computer science workers, but this growth would have been higher if immigration was restricted (Figure 5b). An influx of foreign CS workers depresses the CS wage, and shifts some US workers into non-CS occupations. At the end of the decade, our model implies wages for CS workers would have been between 2.6%-5.1% lower under the open economy (Table 5).

With an increase in the foreign CS workforce, college educated US CS workers shift into non-CS occupations, and this tends to lower the non-CS wage. At the same time, however, as the equilibrium amount of total CS workers increases, so does the marginal product of non-CS college educated workers. This increases the demand for non-CS workers, and tends to increase

their wage making the net effect positive (Figure 5c). Overall, Table 5 shows an increase in the non-CS wage due to immigration, of about 0.04%-0.28% in 2001. As expected both the changes in CS wage and the non CS wage for college graduates are sensitive to what value of λ we choose, but qualitatively our results do not change across specifications.

Since the labor supply of non-college graduates is assumed to be fixed and inelastic, only changes in the demand for non-college graduates determine the difference in their wages under the real and counterfactual scenarios. When the economy is open to immigration, the equilibrium number of total college graduates employed increases due to immigration. This raises the marginal product of non-college graduate labor, and shifts out the demand for non-college graduate workers, raising the overall wage for non-college graduates (Figure 5d). Under the open economy, wages for non-college graduates would have been between 0.43%-0.52% higher by the end of this period (Table 5).[36]

4.3 Prices, Output and the Entry of Firms

While high-skilled immigration affected both employment and wages, it also affects overall output and prices of the different goods produced in the economy. These changes will affect overall consumer welfare, and also the profits accruing to firm owners.

Over the period of study, relative prices of IT goods were falling steadily, and some of this fall can be attributed to the increase in CS employment due to immigration. Figure 6a and Table 5 shows how under the open economy, prices would have been between 1.9%-2.4% lower in 2001.

At the same time, the relative consumption of IT goods was increasing, and this increase would have been lower without the growth in the foreign workforce (Figure 6b). Immigration also raises the profits of firms who can now hire relatively cheaper labor, and this causes new firms to enter the IT sector. Figure 6c shows how by allowing immigration, the number of IT firms would be higher. At the end of this period, there would be between 0.50%-0.56% fewer IT firms if immigration was restricted (Table 5).

5 Welfare

Using our estimated parameters and counterfactual exercises, we can measure the overall economic impacts on the different agents in the economy due to the increase in the number of foreign computer scientists. In order to compare losses and benefits and the distributional

[36] Since the non-college graduate workforce is a lot larger than the CS workforce the relative shift in wages is a lot lower compared to the CS wage.

consequences of immigration we look at the welfare of all types of workers and the owners of firms.

5.1 Calculating Welfare

5.1.1 Calculating Worker Welfare

Given the structure of our CES utility function, we can calculate consumer welfare as a function of the income of each type of agent. For a given income level m_i, the indirect utility of the agent is just the product of his income and the ideal price index. However, since the ideal price index is the numeraire, indirect utility is just the income of each type of worker: $V_i(m_i) = m_i$. We then compare the welfare of individuals under the two scenarios: (a) the real scenario, where high-skill immigration is encouraged under the H-1B program, and (b) the counterfactual scenario where the stock of immigrants is restricted to the 1994 level. For all welfare calculations we will only be focusing on welfare changes for those individuals who are US born, ignoring the changes in welfare for migrant computer scientists.

Workers are divided into four groups: those who are computer scientists and stay in CS occupations in the presence of immigration, those who are CS workers but switch to non-CS work because of immigration, those who were non-CS college graduates even before there was immigration and those who are non-college graduates. We then proceed to calculate welfare changes in two different ways: percent utility changes and compensating variation.

Our model shows that when there is an influx of foreign computer scientists, the equilibrium wage for CS workers falls and pushes some native college educated computer scientists into non-CS work. As the equilibrium number of hired computer scientists increases, the marginal product and hence the demand for other types of workers will also increase, tending to push up their wages. The wage for non-college educated workers and college educated non CS workers unambiguously rises for all specifications of λ.

For those that stay in their occupation groups under both real and counterfactual scenarios we can calculate the percent utility changes by just looking at the percent change in the wage for each group (e.g. the percent change in utility for the CS that stay in CS occupations under the presence of immigration is just the percent change in w between the open and closed economy). For CS that switch occupations to non-CS when we allow for immigration, we use information from both the utility change for the CS that stay and the change for those that were always non-CS college graduates.

By knowing the form of the indirect utility function, we can also calculate how much income we must compensate different types of workers who lose from immigration. This compensating variation (CV) depends on the indirect utility calculated at the original prices P_c and original

income levels m_i, and compare it to a scenario with new prices and income (P'_c, m'_i). A useful feature of the compensating variation is that we can scale up the results using total labor income in the US economy from the data, to measure how much workers should be compensated (in USD) if immigration restrictions were imposed. Given that the the ideal price index is our numeraire, we can write the compensating variation as $CV = m_i - m'_i$.

The number of computer scientists who stay in CS occupations even in the presence of immigration is L_{open}. Their overall change in income in the presence of increased immigration is therefore given by $(w_{closed} - w_{open})L_{open}$. When there is immigration, non college graduate workers benefit from the rise in wages that is caused by the increase in their marginal product. The increase in income for this group is therefore $(r_{open} - r_{closed})\bar{H}$.

Similarly, the number of non-CS college educated workers who were always in these other occupations is given by G_{closed}. Their overall change in income is given by $(s_{closed} - s_{open})G_{closed}$. Given that we find the wages for college educated non-CS workers to be lower in the presence of immigration, there is a loss in income to these workers due to immigration.

Lastly, for the group of workers who switch from CS to non-CS work in the presence of immigration, we must take into account their switching costs and change in utility because of different tastes in each occupation. The marginal worker who switches, experiences a different loss in utility than the infra-marginal worker. The overall change in terms of income equivalent for this group of workers can be approximated by $\frac{1}{2}(L_{closed} - L_{open})\left[(s_{closed} - s_{open}) + (w_{closed} - w_{open})\right]$.[37]

5.1.2 Calculating Profits

In our model, firms in the perfectly competitive residual sector earn no profits. In the monopolistically competitive IT sector, however, only the marginal firm earns 0 profits. In the current set-up we follow Chaney (2008), where there is an underlying mass of firms that already know their entrepreneurial capabilities and choose whether to produce or not given their productivity. There is therefore free-entry into the production decision, that drives the profit for the marginal producing firm down to zero.

For the firms in the IT sector, the marginal producing firm has a productivity ϕ^*, and a profit $\pi(\phi^*) = 0$. Using the notation highlighted in Section 2.1, we know that the average profit for producing firms can be represented by:

$$\int_{\phi^*}^{\infty} \pi(\phi)\mu(\phi)d\phi = \int_{\phi^*}^{\infty} PC^{\frac{1}{\epsilon}} c_j^{\frac{\epsilon-1}{\epsilon}} \mu(\phi)d\phi - w\int_{\phi^*}^{\infty} l_j\mu(\phi)d\phi - s\int_{\phi^*}^{\infty} g_j\mu(\phi)d\phi - r\int_{\phi^*}^{\infty} h_j\mu(\phi)d\phi - f \tag{28}$$

[37] The intuition for this expression is the following: a CS worker who switches, experiences a change in welfare that equals the change in CS wage up to the relative wage that induces them to switch. From that point on, the additional change in welfare will equal the change in the wages of non-CS college grads. We assume that for minor changes in wages the demand curve can be approximated linearly.

The total profits are then the average profits times the number of firms $N = (1-\Psi(\phi > \phi^*))N^e$, where N^e is the number of total potential producers in the sector.

We can also calculate profits for different types of firms using the features of this distribution. For example, we know that the cutoff productivity will change across the regimes where there is immigration and there isn't. In the presence of immigration, firm profits will rise and allow newer firms to enter on the margin.[38] This then allows us to calculate the profits for the new entrants and the incumbent firms separately. Let ϕ^*_{open} and ϕ^*_{closed} be the cutoff values of productivity under each regime. The new firms that enter when there is immigration will have a productivity $\phi_j \in [\phi^*_{open}, \phi^*_{closed}]$. Whereas the incumbents have a productivity $\phi_j \in [\phi^*_{closed}, \infty)$. These cutoffs therefore change the limits of integration and the conditional distribution functions.

The marginal distribution for the incumbents is determined by:

$$\mu_{closed}(\phi) = \begin{cases} \frac{k\phi^{-(k+1)}}{1-\Psi(\phi^*_{closed})}, & \text{if } \phi \geq \phi^* \\ 0, & \text{otherwise} \end{cases}$$

With $\Psi(\phi^*_{closed}) = 1 - \left(\frac{1}{\phi^*_{closed}}\right)^k$

The total profits to incumbents is then these average profits times the number of incumbents: $N_{incumbent} = (1 - \Psi(\phi_{closed}))N^e$. The total profits for new entrants is simply the difference in the profits for incumbents and the total profits for all firms in the open economy scenario.

Such an exercise can also be done to derive the profits for the firm in any percentile. For example, the firm in the 90th percentile has a productivity $\phi_{90} = \frac{1}{0.1}^{\frac{1}{k}}$. Since the number of firms above the 90th percentile is simply $N_{90} = 0.1N_e$,we can derive the profits for these firms in the scenario with and without immigration.

5.2 Welfare Changes Due to Immigration

The changes to the welfare of workers in this economy depends on the changes in income and the prices due to immigration. Figures 7a, 7c and 7e show how much workers, under a regime of restricted immigration, need to be compensated to maintain the same level of utility as they had in the open economy. These numbers have been translated into 1999 USD. Overall worker welfare is higher under immigration, and the amount of the compensating variation (CV) rises steadily between 1994 and 2001. The CV for all workers in 2001 is between \$8.2 and \$10.9 billion depending on the value of λ.

This overall increase in utility due to immigration, however, hides a lot of distributional changes.

[38] Alternatively, in the Melitz (2003) framework of the model , firms will enter at any point of the distribution

Figures 7a, 7c and 7e split up the workers into four groups - (1) those who stay in CS occupations even after immigration, (2) those who switch from CS to non-CS, (3) college graduates who were always non-CS, and (4) non-college graduates. As the figures show, US computer scientists are negatively affected by immigration, while other workers gain. The positive effect for college graduates gets partly offset by the mobility of the college educated across occupations, where CS switch to non-CS occupations depressing the wage. The losses for computer scientists and the gains for non CS college grads get closer to zero when the ease of substitution between CS and college non CS gets higher. On the other hand, the compensating variation for non college grads increases when λ increases. Table 6 summarizes the utility percent changes from allowing immigration and compensating variation for 2001, corroborating the idea that there are significant distributional effects from increased immigration.

While workers, as a whole, benefit from more immigration, firms make higher profits too. In Figures 7b, 7d and 7f the firms are split up into three different categories - (1) 'all incumbents' are only the firms that still produce when immigration is restricted. Amongst these incumbents, the (2) 'above 90th percentile' firms are those that have a productivity level that is above the 90th percentile in the productivity distribution, and similarly (3) '75th to 90th' percentile firms have a productivity level that lies between the 75th and 90th percentiles. Profits for all firms are increasing over this period and most of the profits are captured by the firms in the top ten per-cent of the productivity distribution. While we believe there is considerable heterogeneity in the profits firms receive as a result of the H-1B program it is important to note that the distribution of profits in the model is determined by our assumption on the Pareto distribution of firm productivities. In 2001, the aggregate profits in the IT sector were between \$0.78 and \$0.89 billion (1999 USD), and between \$0.59 to \$0.68 billion went to the firms that had a productivity level above the 90th percentile. Table 9 summarizes the changes in profits for the different values of λ, overall profits increase between 0.61%-0.70% in 2001 when allowing for immigration.

5.3 Alternative modeling specifications

We analyze how two particular features of the IT sector in our model affect our results. The first is our assumption of monopolistic competition and the existence of different varieties in IT products. This makes the IT sector smaller than the perfectly competitive optimal size. An increase in the number of immigrants, and therefore workers, will expand this sector and lead to welfare gains. At the same time, as more firms enter, the increase in varieties benefit consumers as well. The second non-standard feature of our model is the presence of technological spillovers driven by innovation by computer scientists. An increase in the CS work force due to immigration leads to more innovation and has an additional impact on overall production, lowering prices and increasing welfare for consumers.

In Table 7 we compare the monopolistically competitive model with a traditional perfectly competitive set-up, and also shut-down the presence of technological spillovers to study how our results change. In moving from a perfectly competitive to a monopolistically competitive model, the welfare changes due to immigration are roughly similar. There is a slightly larger welfare gain due to immigration in the monopolistically competitive model both in the absence or the presence of technological spillovers. Shutting down the possibility of technological spillovers, however, has a larger impact on the gains from immigration. In the absence of spillovers, $\beta = 0$, the overall gains to worker utility is only between 0.02% and 0.03%, whereas the spillovers $\beta = 0.23$ increase these gains to about 0.21%. How the results change with other values of β is discussed in Appendix A.4. Therefore, while the monopolistic competition assumption does not affect worker welfare much, the presence of technological spillovers does.

One advantage of the monopolistically competitive setup is that it allow us to get a measure of how firm profits are affected by immigration. The profit numbers should be interpreted with caution, however, since our framework implies that profits are simply a fixed proportion of total revenues. Nonetheless, given that IT firms spend a substantial amount of funds in lobbying Congress to raise the H-1B cap, it is reasonable to believe that firms stand to benefit from an influx of high-skill immigrants.

Importantly, our model includes the labor supply decisions of college educated US workers. This allows students and workers to move out of immigrant intensive fields and occupations when there is an influx of high-skill workers from abroad. The negative effects on CS workers is mitigated as US CS workers switch to non-CS jobs, and fewer students graduate with CS degrees. However, since CS workers are also innovators, the economy as a whole no longer benefits as much from technological improvements when US workers leave CS occupations. In Table 8 we compare our baseline model that allows for labor supply decisions, to an inelastic supply model where US students and workers are no longer allowed to change their decisions in the face of high-skill immigration. Immigration has an even more of a negative impact on US CS workers when we restrict adjustments on the labor supply side. Since workers can no longer switch into non-CS occupations, the increase in labor supply from abroad depresses CS wages and hurts CS workers the most. On the other hand, welfare in the economy as a whole increases since there are more computer scientists and hence more innovators.

6 Discussion

Isolating the impacts of high-skill immigration is challenging in the absence of credible instruments that exogenously vary the share of foreign workers. Nonetheless, given the rapidly increasing share of immigrants in the skilled labor force, it is an important issue to examine. We develop a general equilibrium model of the US economy, calibrated using data from 1994

to 2001, to estimate how the increasing share of foreign high-skill workers affects the welfare of different types of workers, firms and consumers. We do so by examining the welfare of US natives under a counterfactual scenario where we restrict the fraction of immigrants to their 1994 levels.

While our conclusions depend on the specifics of our model, we believe them to be reasonable. As long as the supply curve of US workers is not infinitely elastic, and we believe that evidence indicates rather conclusively that it is not, the availability of high-skill foreign immigrants will shift out the supply of high-skill workers in the US economy. However, as long as the demand curve for high-skill workers is downward sloping, the influx of foreign high-skill workers will both crowd out and lower the wages of US high-skill workers. As a result, output in the high-skill intensive sector of the economy will rise, but will rise less than if the crowd out effects were negligible. The fact that high-skill workers contribute to innovation tends to mute such crowd-out effects, but our results suggest such effects are not nearly large enough to fully compensate for the crowd-out.

Overall, our results suggest that high-skill foreign workers contribute to the well-being of the typical US consumer, mainly through the assumption that these workers contribute to innovation at the same rate as US high-skill workers. Indeed, under our calibrations, accounting for foreign workers' effect on innovation, the gains to consumers are an order of magnitude larger than gains excluding this effect. At some level, this is hardly surprising. While simple models of the impact of immigration on native welfare suggests the immigrant surplus is second order (Borjas, 1999), if the immigrants shift out the production possibility frontier, their effect will be first order.

In our model, immigration also raises profits in the IT sector. While the magnitude of these gains depends on the markup in the IT sector, as long as there is a markup, which we consider safe to assume, high-skill immigrant labor raises IT sector profits. It is then no surprise that Bill Gates and other IT executives lobby in favor of increasing quotas for high-skill immigrants.

Although our results suggest that the introduction and expansion of the H-1B program in the 1990s brought gains to both US consumers and IT sector entrepreneurs, we also found indications of losses for US computer scientists and potential computer scientists. Recent work (Peri and Sparber, 2009, 2011) has emphasized the importance of immigration affecting the occupational choice of US natives. Our results tend to support the importance of this view. Indeed, our estimates suggest that high-skill immigration has had a significant effect on the choices made by US workers and students.

Researchers (e.g. Peri and Sparber, 2011) have emphasized that high-skill immigrants have the potential for opening up opportunities for US workers – someone who might otherwise have been an engineer or computer scientist now becomes a manager. We have no doubt that this is true and, in a primitive way, we have built this into our model. The influx of skilled

immigrants induces some college graduates to leave CS and raises the productivity of non-CS college graduates. Still, for many college graduates who entered or might have entered the CS field, their options have been curtailed.

Our model is far too simple to allow for policy evaluations of alternatives to our current system of high-skill immigration. However, we note that our model (and simple economic reasoning) suggests that high-skill immigration does tend to crowd out US workers to some extent. We suspect that allowing essentially unlimited immigration of high-skill workers by, for instance, awarding green cards to all foreign students attending US colleges and universities would have dramatic effects on the US labor market. Not all of these would be positive.

In the end we want to emphasize the limitations of our work. While our focus is on how the influx of foreign workers affect the US, we recognize that US policy on high-skill immigration has profound effects on both labor-sending countries and on other countries that produce in the IT sector. Also, our analysis is constrained to the 1990s, whereas in the long run, US immigration policy is likely to affect the position of the US in the world economy. We leave exploration of these issues to future research.

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Tables and Figures

Table 1: Immigration and the Computer Science Workforce

Year	1970	1980	1990	2000	2010
Computer Scientists as a fraction of workers with a BA/MA	1.68%	1.83%	3.30%	5.66%	5.28%
Computer Scientists as a fraction of STEM college graduates	16.86%	23.60%	35.99%	53.31%	54.90%
Immigrants as a fraction of BA/MAs	2.10%	5.43%	6.86%	8.41%	12.77%
Immigrants as a fraction of Computer Scientists	2.37%	7.09%	11.06%	18.59%	27.82%
Immigrants as a fraction of Other STEM workers	3.63%	9.72%	10.71%	12.69%	18.21%

Note: Sample restricted to employed workers with a Bachelor's or a Master's degree. Definition of Computer Scientists and STEM workers determined by occupational coding (for details see Data Appendix A.2). Immigrant defined as one born abroad, and migrated to the US after the age of 18.
Source: US Census (years 1970 to 2000); ACS (2010)

Table 2: Calibrated Parameters from the Product Market

Time-Invariant Parameters				
	σ	1.00	k	2.62
	ϵ	3.20	N_e	0.25
	τ	1.70	f	1.07-1.24
	β	0.23	ϕ_{min}	1

Time-Varying Parameters									
		1994	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**
γ		0.042	0.046	0.050	0.052	0.054	0.055	0.055	0.054
γ_W		0.014	0.015	0.015	0.016	0.014	0.015	0.016	0.013
ψ_1		0.522	0.524	0.525	0.524	0.523	0.521	0.517	0.513
ψ_2		0.055	0.054	0.054	0.053	0.053	0.052	0.052	0.051
α_c		0.438	0.432	0.427	0.419	0.410	0.401	0.395	0.390
α_y		0.502	0.494	0.486	0.479	0.473	0.468	0.465	0.463
	$\lambda = 1$	0.053	0.055	0.059	0.063	0.067	0.069	0.073	0.072
δ	$\lambda = 2$	0.224	0.227	0.233	0.240	0.248	0.253	0.262	0.260
	$\lambda = 4$	0.395	0.398	0.401	0.405	0.414	0.420	0.430	0.428
	$\lambda = 1$	0.217	0.215	0.215	0.218	0.225	0.237	0.249	0.270
Δ	$\lambda = 2$	0.174	0.168	0.153	0.147	0.146	0.157	0.158	0.175
	$\lambda = 4$	0.073	0.066	0.048	0.039	0.036	0.046	0.042	0.057

σ: Elasticity of substitution between C and Y; ϵ: elasticity of substitution across IT varieties; τ: the elasticity of substitution between college and non college graduates; β: the technological spillover of computer scientists in IT; f: fixed cost of production; N_e: mass of potential producers; k and ϕ_{min}: distribution and scale parameters from the Pareto distribution.

γ: Distributional parameter of domestic CES utility; γ_W: Distributional parameter of foreign CES utility; ψ_1, ψ_2: Production function parameters for Intermediate inputs in IT and the Other Sector respectively; α_c, α_y: Distributional parameter for non college grads in the IT and Other sector production function; δ: Distributional parameter for computer scientists in both sectors; Δ: distributional parameter for computer scientists in IT. λ: Elasticity of substitution between CS and non-CS college grads.

Table 3: Normalized Population and Growth as Observed in the Data

Year	X_t	L_{tF}	L_{tn}	G_t	H_t
1994	100.00	0.13	0.99	24.30	74.59
1995	101.18	0.16	1.02	24.85	75.16
1996	103.31	0.19	1.12	25.61	76.39
1997	105.25	0.24	1.20	26.26	77.55
1998	107.35	0.26	1.27	27.06	78.76
1999	109.12	0.31	1.30	27.85	79.67
2000	110.95	0.37	1.35	28.71	80.52
2001	111.77	0.40	1.37	29.51	80.49

Total working population as shown in the CPS is normalized to 100 in 1994. For subsequent years we allow total population to grow at the same rate than the working population in the US. The shares of each type of occupation are then used to calculate the total number of workers in each category.

Table 4: Labor Supply Calibrated Parameters

Parameter	Description	Calibrated Value		
		$\lambda = 1$	$\lambda = 2$	$\lambda = 4$
σ_0	Std dev of study-area taste shocks	0.0141	0.0215	0.0217
σ_1	Std dev of occupation taste shocks	0.9420	0.8887	0.9282
θ_0	Mean taste for not studying CS	-0.1341	-0.1072	-0.1362
θ_1	Mean taste for not working in CS	2.1766	1.8627	1.9278
η_1	Sector switching cost (constant)	0.3265	0.4059	0.4145
η_2	Sector switching cost (linear)	0.0307	0.0529	0.0488
η_3	Sector switching cost (quadratic)	-0.0001	-0.0007	-0.0006

Table 5: Percent Changes when Allowing Immigration - 2001

	$\lambda = 1$	$\lambda = 2$	$\lambda = 4$
Relative Price	-1.86%	-1.85%	-2.42%
Relative Quantity	1.89%	1.89%	2.48%
Number of Firms	0.50%	0.51%	0.56%
Wage Computer Scientists	-5.13%	-3.47%	-2.57%
Wage College Graduates non CS	0.28%	0.10%	0.04%
Wage Non College Graduates	0.43%	0.44%	0.52%
Total Employment in CS	6.39%	8.00%	11.47%
US Computer Scientists	-10.81%	-9.32%	-6.12%
College Graduates non CS	0.57%	0.48%	0.30%

Percent changes are calculated using the endogenous variables from the closed and open economy. For each year we consider the situation of going from a closed to an open economy (allowing immigration), that is $(\frac{X_{open}}{X_{closed}} - 1) \times 100$. Results shown for different values of λ and only look at year 2001.

Table 6: Percent change in Utility when allowing for Immigration and Compensating Variation

	Percent Change in Utility			Compensating Variation (million USD)		
	$\lambda = 1$	$\lambda = 2$	$\lambda = 4$	$\lambda = 1$	$\lambda = 2$	$\lambda = 4$
All US workers	0.20%	0.21%	0.27%	8204	8290	10904
College Graduates - All	-0.12%	-0.16%	-0.14%	-1955	-2453	-2110
Computer Scientists that stay	-5.13%	-3.47%	-2.57%	-5951	-3752	-2631
Computer Scientists that switch	-2.48%	-1.71%	-1.27%	-348	-189	-85
College Graduates non CS that stay	0.28%	0.10%	0.04%	4344	1488	606
Non College Graduates	0.43%	0.44%	0.52%	10159	10743	13014

We compare utility changes when going from a closed to an open economy so percent changes are calculated for each year and subgroup as: $(\frac{V_{open}}{V_{closed}} - 1) \times 100$, where V is indirect utility for that specific group. Compensating Variation figures are expressed in million USD.

Table 7: Percent change in Utility - perfect competition vs. monopolistic competition in the IT sector

	Perfectly competitive		Monopolistic competition	
	$\beta = 0$	$\beta = 0.23$	$\beta = 0$	$\beta = 0.23$
All US workers	0.02%	0.20%	0.03%	0.21%
College Graduates - All	-0.34%	-0.16%	-0.34%	-0.16%
Computer Scientists that stay	-3.76%	-3.58%	-3.64%	-3.47%
Computer Scientists that switch	-1.90%	-1.76%	-1.85%	-1.71%
College Graduates non CS that stay	-0.08%	0.10%	-0.08%	0.10%
Non College Graduates	0.25%	0.43%	0.26%	0.44%

We compare utility changes when going from a closed to an open economy so percent changes are calculated for each year and subgroup as: $(\frac{V_{open}}{V_{closed}} - 1) \times 100$, where V is indirect utility for that specific group. In the perfectly competitive cases we assume that the IT sector is no longer under monopolistic competition. The $\beta = 0$ refers to the case where there is no spillover effect in the IT sector while the $\beta = 0.23$ refers to the spillover case. In all cases $\lambda = 2$.

Table 8: Changes in Profits and Income for different labor supply specifications

	Percent Change in Income/Profits		Compensating Variation/Change in Profits (USD million)	
	Baseline	Inelastic supply	Baseline	Inelastic supply
All US workers	0.21%	0.46%	8290	17798
College Graduates - All	-0.16%	0.01%	-2453	225
Computer Scientists that stay	-3.47%	-7.51%	-3752	-8467
Computer Scientists that switch	-1.71%	-	-189	-
College Graduates non CS that stay	0.10%	0.60%	1488	8692
Non College Graduates	0.44%	0.72%	10743	17572
Profits	0.61%	0.94%	783	1197

The baseline case is when we apply our full labor supply model for college graduates. The inelastic case shows what happens when workers are not allowed to change occupations or degree-choice decisions. All specifications use a value of $\lambda = 2$, $\sigma = 1$ and $\beta = 0.23$. Dollar values for compensating variation and profits are in millions of 1999 USD. The scaling up in to USD was done using CPS data for the total amount of labor income. Changes in Income for different worker groups and profits are calculated as $(\frac{X_{open}}{X_{closed}} - 1) \times 100$

Table 9: Percent change in Profits when allowing for Immigration - 2001

	$\lambda = 1$		$\lambda = 2$		$\lambda = 4$	
	Share of Profits	Percent Change	Share of Profits	Percent Change	Share of Profits	Percent Change
All Firms		0.61%		0.62%		0.70%
All Incumbent Firms	100.00%	0.61%	100.00%	0.62%	100.00%	0.70%
90th-100th percentile	84.82%	0.54%	85.09%	0.55%	85.05%	0.62%
75th-90th percentile	9.64%	0.71%	9.59%	0.73%	9.60%	0.82%
<75th	5.54%	1.45%	5.32%	1.51%	5.36%	1.66%

Columns titled "Share of Profits" show the share of profits among all incumbents by firm size for 2001 in the open economy. We compare profit changes when going form a closed to an open economy so percent changes in aggregate profits for each year and subgroup are calculated as: $(\frac{\Pi_{open}}{\Pi_{closed}} - 1) \times 100$. Percentiles are defined using the Pareto distribution we are assuming for productivities in the market. Rows 2-5 only consider incumbent firms (those that operate under the open and closed economy), Row 1 shows the growth rate between open and closed taking into account the marginal firms that start producing in the open economy. Results shown for different values of λ and only look at year 2001.

Table 10: Changes in Profits and Income for different elasticities of substitution between IT and non IT good in consumer utility

	Percent Change in Income/Profits			Compensating Variation/Change in Profits (USD million)		
	$\sigma = 1$	$\sigma = 2$	$\sigma = 5$	$\sigma = 1$	$\sigma = 2$	$\sigma = 5$
All US workers	0.21%	0.25%	0.41%	8290	32760	102943
College Graduates - All	-0.16%	-0.11%	0.07%	-2453	7060	34637
Computer Scientists that stay	-3.47%	-3.65%	-3.43%	-3752	-3360	-1471
Computer Scientists that switch	-1.71%	-1.78%	-1.61%	-189	-127	48
College Graduates non CS that stay	0.10%	0.16%	0.34%	1488	10547	36061
Non College Graduates	0.44%	0.48%	0.63%	10743	25700	68305
Profits	0.62%	1.66%	7.70%	783	2106	9160

All specifications us a value of $\lambda = 2$ and $\beta = 0.23$. Dollar values for Compensating Variation and Profits are in millions of 1999 USD. The scaling up in to USD was done using CPS data for the total amount of labor income. Changes in Income for different worker groups and profits are calculated as $(\frac{X_{open}}{X_{closed}} - 1) \times 100$

Table 11: Changes in Profits and Income for different values of the technological spillover parameter

	Percent Change in Income/Profits				Compensating Variation/Change in Profits (USD million)			
	$\beta = 0$	$\beta = 0.1$	$\beta = 0.233$	$\beta = 0.5$	$\beta = 0$	$\beta = 0.1$	$\beta = 0.233$	$\beta = 0.5$
All US workers	0.03%	0.10%	0.21%	0.41%	1051	4150	8290	16522
College Graduates - All	-0.34%	-0.26%	-0.16%	0.05%	-5275	-4066	-2453	758
Computer Scientists that stay	-3.64%	-3.57%	-3.47%	-3.27%	-3945	-3862	-3752	-3530
Computer Scientists that switch	-1.85%	-1.79%	-1.71%	-1.54%	-205	-198	-189	-171
College Graduates non CS that stay	-0.08%	0.00%	0.10%	0.31%	-1125	-6	1488	4458
Non College Graduates	0.26%	0.33%	0.44%	0.64%	6326	8216	10743	15764
Profits	0.43%	0.51%	0.62%	0.82%	554	653	783	1047

All specifications us a value of $\lambda = 2$ and $\sigma = 1$. Dollar values for Compensating variation and Profits are in millions of 1999 USD. The scaling up in to USD was done using CPS data for the total amount of labor income. Changes in Income for different worker groups and profits are calculated as $(\frac{X_{open}}{X_{closed}} - 1) \times 100$

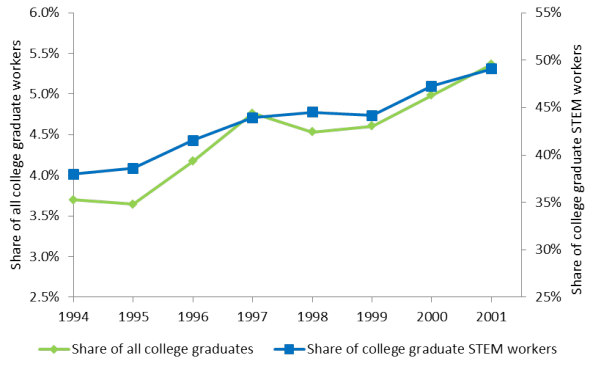
Table 12: Changes in Profits and Income for different values of the elasticity of substitution across varieties in consumer utility

	Percent Change in Income/Profits		Compensating Variation/Change in Profits (USD million)	
	$\epsilon = 2$	$\epsilon = 3.2$	$\epsilon = 2$	$\epsilon = 3.2$
All US workers	0.26%	0.21%	10272	8290
College Graduates - All	-0.11%	-0.16%	-1641	-2453
Computer Scientists that stay	-3.78%	-3.47%	-4000	-3752
Computer Scientists that switch	-1.83%	-1.71%	-181	-189
College Graduates non CS that stay	0.18%	0.10%	2540	1488
Non College Graduates	0.50%	0.44%	11913	10743
Profits	0.67%	0.62%	615	783

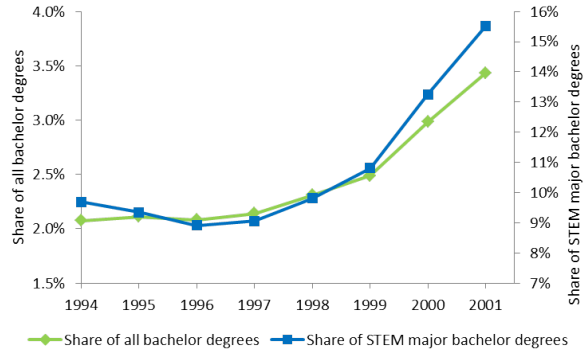
All specifications us a value of $\lambda = 2$, $\sigma = 1$ and $\beta = 0.23$. Dollar values for Compensating variation and Profits are in millions of 1999 USD. The scaling up in to USD was done using CPS data for the total amount of labor income. Changes in Income for different worker groups and profits are calculated as $(\frac{X_{open}}{X_{closed}} - 1) \times 100$

Figure 1: High-Skilled Immigration and the IT Boom

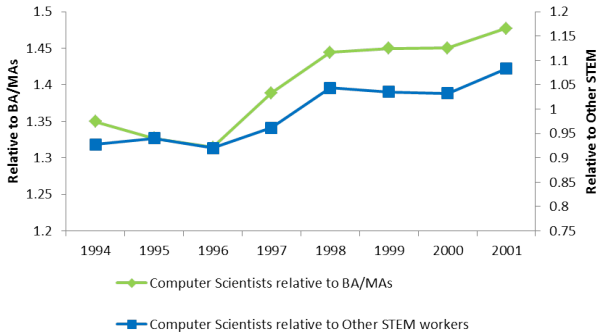
(a) Fraction of Computer Scientists in US Workforce



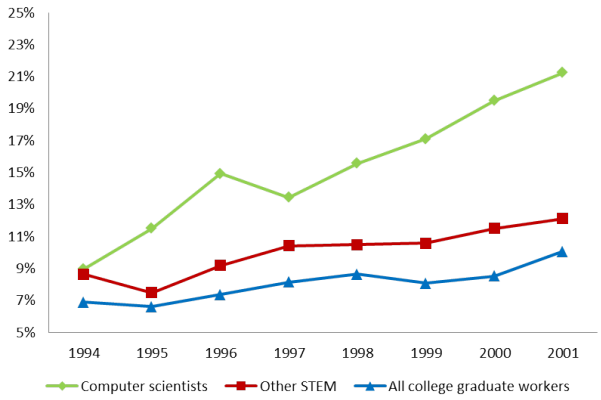
(b) Computer Science Fraction of Bachelor Degrees



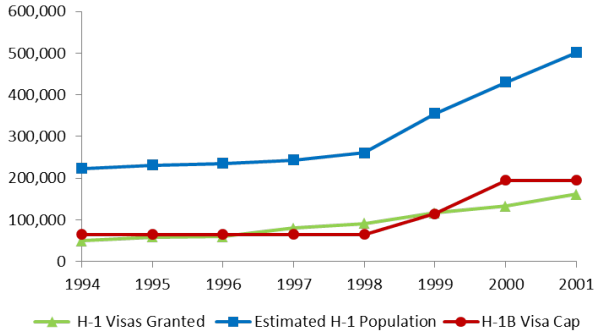
(c) Earnings of Computer Scientists Relative to Other groups



(d) Immigrants as Fraction of Workers by Occupation



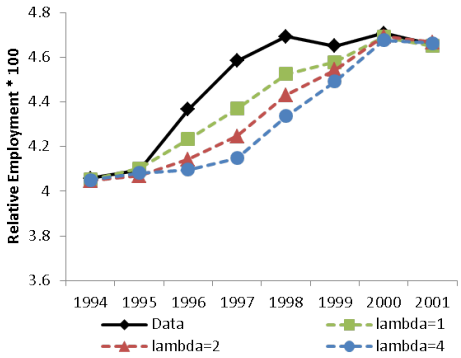
(e) H-1 Visas



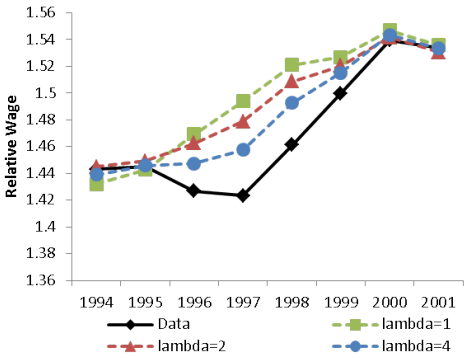
Sources: Figure 1a, 1c and 1d March Current Population Survey (CPS). Figure 1b is from IPEDS (The Integrated Postsecondary Education Data System). Figure 1e author's calculations updating Lowell (2000).

Figure 2: Calibrating Labor Supply Parameters

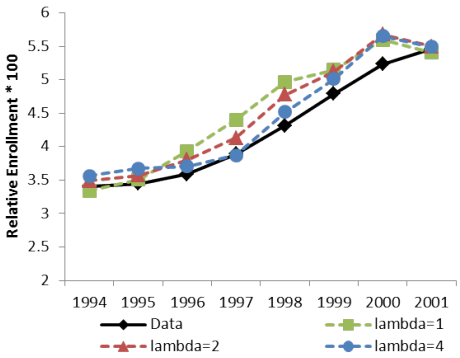
(a) Matching Relative Labor Supply



(b) Matching Relative Wages



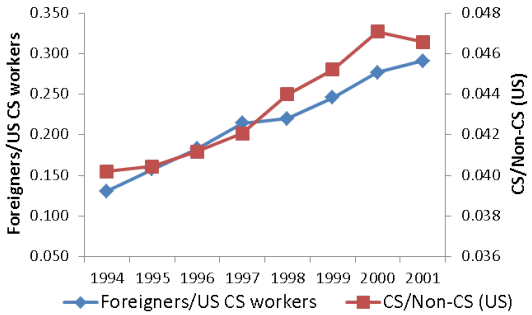
(c) Matching Relative Degree Attainment



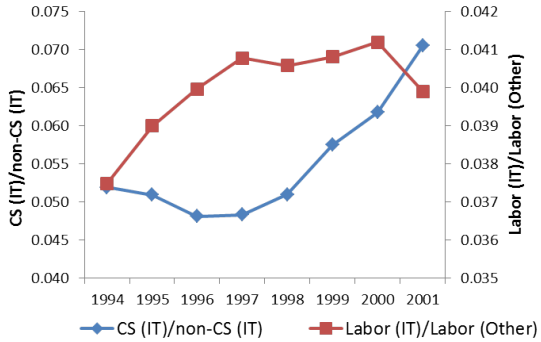
In the calibration exercise, the years 1994 and 2001 were used to match the data for employment and wages, whereas the years 1994,1997 and 2001 was used to match the data on degree attainment (lagged two year). The years in between are an out-of-sample test. Wage and employment data come from the March CPS, whereas degree data is from IPEDS. See Appendix A.2 for more details about the data. See Appendix A.3 for a longer-run view of the out-of-sample tests in later years.

Figure 3: Endogenous Variables Over Time

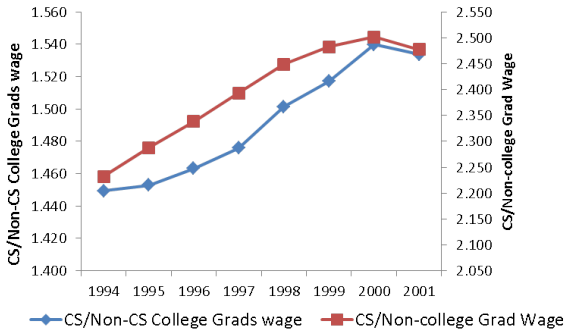
(a) Ratio of Foreign to US Computer Scientists and US CS to US College Graduates



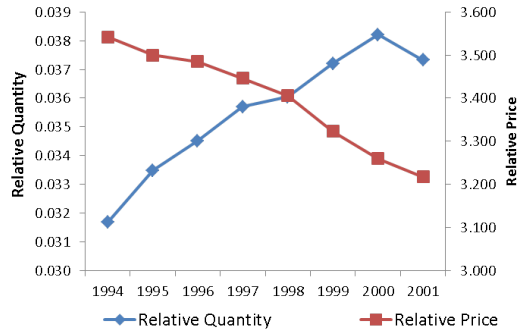
(b) Computer Science Labor and Total Labor in IT



(c) Relative wages for CS workers



(d) Relative Price and Quantity of the IT Good



Model predictions for ratio of endogenous variables over time:

(a) Foreign CS workers to US CS workers $\left(\frac{L_{Foreign}}{L_{US}}\right)$, and for US CS workers to all US College Graduate workers $\left(\frac{L_{US}}{L_{US}+G}\right)$,

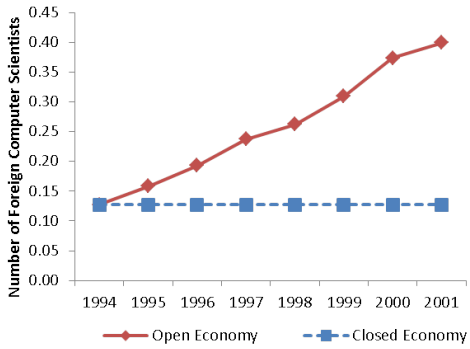
(b) Computer science labor to non-CS labor in the IT sector $\left(\frac{L_c}{G_c+H_c}\right)$ and the total labor in IT relative to total labor in the other sector $\left(\frac{L_c+G_c+H_c}{L_y+G_y+H_y}\right)$

(c) Computer science wage relative to non-CS college graduate wage $\left(\frac{w}{s}\right)$ and the computer science wage relative to non-college graduate wage $\left(\frac{w}{r}\right)$

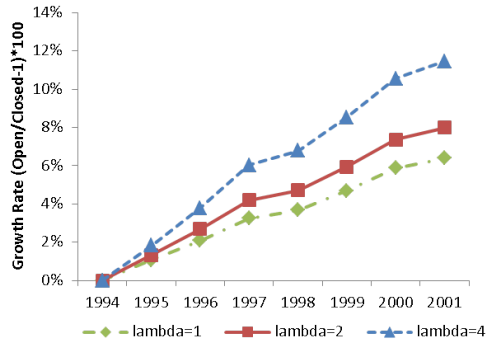
(d) Relative prices for the IT good $\left(\frac{P_c}{P_y}\right)$ and relative consumption $\left(\frac{C}{Y}\right)$.

Figure 4: Employment Under the Real and Counterfactual Scenarios

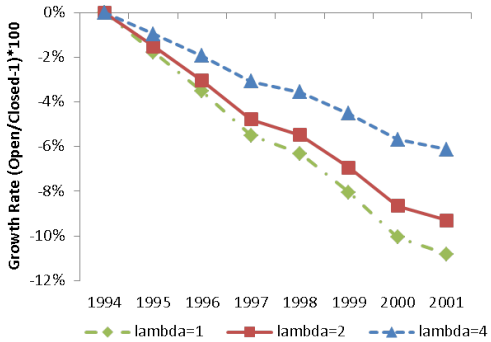
(a) Foreign Computer Scientists



(b) Total Computer Scientists



(c) US Computer Scientists



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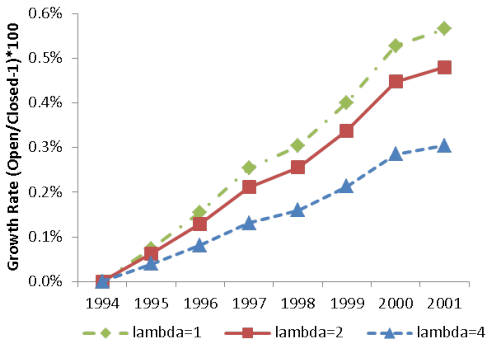
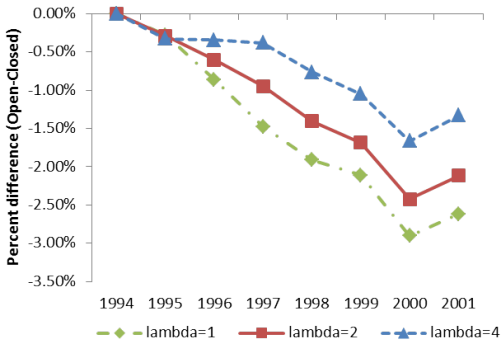
(d) Non-CS College Educated Workers



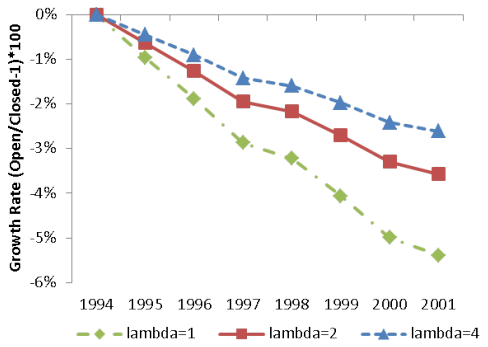
(e) Fraction of CS Degrees



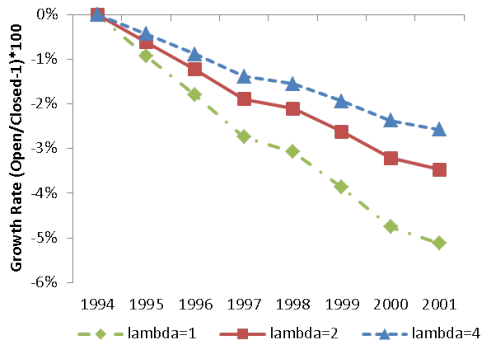
The closed economy is where immigration is restricted to the 1994 levels, whereas in the open economy the stock of immigrants grow according to the data. Total size of the workforce is normalized to 100 in 1994.

Figure 5: Wages Under the Real and Counterfactual Scenarios

(a) Wages of CS Relative to Non-CS College Wage



(b) Wages for Computer Scientists



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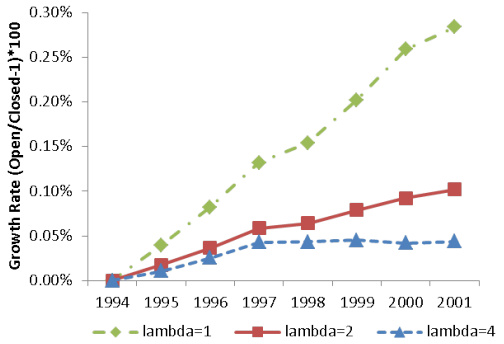
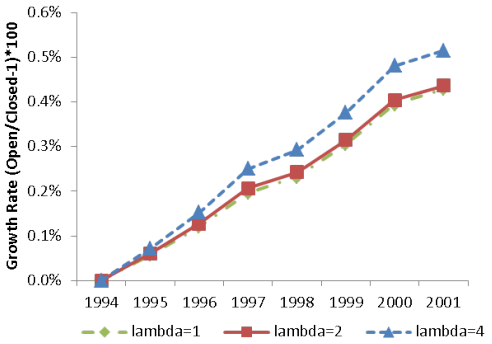
(c) Wages for Non-CS College Educated Workers



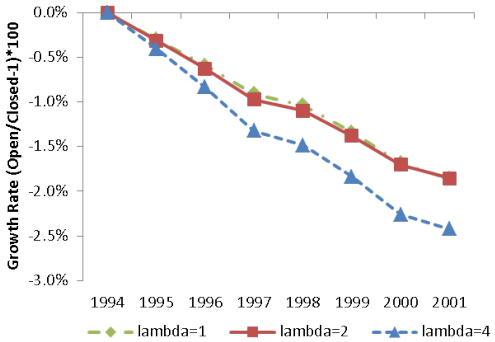
(d) Wages for Non College Educated Workers



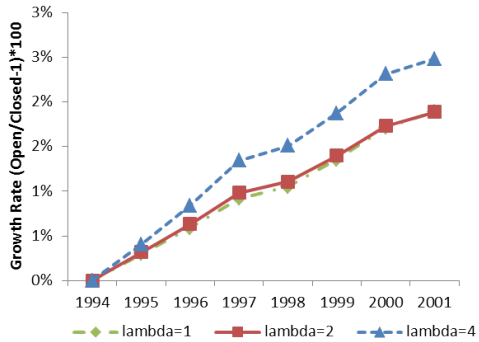
The closed economy is where immigration is restricted to the 1994 levels, whereas in the open economy the stock of immigrants grow according to the data. All monetary values are in units of the numeraire (the consumption bundle).

Figure 6: Output and Prices Under the Real and Counterfactual Scenario

(a) Price of IT Good relative to the Other Good



(b) Consumption of IT Good relative to the Other Good



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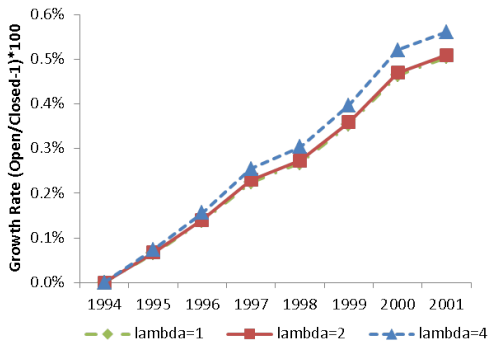
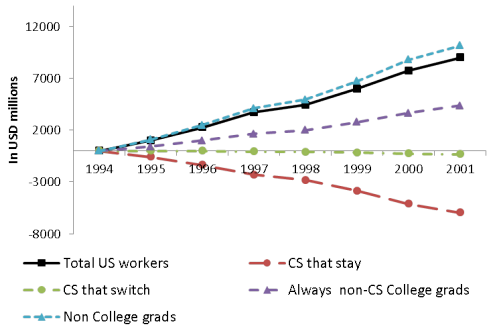
(c) Number of IT firms



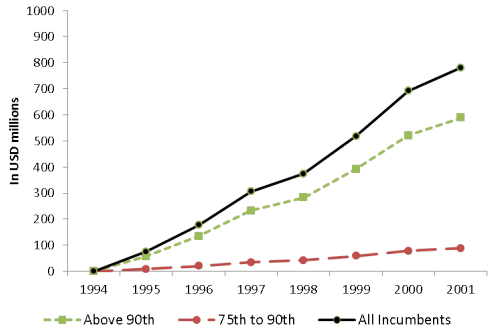
The closed economy is where immigration is restricted to the 1994 levels, whereas in the open economy the stock of immigrants grow according to the data. Prices are in units of the numeraire (the consumption bundle).

Figure 7: Welfare Changes Due to Immigration

(a) Compensating Variation ($\lambda = 1$)



(b) Change in Profits Due to Immigration ($\lambda = 1$)



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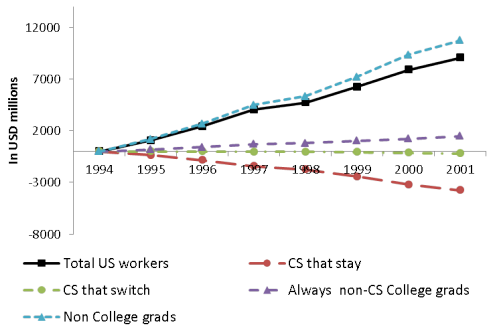
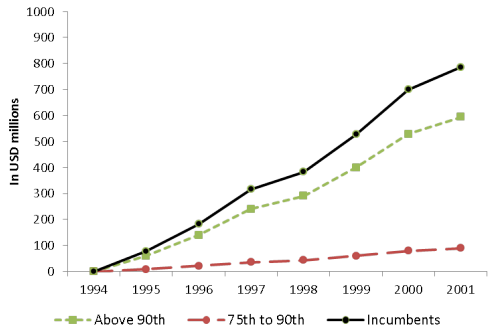
(c) Compensating Variation ($\lambda = 2$)



(d) Change in Profits Due to Immigration ($\lambda = 2$)



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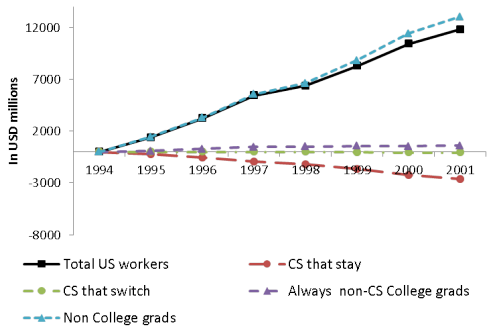
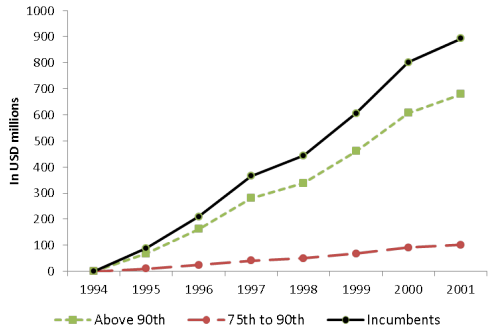
(e) Compensating Variation ($\lambda = 4$)



(f) Change in Profits Due to Immigration ($\lambda = 4$)



The closed economy is where immigration is restricted to the 1994 levels, whereas in the open economy the stock of immigrants grow according to the data. Compensating variation in this scenario is how much the workers must be compensated if immigration is restricted to the 1994 level. Compensating variation and Profits are in millions of 1999 USD. The scaling up in to USD was done using CPS data for the total amount of labor income across each year separately. Figures 7a, 7c and 7e split up the workers into four groups - (1) those who stay in CS occupations even after immigration, (2) those who switch from CS to non-CS, (3) college graduates who were always non-CS, and (4) non-college graduates. Figures 7b, 7d and 7f split up the firms into three different categories - (1) 'all incumbents' are only the firms that still produce when immigration is restricted. Amongst these incumbents, the (2) 'above 90th percentile' firms are those that have a productivity level that is above the 90th percentile in the productivity distribution, and similarly (3) '75th to 90th' percentile firms have a productivity level that lies between the 75th and 90th percentiles of the Pareto productivity distribution.

A Appendix

A.1 Additional Model Details

A.1.1 Consumer Demand for Goods

Given the consumer utility functions described in Section 2.1.1, it is possible to write the price index P in the form of equation 29:

$$P_c = \left(\int_{\nu \in \Omega} p_i^{1-\epsilon} d\nu \right)^{\frac{1}{1-\epsilon}} \tag{29}$$

Consumers maximize utility in equation 1 subject to a budget constraint $m = P_c C_d + P_Y Y_d$, where m is total income. The utility maximizing first order condition for a given variety is therefore:

$$\left(\frac{c_{di}}{C_d} \right)^{-\frac{1}{\epsilon}} = \frac{p_i}{P} \tag{30}$$

We can then write the demand for aggregate goods as a function of prices, total income m and the parameters γ and σ.

$$C_d = \frac{m}{P_c + P_Y \left(\frac{1-\gamma}{\gamma} \frac{P_c}{P_Y} \right)^{\sigma}} \tag{31}$$

$$Y_d = \frac{m \left(\frac{1-\gamma}{\gamma} \frac{P_c}{P_Y} \right)^{\sigma}}{P_c + \left(\frac{1-\gamma}{\gamma} \frac{P_c}{P_Y} \right)^{\sigma}} \tag{32}$$

A.1.2 Labor Supply Derivations

In order to determine the labor supply of US born workers, we use the setup described in Section 2.3. First we study the probability of students enrolling in computer science degrees. Given the distributional assumptions and equation 15, it follows that the probability (q_t^{cs}) that a student graduates with a computer science degree can be written in logistic form:

$$q_t^{cs} = [1 + exp(-(\rho^2 \mathbb{E}_{t-2}[V_{22}^{cs} - V_{22}^{o}] - \theta_o)/\sigma_0)]^{-1} \tag{33}$$

This set-up allows us to map the graduating probability described above to employment. Let $(\overline{L_t^a + G_t^a})$ be the number of college graduates with age a in time period t, then the number of graduates with a computer science degree in year t is represented by $R_t = q_t^{cs}(\overline{L_t^{22} + G_t^{22}})$.

Next, we derive the occupational choice decisions based on the set up in Section 2.3.2. Defining $q_{t,a}^{dD}$ as the probability that a worker at age a between 22 and 64 moves from occupation d to occupation D, it follows from the distributional assumptions that the probability of workers switching from computer-science to other occupations, and vice versa can be represented as:

$$q_{t,a}^{o,cs} = [1 + exp(-(w_t - s_t - \zeta(a) - \theta_1 + \rho\mathbb{E}_t[V_{t+1,a+1}^{cs} - V_{t+1,a+1}^{o}])/\sigma_1)]^{-1} \tag{34}$$

$$q_{t,a}^{cs,o} = [1 + exp(-(s_t - w_t - \zeta(a) + \theta_1 + \rho\mathbb{E}_t[V_{t+1,a+1}^{o} - V_{t+1,a+1}^{cs}])/\sigma_1)]^{-1} \tag{35}$$

Here we can see that the switching probabilities depend upon both the current wage differential and expected future career prospects in each occupation. The standard deviation of the taste shocks, the sector attractiveness parameter and the cost of switching occupations will affect the sensitivity of occupational switching to changes in relative career prospects.

Since individuals are forward looking, the working decisions depend upon the equilibrium distribution of their career prospects. Under the extreme value errors assumption, we can use the properties of the idiosyncratic taste shocks distribution to derive the expected values of career prospects (Rust (1987)). The expected value function for an individual at age a between 22 and 64 working as a computer scientists or in another occupation are respectively:

$$\mathbb{E}_t V_{t+1,a+1}^{cs} = \sigma_1 \mathbb{E}_t[\varpi + ln\{exp((w_{t+1} + \rho\mathbb{E}_{t+1}V_{t+2,a+2}^{cs})/\sigma_1) + exp((s_{t+1} - \zeta(a) + \theta_1 + \rho\mathbb{E}_{t+1}V_{t+2,a+2}^{o})/\sigma_1)\}] \tag{36}$$

$$\mathbb{E}_t V_{t+1,a+1}^{o} = \sigma_1 \mathbb{E}_t[\varpi + ln\{exp((s_{t+1} + \theta_1 + \rho\mathbb{E}_{t+1}V_{t+2,a+2}^{o})/\sigma_1) + exp((w_{t+1} - \zeta(a) + \rho\mathbb{E}_{t+1}V_{t+2,a+2}^{cs})/\sigma_1)\}] \tag{37}$$

where gamma $\varpi \cong 0.577$ is the Euler's constant and the expectations are taken with respect to future taste shocks.

Given this set-up we can use the occupational-switching probabilities to derive the aggregate employment in each sector. Since we allow workers at age 22 to also pay the switching costs and get their first job in an occupation that is different from their field of study, the number of computer scientists at age 22 is a function of the number of recent graduates with a computer science degree and the occupational-switching probabilities:

$$L_{nt}^{22} = (1 - q_{t,22}^{cs,o})R_t + q_{t,22}^{o,cs}[(L_{nt}^{22} + G_t^{22}) - R_t] \tag{38}$$

$$G_t^{22} = (1 - q_{t,22}^{o,cs})[(L_{nt}^{22} + G_t^{22}) - R_t] + q_{t,22}^{cs,o} R_t \tag{39}$$

where R_t is the number of recent graduates with a computer science degree, and $(L_{nt}^{22}+G_t^{22})-R_t$ is the number of college graduates with any other degree. Similarly, the supply of computer scientists at age a from 23-65 is a function of past employment in each occupation and the switching probabilities:

$$L_{nt}^a = (1 - q_{t,a}^{cs,o}) L_{n,t-1}^{a-1} + q_{t,a}^{o,cs}[G_{t-1}^{a-1}] \tag{40}$$

$$G_t^a = (1 - q_{t,a}^{o,cs}) G_{t-1}^{a-1} + q_{t,a}^{cs,o}[L_{n,t-1}^{a-1}] \tag{41}$$

where L_{nt}^a is the exogenous number of workers in computer science at age a in time period t, and G_t^a is the number of workers at age a working in other occupations.

The aggregate domestic labor supply of computer scientists and other workers is the sum across all ages:

$$L_{nt} = \sum_{a=22}^{a=65} L_{nt}^a \tag{42}$$

$$G_t = \sum_{a=22}^{a=65} G_t^a \tag{43}$$

Here we can see that the labor supply in each occupation depends on past employment, new college graduates and on wages through the occupational switching probabilities.

A.1.3 Market Clearing Conditions

The following equations describe the market clearing conditions for the labor and output markets. Total consumer expenditure equals labor income plus firm profits (equation 44):

$$P_{tc} C_{dt}^* + P_{yt} Y_{dt}^* = m = w_t(L_{nt}^* + L_{Ft}^*) + s_t G_t^* + r_t H_t^* + (\Pi_t + P_{yt} f N_t) \tag{44}$$

Total quantity produced in the IT sector equals domestic consumer demand, intermediate inputs in the other sector, and exports (equation 45):

$$N_t^{\frac{\epsilon}{\epsilon-1}} \left(\int_{\phi_t^*}^{\infty} c_{it}^{\frac{\epsilon-1}{\epsilon}} \mu(\phi) d\phi \right)^{\frac{\epsilon}{\epsilon-1}} = C_t^* = C_{dt}^* + C_{yt}^* + C_{Wt}^* \tag{45}$$

Total quantity produced in the other sector, net of inputs, equals domestic consumer demand and intermediate inputs in the other sector (equation 46):

$$C_y^{*\psi_2} X_y^{*1-\psi_2} = Y_t^* = Y_{dt}^* + Y_{Ct}^* + fN_t^* - Y_{IMt}^* \tag{46}$$

Trade in goods is balanced:

$$P_{ct}^* C_{Wt}^* = P_{yt}^* Y_{IMt}^* \tag{47}$$

Given that the supply of non college graduates is inelastic $\bar{H}_t$, and the demand comes from both sectors, their labor market clears as in equation 48:

$$\bar{H}_t = H_{ct}^* + H_{yt}^* \tag{48}$$

Total labor supply for college graduates (CS and non CS) is fixed, such that total demand for college graduates has to be equal to total supply in each period (equation 49):

$$\overline{L_{nt} + G_t} + \bar{L}_F = L_t^* + G_t^* = L_{ct}^* + L_{yt}^* + G_{ct}^* + G_{yt}^* \tag{49}$$

A.2 Details of the Data Used

This study draws on a variety of datasets. Our descriptive statistics in Table 1 rely on the IPUMS Census from 1970 to 2000. We restrict the sample to employed workers. We use the IPUMS suggested occupation crosswalk and define computer scientists as computer systems analysts, computer scientists and computer software developers with at least a BA degree. We define foreigners as either naturalized citizens or non-citizens who immigrated after the age of 18. For early Census years the year of immigration is only available in ranges. In order to construct a precise year of immigration value for workers in those samples we choose to select a random value within the year range for each individual.

Data on earnings, domestic employment and foreign employment used in the calibration procedure and in the descriptive figures come from the March CPS, obtained from the IPUMS and NBER websites. The sample consists of employed persons with at least a BA degree. A person is defined as foreign if he/she was born outside the United States and immigrated after the age of 18. Earnings are deflated to 1999 dollars, and top-coded values are multiplied by 1.4.

In our analysis we drop imputed earnings. In order to identify these imputed values, we use a methodology similar to (Bollinger and Hirsch (2007)). From the IPUMS database we use the qinclongj and qincwage variables, and from the NBER database we use the FL665 flag to identify imputations. The database also contains ten Census Bureau flags that identify a small fraction (less than 1%) of earnings as allocated. Over the period under study around 26% of earnings were allocated. This fraction of imputations varies over time - between 19.14% (in 1994) and 29.47% (in 2003). These numbers are consistent with (Bollinger and Hirsch (2007)) who find that between 1998 and 2006, the non-response rate was about 20%. The small difference in our numbers arises both from using a different sample (restricted to those with BA/MA degree) and because non-response is not the only reason the CPS imputes earnings.

In order to define workers in Computer Science we use the occupational codes in the CPS Outgoing Rotation Group (CPS-ORG) data set. The occupational coding in the CPS-ORG up to 2002 uses the 1990 Census definition. We consider as Computer Scientists those under the occupational titles of: "055 Electrical and electronic," "064 Computer systems analysts and scientists" and "229 Computer programmers".

College degree attainment data is based on Integrated Post-secondary Education Data System (IPEDS) Completions Survey. It consists of bachelor's degrees awarded by the NSF population of institutions. We consider enrollment in computer science and electrical engineer as the number of degrees awarded in these fields lagged by 2 years. For 1994 and 1995, degree attainment in electrical engineering was not available by native and foreign students but only shown together with all engineering degrees. We input the data for these two years by looking at the average growth in electrical engineering for 1996-2002.

In descriptive statistics, we compare the computer science workforce to STEM workers. STEM occupations are defined as engineers, computer systems analysts and computer scientists, computer software developers, operations and systems researchers and analysts, actuaries, statisticians, mathematicians and mathematical scientists, physicists and astronomers, chemists, atmospheric and space scientists, geologists, physical scientists n.e.c., agricultural and food scientists, biological scientists, foresters and conservation scientists, and medical scientists.

We use data on the prices, quantities, costs and value added from the Bureau of Economic Analysis (BEA) since this source allows us to look into data for specific industry groups. Data on firm entry and exit comes from the Business Dynamic Statistics (BDS), and the 1992 Census' Statistics of U.S. Businesses (SUSB). In these data sets we define the IT sector as the sub-sectors of "Computer and electronic product manufacturing," "Publishing industries, except Internet (includes software)," "Data processing, Internet publishing, and other information services" and "Computer systems design and related services" according to the NAICS 2002 classification. The Non IT sector is defined as all other sectors in the economy.

A.3 Extended Out-of-Sample Tests (until 2015)

In section 3.3 we describe how we calibrate our labor supply parameters for the period 1994-2001.We matched observed moments of relative wages, employment and enrollment for three years, and performed an out-of-sample test for the years in between, as shown in Figure 2. A natural question to ask is whether our calibrated parameters are able to predict movements in key data series for the years post 2001, as an additional out of sample test of our model.

In Figure A.1, we perform such an out of sample analysis. To do this, we constructed the relative labor supply shocks Z_t from equation 27 using information on the relative wages, relative native employment and relative foreign employment for the period 2002-2015 together with the relative labor demand curve for the base year 1994. In a second step, we fed those shocks into our labor supply model using the parameters calibrated for the 1994-2001 period to observe how relative wages, employment and enrollment series are predicted by our model for the post 2001 period. As can be seen in Figure A.1, we consistently predict employment and wages for the post-2001 years, but overestimate enrollment rates for the years 2005 onward.

A.4 Sensitivity Analysis

We check how sensitive our results are to variations in key parameters and specifications of the model. So far we have presented all our results for three different values of λ. Despite slight differences in the magnitudes of changes in income and profits, the results are qualitatively similar across different values of this parameter. For simplicity we fix $\lambda = 2$ when doing our sensitivity analysis on all the other parameters of the model.

First we look at how sensitive our results are to variations in the elasticity of substitution between the IT good and the non IT good, represented by the parameter σ. As we see in Table 10, the more elastic the relative product demand curve, the larger the income increase for all US workers is when we allow for immigration. This is consistent with economic intuition since a higher value of σ implies that consumers are more willing to substitute consumption from non-IT to IT goods. When we allow for immigration, the larger number of computer scientists in the economy increases the size of the IT sector and consumers shift into consuming more IT goods. Profits for IT firms rise and workers that are complements to CS workers are better off for higher values of σ. Furthermore, since IT production drives technological change, as and when more resources are devoted to IT for higher values of σ, the price of IT goods falls increasing overall welfare. Overall our qualitative results are similar for different values of σ with the only difference being that for high values of σ the population of all college graduates is better off due to immigration.

We also vary the technological change parameter and check how sensitive our results are to

reasonable values of β. Our calibrated value of β is 0.233, and we re-do our results for values of 0, 0.1 and 0.5. Table 11 shows how the compensating variation and profits change as we vary β. Immigration is benefecial for higher values of β, for all types of US workers and firms since a larger CS workforce increases the gains from technology. Firms directly benefit from higher output, whereas consumers benefit from lower prices as the value of β rises. Overall, however, our qualitative results are similar across the different β levels. The only qualitative difference is that for the scenario where there is no technological progress ($\beta = 0$), the sub population of college graduates non CS are worse off when there is immigration. This happens because without the spillover of aggregate computer scientists, the positive effect they had for being complements to CS gets smaller and is offset by the lower wages caused by CS switching occupations.

Last, we vary the elasticity of substitution between varieties of the IT good ϵ across a reasonable range. In Section 5.3 we discuss results for the baseline case where the goods are perfect substitutes and all IT firms are similar. In Table 12 we see that as we lower the elasticity of substitution ϵ to from a value of 3.2 to 2, the overall welfare gains from immigration are enhanced. While close substitutes in the labor market are worse off for smaller values of ϵ, complements are better off. The overall impacts, however, are similar both qualitatively and quantitatively.

In other results, we test to see whether using a Melitz (2003) style model of entry significantly affects our conclusions and found out that it does not. In our baseline model there is an underlying fixed number of potential entrepreneurs that always know their level of productivity ϕ_j, a set-up closer to Chaney (2008). An alternative set-up is one where firms do not initially know their level of productivity ϕ_j, but must pay a fixed sunk cost f_e to draw their level of productivity from the known distribution. Firms wish to pay this cost as long as their expected profits are positive. As more firms draw and produce, expected profits fall till they are zero. Once a firm draws their productivity ϕ_j, they may choose to pay another fixed cost f and produce if $\phi_j > \phi^*$. This setup is closer to the one described by Melitz (2003).[39]

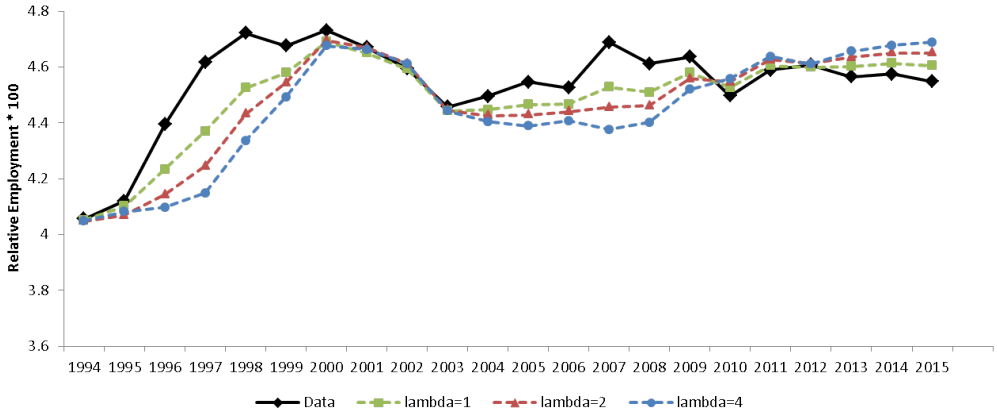
We may expect these set-ups to have different implications for firm profits and overall welfare. In our baseline model, an increase in immigration, tends to increase firm profits and the marginal firms enter into producing goods. Since all firms already know their productivity level, the more productive firms always produce. The new entrants are therefore firms that have a productivity level in the immediate neighborhood of ϕ^*. The overall increase in productivity, therefore, is small since the new entrants are firms that have relatively low productivity. Furthermore, the increase in profits is almost entirely captured by the larger firms. In the alternative Melitz (2003) framework, entry may happen at any part of the productivity distribution. When the expected profits rise because of immigration, new entrants may potentially draw very high

[39] To see a discussion about these two models in the context of immigration models, see di Giovanni et al. (2015).

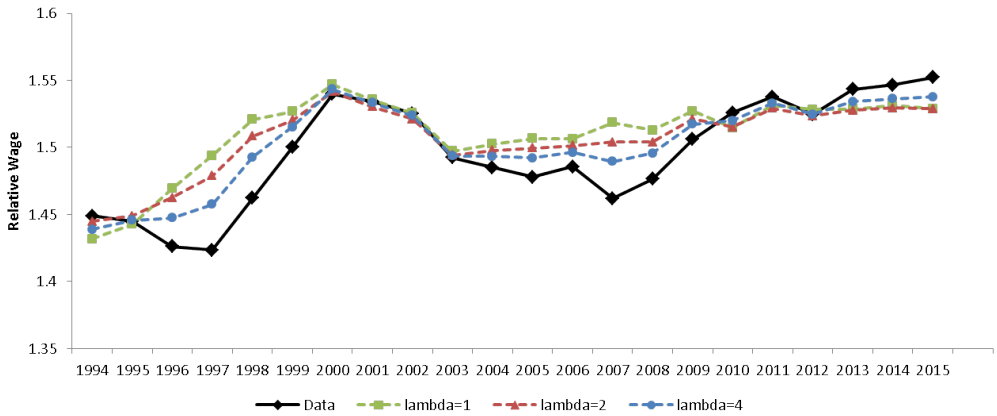
levels of productivity and enter at the extreme tails of the distribution. The overall increase in productivity is higher which drives down the price of the IT good, and increases consumer utility. Furthermore, the new entrants capture all the increase in profits whereas the profits for the incumbents do not change. Compared to the baseline model, we find that the change in welfare due to immigration is higher under the Melitz entry set-up both because of higher aggregate profits and consumer utility. This is because the new firms that enter the industry are not just the firms with marginal productivity, but could also be firms with very high levels of productivity. These firms have higher profits, and drive down the output prices more. Qualitatively, however, all our results stay the same across the two models.

Figure A.1: Employment, Wages and Enrollment (1994 to 2015)

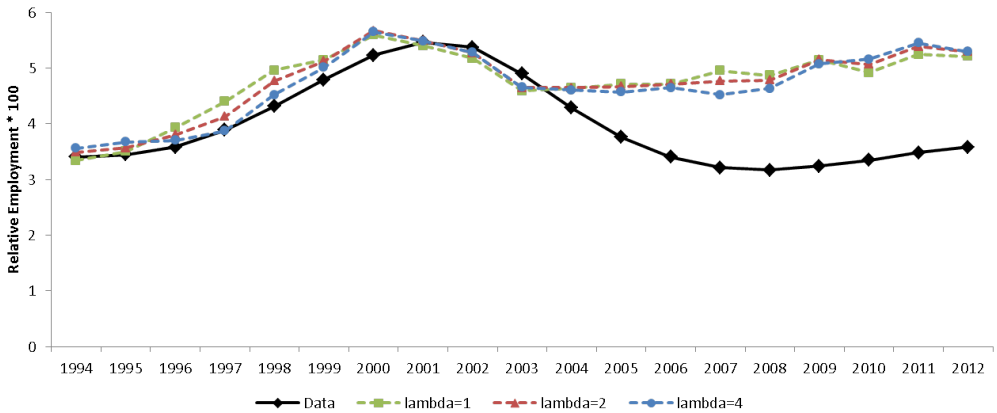
(a) Matching Relative Labor Supply



(b) Matching Relative Wages



(c) Matching Relative Degree Attainment



In the calibration exercise, the years 1994 and 2001 were used to match the data for employment and wages, whereas the years 1994,1997 and 2001 was used to match the data on degree attainment (lagged two year). The years in between, and post-2001, are an out-of-sample test. Wage and employment data come from the March CPS, whereas degree data is from IPEDS. See Appendix A.2 for more details about the data.