

The IT Boom and Other Unintended Consequences of Chasing the American Dream*

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April 2017

Abstract

We study how US immigration policy coupled with the Internet boom affected not just the US economy, but also led to a tech boom in India. Indian students enrolled in engineering schools to gain employment in the rapidly growing US IT industry via the H-1B visa program. Those who could not join the US workforce, due to the H-1B cap, remained in India, enabling the growth of an Indian IT sector. Those who returned with acquired human capital and technology after the expiration of their H-1Bs also contributed to the growing tech-workforce in India. The increase in IT sector productivity allowed India to eventually surpass the US in software exports. Our general equilibrium model captures firm-hiring across various occupations, innovation and technology diffusion, and dynamic worker decisions to choose occupations and fields of major in both the US and India. Supported by a rich descriptive analysis of the changes in the 1990s and 2000s, we match data moments and show that our model captures levels and trends of key variables in validation tests. We perform counterfactual exercises and find that the H-1B program induced Indians to switch to computer science (CS) occupations, increasing the CS workforce in India and raising overall IT output in India by 5%. It also induced US workers to switch to non-CS occupations, reducing the US native CS workforce by 9%. Consumers in both countries benefit as prices in IT are lower and overall IT output is larger. The combined income of both countries is higher by 0.36% because of this high-skilled migration.

JEL: I25, J30, J61

Keywords: High-skill immigration, H-1B visas, India, computer scientists, IT sector

*We thank Dominick Bartelme, John Bound, Andrei Levchenko, Sebastian Sotelo and seminar participants at Michigan, Purdue, Montevideo, Riverside, Raleigh (Society of Labor Economists), Western Ontario (Labour Day), Mt Holyoke and New Delhi (ISI) for insightful comments. The authors would like to acknowledge the Alfred P. Sloan Foundation and the NBER Fellowship on High-Skill Immigration for generous research support.

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Migration policy, and the skills of migrants, have been at the forefront of elections, policy debates, and academic discourse throughout the world. The effects of high-skill migration, as exemplified by the high-profile US H-1B program, are theoretically ambiguous for both the sending and receiving countries. For instance, native workers in the receiving country may benefit if they are complements to immigrants, or suffer if they are substitutes. The sending country may experience brain drain as human capital departs, or experience brain gain as the opportunity to migrate induces human capital accumulation. Immigration can attract global talent and lead to production growth in the receiving country, but migration-induced technological catch-up may contrarily shift production to the sending country. We resolve these ambiguities by modeling and empirically measuring the long-term welfare consequences of high-skill migration under the H-1B program, and how the combination of the US IT boom and immigration policies led to a boom halfway across the world in India.

We model firm-production, trade and the forward-looking decisions of workers and students in both countries, to closely capture important trends in the data that we first describe in detail. Innovation rapidly expanded the US IT sector in the early 1990s (Bound et al., 2015; Kerr, 2013a), and a few years later the IT sector in India quickly grew from 1.2% of GDP in 1998 to 7.5% in 2012 (NASSCOM, 2012). Indian workers and students responded to these booms and migration opportunities by accumulating computer science skills valuable both at home and abroad. While a fraction of these workers entered the US labor market via the restricted supply of H-1B visas, many joined the rapidly growing IT sector in India. We then calibrate our model using data from various sources and countries, and perform out-of-sample tests to show that our model captures these trends. Next, we perform counterfactual exercises that change the number of immigrants allowed into the country. Given that 70% of H-1B visas went to Indian workers by 2014, our results indicate that the H-1B program and the tech boom had a powerful impact on IT sectors in both countries. By the early-2000s, many workers returned to India once their visas expired with newly acquired knowhow and connections. This additionally facilitated the US-led boom to spread to India, and by the mid-2000s India surpassed the US as the major exporter of software. Despite various distributional effects, our results indicate that world incomes are higher by 0.36% under H-1B induced migration.

In Section 1 we first use descriptive trends and background information to describe our storyline and ground our model. Starting in the early 1990s, innovation in the US IT sector led to a growth in IT firms, computer science (CS) employment and wages, and enrollment in CS degrees (Figures 1a to 1c). An immigration policy that favored high-skill immigrants led to an increasing proportion of foreigners in the US computer-science workforce (Figure 1e). The foreign fraction of CS workers grew considerably from 9% in 1994 to 24% in 2012; much faster than the foreign fraction of all workers in STEM occupations (Figure 1d). By the mid-2000s more than half of all H-1B visas were awarded to Indians (USCIS, 2014). This fraction was higher among CS occupations: by 2014, 86% of all computer science H-1B visas were awarded

to Indians, and only 5% were awarded to candidates from China (Computerworld, 2015). This made India the largest contributor of foreign computer scientists (Figure 2d). Even though all the top firms that hired H-1Bs are in IT, the top 9 had India as their primary employment base (Table 1).

CS wages in the US are many times higher than in India, and a significant fraction of Indian born CS workers are employed in the US (Figure 1f and Clemens (2013)). Given this large wage differential and a non-trivial probability of migrating to the US, many more Indian students started enrolling in engineering schools (Figure 2a). However, the number of available H-1B visas was capped, so a large number of Indian workers that would have preferred to work in the US, had to seek employment in India. Furthermore, since H-1Bs expire after 3 to 6 years, many of these workers returned to India, bringing with them their accumulated human capital, technological knowhow and connections, facilitating further technological diffusion (Kerr, 2008). This educated workforce in India enabled the Indian IT sector to grow rapidly, with new firms joining the race and older firms expanding, and over time, India became a major producer of software eroding the US dominance in IT exports (Figure 2b and 2c). This boom missed many other countries but settled on India. India has not only historically had high quality engineering schools that train potentially lower-wage, English-speaking workers but had also developed strong networks with the US sector during the earlier hardware boom (Arora et al., 2001; Bhatnagar, 2005).

In Section 2 we capture these descriptive patterns within the framework of a general equilibrium model that contains five crucial features. First, we model how US firms hire both US and foreign workers, and Indian firms hire workers from India. Importantly, firms hire three different types of workers – computer scientists, non-CS college graduates and non college graduates. As immigration increases the size of the computer science workforce, firms demand more workers in complementary occupations, such as managerial positions. At the same time, skill-biased technical change shifts labor demand in favor of high-skill occupations. Computer scientists, both domestic and foreign, are innovators and increase the overall productivity of firms in the IT sector via the generation of non-excludable ideas (Kerr, 2010). Under this directed technological change, an increase in the relative size of the computer science workforce makes India relatively more productive over time. In India, the return migrants are not perfect substitutes with those that never migrated, as they may return with acquired human capital.

Second, the IT sector produces a continuum of varieties, the productivities of which differ across countries. Restricting immigration, or more rapid growth in the Indian IT sector can shift some of the production of these varieties from the US to India. Consumers benefit from lower prices, and the final goods sector of the economy uses software as an intermediate input in production; an expansion in the IT sector raises overall productivity in the final goods sector as well.

Third, to capture the trade patterns, we encapsulate the canonical [Eaton and Kortum \(2002\)](#) framework into our model. All goods are tradable with asymmetric trade costs and each country will have a comparative advantage in producing some of the varieties. Both countries are competing for the world market, so the potential to trade allows India to grow, as more and more people specialize in the high innovation IT sector. At the same time, in both countries, the wage impacts of immigration are muted by trade as resources are shifted across sectors ([Ventura, 1997](#)).

While the above three features capture the product and the labor demand aspects of the economy, the next two capture important labor supply decisions. The fourth feature is that students in both countries have heterogeneous preferences, and make dynamic decisions on choosing their college major given their expected future earnings in different occupations. Changes to expected earnings, driven by innovation shocks and immigration policies, have long-run effects on human capital accumulation and the labor supply elasticity.

Fifth, after graduation, workers (also with heterogeneous preferences), choose every year to either continue working in their current occupation or switch occupations given the labor demand shocks and their expected future benefits in each occupation. It is costly to switch occupations, a cost that increases with age. Indian CS workers pay an additional cost of migration and earn higher wages in the US if they win the H-1B lottery. Importantly, as expected earnings change with immigration policy, workers switch occupations mitigating either the positive or negative wage impacts of immigration.

The occupation switching elasticity along with the college-major choice determines the labor supply elasticity, which plays a crucial role in the distributional effects of immigration on the different types of workers. Importantly, given the dynamic nature of the decisions, even though the short run labor supply curve is relatively inelastic, the long run labor supply curve is fairly elastic as students choose different majors. This means that reduced form estimates of contemporaneous responses to immigrant changes will not pick up the entirety of the labor supply adjustments.

This model includes many countervailing forces, making the theoretical impacts of the H-1B program ambiguous. For instance, the effects of brain-drain from India, compete with brain-gain as more Indians try to acquire skills valued in the US, and as return migrants bring back acquired knowhow. Similarly ambiguous is the impact on the US IT sector: on the one hand, an influx of computer scientists helps the US IT sector grow, but on the other hand the H-1B program spurs growth in the competing Indian IT sector, thus eroding the US's market share.

Distributional impacts on different types of workers are similarly ambiguous. Computer science wage growth may be depressed by rapid inflows of immigrants, but an increased CS workforce can lead to more innovation raising the demand and wages for all workers. The demand for

non-CS workers may rise not just because of innovation, but also because they are complements to CS workers in the production process; however, depressed CS wages may encourage US born CS workers to switch to non-CS occupations, lowering non-CS wages as well. As the IT sector grows in both countries, consumers are better off because they have more efficient and affordable products, and sectors that use IT as an intermediate goods are more productive.

In Section 3 we calibrate the model with the aim of resolving these theoretically ambiguous effects, and in order to perform counter-factual exercises. The production side decisions help us determine the exogenous innovation shocks that shift the labor demand curve out every year, and allow us to trace out the labor supply curve. We then rely on methods from the trade literature to estimate trade costs and technology parameters. We show that our model does a good job of matching both levels and trends in wages, employment and IT sector output in out-of-sample tests for both countries (Section 4).

In Section 5, we conduct counter-factual exercises to study the impact of less restrictive immigration policy on both the US and Indian IT sectors. We also evaluate the effects of possible policies being circulated in Congressional draft bills. By shutting-down certain parts of our model we are able to ascertain how important each feature of our model is in contributing to our results.

Our results indicate that US immigration policy did play a significant role in the spread of the IT boom from the US to India. The possibility of migrating to the US under the H-1B program incentivized students and workers in India to choose CS degrees and occupations. Those that returned after the expiration of their visas contributed to this growing CS workforce and enabled the increases in technological productivity in India. We show that the H-1B program led to an increase of 21% in the size of the non-migrant Indian CS workforce in 2010. However, the migration led US native CS workers to switch to non-CS occupations and is therefore associated with a fall in the US native CS workforce by as much as 9% in 2010.

An increase in the size of the Indian CS workforce also led to an increase in productivity in the Indian IT sector. Under the H-1B program, production shifts to India – the share of world IT output that comes from the US is 1% lower, and Indian IT output increases by 5% in 2010. The shift in production to India, however, hurts some US workers – most notably, US born computer scientists. World IT output increases by 0.45% and the US-India combined incomes are higher by 0.36% under the H-1B regime.

In Section 6 we discuss these results in relation to the larger literature on labor, trade, technological diffusion and migration. Our paper is innovative in many ways. First, we incorporate migration and endogenous human capital accumulation into a model of trade and technological diffusion. In doing so we synthesize different insights from a broad literature, and add crucial features overlooked by the literature. On the one hand, North-South trade may hinder structural transformation as developing economies specialize in less productive sectors (Matsuyama,

1992). On the other hand, technological diffusion can help developing countries catch up with more developed ones (Krugman, 1979). Since migrants accumulate human capital and technical knowhow in the US and return with this knowledge to India, this speeds up technological diffusion and catch-up (Kerr, 2008). As Davis and Weinstein (2002) highlight, immigration-induced catch-up may also deteriorate the terms of trade for the country with superior technology – in this case, the US. Furthermore, depending on the rate of technical change, offshoring will benefit workers in developing countries but may harm workers in developed economies (Acemoglu et al., 2015). Alternatively, Freeman (2006b) argues that immigration can help the US maintain its advantage by attracting global talent. Such analyses, however, miss the incentives to invest in human capital, and the corresponding growth in production for sending countries – features that play an important role in our analysis.

Second, our paper addresses some crucial issues raised by the labor literature on the impacts of high-skill immigrants on the US economy. High-skill immigrants could impart benefits to employers, complementary inputs used in production, and to consumers, and in general may be valuable innovators that improve technology (Foley and Kerr, 2013). However, they potentially impose some costs on domestic workers who are close substitutes (Borjas, 1999). 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 and Sparber, 2011). If high skill immigrants contribute to the generation of knowledge and productivity through patenting and innovation, then this serves 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, 2006b). In Bound, Khanna, and Morales (2016), we look at the short-run effects on the welfare of workers in the receiving country, abstracting away from the role played by other countries. Building on our prior work in Bound, Khanna, and Morales (2016), we are now able to capture long-run effects since we also model the growth of the tech sector in India, which greatly affects incomes in the US.

Third, ours is one of the few papers to look at sectoral transformation to high-skill production in emerging economies that send immigrants rather than receive them. The Indian case is interesting in particular because Indians made up the majority of H-1B visas, and the country experienced a tech boom that substantially contributed to the country’s rapid economic growth. The IT sector boom and immigration policy in the US, and the Indian growth-story are therefore closely linked, and studying this boom can help us understand how workforce skill transitions may come about in developing countries. Importantly, we show that US immigration policy can affect structural development half-way across the world, in India.

Last, the paper addresses the debate regarding brain-drain and brain-gain (Beine et al., 2001; Dinkleman and Mariotti, 2016; Shrestha, 2016; Stark, 2004; Stark et al., 1997). While many commentators worry about the fact that a large number of well-educated Indians leave the country for work in the US, this paper shows how better paid jobs may also incentivize stu-

dents to choose certain majors and supply a highly-educated workforce to Indian firms as well. Migrants that return with newly acquired human capital and technical knowhow help develop the IT sector at home.

1 The Tech Boom in the US and India

1.1 The Internet Boom in the US and the H-1B Visa

Starting in the mid 1990s, the usage of the Internet for commercial purposes grew rapidly in the US (Leiner et al., 1997).¹ This led to an increase in demand for computer scientists, and a rise in R&D expenditures for the firms. The entry and growth of tech firms like Yahoo, Amazon and eBay helped sustain the “boom” in the IT sector till the end of the century.

These changes had a significant impact on the market for IT workers. The number of computer scientists or computer software developers (CS) increased by 161% between the years 1990 and 2000 (US Census), whereas during the same period, the total number of workers with at least a bachelor degree increased by 27%, while the number of workers in other STEM occupations increased by 14%. Table 2 and Figure 1a show that CS, as a share of the college educated workforce and the STEM workforce, rises dramatically in the second half of the 1990s – the same period as the dissemination of the Internet. By the turn of the century more than half of all STEM workers are computer scientists. This rising demand for computer scientists also affected educational choices of US students. In Figure 1b, it is clear that the number of bachelor degrees awarded in CS relative to the total number of bachelor degrees increased dramatically from about 2% in 1995 to more than 4% in 2002, showing that the decision to study computer science also responded to the Internet boom.

Employment adjustments for computer scientists disproportionately favored foreigners (Table 2 and Figure 1d). In 1994, foreigners were less represented among individuals working as computer scientists than in other STEM occupations, but given the dramatic growth in the second half of the 1990s, by 2012 foreigners comprised almost one-fourth of the CS workforce.

This trend in foreign representation in the workforce was sustained by a few developments. Freeman (2009), and Bound et al. (2014), attribute some of these changes to the dramatic increase in college educated (science and engineering) workers in India where the number of first degrees conferred in science and engineering rose from about 176 thousand in 1990 to 455 thousand in 2000. The second development was The Immigration Act of 1990 which established the H-1B visa program for temporary workers in “specialty occupations,” defined as requiring *theoretical and practical application of a body of highly specialized knowledge in a field of human*

¹The decommissioning of the National Science Foundation Network in April of 1995 is considered crucial for introducing nationwide commercial traffic on the Internet.

endeavor including, but not limited to, architecture, engineering, mathematics, physical sciences, social sciences, medicine and health, education, law, accounting, business specialties, theology, and the arts.

In order to hire a foreigner on an H-1B visa the firm must first file a Labor Condition Application (LCA), and pay them the greater of the actual compensation paid to other employees in the same job or the prevailing compensation for that occupation. After which, the H-1B prospective must demonstrate to the US Citizenship and Immigration Services Bureau (USCIS) in the Department of Homeland Security (DHS) that they have the requisite amount of education and work experience for the posted positions. USCIS then may approve the petition for the H-1B non-immigrant for a period up to three years, which can be extended up to six years. After which employers can sponsor a green card, each country is eligible for only a specific number of those. The U.S. General Accounting Office 2011 survey estimates the legal and administrative costs associated with each H-1B hire to range from 2.3 to 7.5 thousand dollars. It therefore seems reasonable to assume that employers must expect some cost or productivity advantage when hiring foreigners.

In the early years, the H-1B cap of 65,000 new visas was never reached, but by the time the IT boom was starting in the mid-1990s, the cap started binding and the allocation was filled on a first come, first served basis. Figure 1e shows the growth in the number of H-1 visas issued over the last three decades, the stock of H-1 visas in the economy each year, and changes in the H-1B visa cap. The cap was raised to 115,000 in 1999 and to 195,000 for 2000-2003, and then reverted back to 65,000 thereafter. The 2000 legislation that raised the cap also excluded universities and non-profit research facilities from it, and a 2004 change added an extra 20,000 visas for foreigners who received a masters degree in the US.

According to the [USINS \(2000\)](#), the number of H-1B visas awarded to computer-related occupations in 1999 was about two-thirds of the visas, and [U.S. Department of Commerce \(2000\)](#) estimated that during the late 1990s, 28% of programmer jobs in the US went to H-1B visa holders. H-1B visas, therefore, became an important source of labor for the technology sector. The National Survey of College Graduates (NSCG) shows that 55% of foreigners working in CS fields in 2003 arrived in the US on a temporary working (H-1B) or a student type visa (F-1, J-1). At the same time, a substantial fraction of this immigrant IT workforce was educated abroad. Table 3 shows the fraction of workers, and specifically IT workers, by the location of their highest degrees. Given that such a large proportion obtain their bachelor's degrees in other countries, the education sector abroad to plays a major role in the US tech boom as well ([Bound et al., 2014](#)).

1.2 The Impact of High Skill Immigrants on the US Workforce

Some commentators argue that given the excess supply of highly qualified foreigners willing to take the jobs, and given the lack of portability of the H-1B visa, immigrant workers are not in a position to search for higher wages, allowing firms to undercut and replace US workers (Kirkegaard, 2005; Matloff, 2003). Critics of the H-1B program claim employers find hiring foreign high skilled labor an attractive alternative and that such hiring either “crowds out” natives from jobs or put downward pressure on their wages (Doran et al., 2017).

Immigrants may, on the other hand, have impacts on the innovative capacity of the firm. Kerr and Lincoln (2010) and Hunt and Gauthier-Loiselle (2010) provide evidence on the link between variation in immigrant flows and innovation measured by patenting, suggesting that the net impact of immigration is positive rather than simply substituting for native employment.² 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.

Bound et al. (2015) proposes an alternative interpretation to Kerr and Lincoln (2010) results. Even though employers face costs to hire immigrant labor and are bound to pay the going wage, firms might disproportionately hire immigrants only when the demand for workers is increasing. In this case, immigrants would not replace incumbent workers or depress wages, but stem the *growth* in wages and employment for natives. Bound et al. (2015) find that wages for computer scientists would have been 2.8-3.8% higher, and the number of Americans employed as computers scientists would have been 7.0-13.6% higher in 2004 if firms could not hire more foreigners than they could in 1994. In contrast, total CS employment would have been 3.8-9.0% lower, and consequently output smaller.

While the approach in Bound et al. (2015) is distinctly partial equilibrium in nature, Bound, Khanna, and Morales (2016) extends this analysis into a general equilibrium model of the US economy.³ Doing so allows them to conduct a comprehensive welfare analysis and study the distributional implications of the H-1B program. Importantly, by modeling the firms’ decisions, including the spillovers from technological innovation, they derive the labor demand curve for different types of workers. Bound, Khanna, and Morales (2016) find that even though US computer scientists are hurt by immigration, complements in production, consumers and firm entrepreneurs benefit substantially.

While these papers focus only on the US labor market, we include the crucial role played by India as the largest contributor to this boom. For the purposes of studying only the direct impact on US wages, employment and output, these other papers do not model the foreign side

²Xu (2016) shows how technology invented by migrants may affect growth in the destination country.

³Lee (2016) also has a general equilibrium model, but does not model endogenous human capital acquisition, which Bound, Khanna, and Morales (2016) find to be quite important.

of things. To study the linkages across the countries and the feedback into the US industry, this paper will model what happened on both sides of the world.

1.3 A Brief History of Indian IT & its Relationship with the US

With large-scale economic reforms in the early 1990s, the IT industry in India was opened up, and there was a spurt in the entry of multinational firms and demand for software services. On-site work dominated because otherwise software had to be transported on tapes which faced heavy import duties. But in 1992, satellite links were set up in Software Technology Parks (STP) negating the need for some kinds of on-site work and this boosted the off-shoring of work to India.⁴ One estimate suggests that by 1996, India had 16% of the globalized market in customized software, and more than 100 out of the Fortune 500s had outsourced to them (Dataquest, 1996).

In August 1995, the internet was introduced to households in the Indian metros, and by 1998, when the government deregulated the internet-suppliers monopoly, there were already more than 1 million internet users in India. The Net allowed many more firms access to the markets abroad since it was cheaper to obtain phone lines than satellite links (Desai, 2003). The Y2K threat was a boon to the Indian industry, as “*Y2K projects were an important source of revenue for Indian firms*” (Arora et al., 2001), and this helped build reputation with their US counterparts. One commentator notes that the industry “*grew on the strength of Y2K and never looked back*” (Dataquest, 2003). The low-wage advantage is one of the earliest explanations advanced to describe the growth in Indian IT (Heeks, 1995). Arora et al. (2001) note that by the turn of the century, India had the largest number of people working in the industry and the highest revenue growth

A large part of the success of Indian firms is attributed to high-skilled Indian immigrants in the US. Bhatnagar (2005) notes that Indian professionals in Silicon Valley “*built personal networks and valuable reputations and used their growing influence within US companies to help Indian companies get a foot in the door*” of the expanding IT work. This reputation was largely built in the on-site consulting phase of the early 1990s. As Banerjee and Duflo (2000) note, reputation is essential in an industry like this because a lot of contracts are for customized software and can lead to hold-ups which a court of law may find difficult to arbitrate over. A fraction of Indian computer scientists also became senior managers at tech firms (Saxenian, 1999). Indians headed about 3% of tech companies started between 1980 and 1985, but by 1995 they headed about 10% of them. At around the same time, NASSCOM estimated that about 200,000 Indian software professionals were working on H-1B visas.

⁴Kumar (2001) notes another significant advantage for the Indian industry – the 12-hour time lag between India and the US virtually doubled the working time per day and cut the development life-cycle by half.

Indian firms are the largest sponsors of H-1B visas to the US, and use the program as a way to set up a base in the US with a ready supply of workers from India. The US has a large market for client services and demand for software development, along with more capital, technology and industrial agglomeration, making it an attractive location for Indian firms. Indian firms have the advantage of extensive networks and an in-depth knowledge of the Indian labor market to hire these workers. Even non-Indian firms are big employers of H-1Bs, some of which have Indians as their largest employment-base. Table 1 shows that 10 out of the top 11 H-1B firms have Indians as their primary employment base. Indian citizens, are therefore, the largest beneficiaries of the H-1B visa program, with about 70% of all H-1Bs in 2014 being awarded to Indians (USCIS, 2014).

After 2010, there was a shift in H-1B usage towards outsourcing firms (Park, 2015). Also, using administrative data, we see that despite being stable for many years, after 2012 there was a rapid increase in Indian students enrolling in Engineering degrees at US universities. Since our model may not capture certain components of these shift we end our analysis in 2010.

The US has historically been the largest exporter of software products, and continues to produce the largest number of patents in the industry. US multinationals entered the Indian market by setting up liaison offices and subsidiaries. While they initially intended to sell to the Indian market, they shifted to using India as a place for software development (Arora et al., 2001). By 1997, the US accounted for about 58% of the all export revenues. By the mid-2000s, however, India overtakes the US as the major exporter of IT products (Figure 2c).

Unlike most Indian industries that focus on the large domestic market, the Indian IT firm is significantly export oriented; catering to a consumer base abroad that has the purchasing power for its products (Figure 2b). It is clear that most of the early-growth was export-led growth since by the turn of the century, software exports accounted for 26% of all exports, whereas in 1995 it was only 2% of all exports. Moreover, till about the end of the 1990s, most of these exports involved the physical presence of Indian workers at an overseas work-site. Over time, however, Indian IT firms moved from providing low-cost programming abroad to more comprehensive software development services for their overseas clients that was directly exported from India. Bhatnagar (2005) describes how, in 1995, 66% of all Indian IT exports involved an Indian worker on a foreign work-site, but this number fell to 29% by 2005.

By 2001 exports had reached about \$6 billion, growing at about 50-60% annually from the mid-1990s. By this time, only five of the top twenty exporters were subsidiaries of foreign firms, indicating that software exports were largely products of Indian firms.⁵ NASSCOM estimates that while about 0.16 million software professionals worked in India in 1996, this number more than doubled to about 0.34 million by 2000, showing that the industry generated about 60,000

⁵This is in stark contrast to the Irish software industry, where the bulk of the exports were US firms based in Ireland (Athreya, 2005).

jobs a year around this period. In the three years around the dot-com crash, the compound annual growth of employment was about 28.5% (Kumar, 2001).

1.4 Indian Students and College Choice

The boom in the US also affected the education sector in India. Bhatnagar (2005) notes that “*growth (in training and degrees) was also driven by larger salaries in the IT industry abroad.*” To meet the rising demand for workers, engineering schools introduced more computer science oriented degrees, and companies started their own training divisions in the 1980s, building technical skills for the industry (Figure 2a). In India, most programmers and chief executives in IT companies are predominantly trained as engineers (Desai, 2003). Science graduates and those with master’s degrees in CS make up the rest. A NASSCOM-Hewitt survey found that 88% of firms visited engineering colleges to recruit, and 47% recruited *only* there.

A survey by Arora and Athreye (2002) found that 80% of all software professionals employed had engineering degrees, and over time a number of engineering colleges have increased their emphasis on IT and even IT management. The salaries are among the highest across industries, growing at a steady rate, and some firms even offer stock options. Despite this, the attrition is quite high, as they “*migrate to better paid jobs in other countries.*” (Kumar, 2006).

A number of Indian students also come to the US for higher education purposes, plausibly exploring this as a pathway to the US labor market, and many of these students stay on to obtain work visas (Bound et al., 2014). Nonetheless, before 2012, the bulk of Indian workers get their degrees at Indian universities.⁶ India has historically been better at technical education like engineering and medicine, and has the advantage of using the English-language over East Asian countries (Arora et al., 2001). Over the last few decades, there has also been consistent growth in the number of new undergraduate engineering schools being opened to cater to the burgeoning demand (Figure 2a and NASSCOM (2012)). The new engineering colleges consist of both private and publicly colleges, some of which are high-quality Indian Institutes of Technology (IITs) and National Institutes of Technology (NITs), but many of lower quality as well.

2 Model

We model the market for high-skill immigrants, focusing on decisions made by firms and workers in both the US and India. Our model, consists of two main sections: in Section 2.1 we discuss

⁶Based on our calculations using student visa data obtained via a Freedom of Information request to USCIS, we estimate that between 2004 and 2012, there were about 20,000 student visas granted to Indian STEM students (broadly defined). Since 2012 this number has rapidly increased.

how goods are produced and sold to consumers, whereas in Section 2.2 we model the labor supply decisions of college graduates in both countries. The product market is assumed to be static, so firms and consumers make decisions each period conditional on the parameters of the model and the availability of each type of labor in the economy during that period. The college labor market, on the other hand, is assumed to have a dynamic horizon. Since human capital investments and career choices have long term payoffs, workers in both countries are allowed to choose their fields of study and occupations based on the information they have today and their expected payoffs in the future. Finally, in Section 2.3 we describe the equilibrium, where we also detail how the labor demand curve in the US shifts over time given the technological boom in the 1990s.

2.1 Product Market

2.1.1 The Household Problem

Consumers in each economy supply one unit of labor each, and have the same preferences over the final good Y , which has Constant Elasticity of Substitution (CES) form over the different varieties $v \in [0, 1]$.⁷

$$Y = \left(\int_0^1 y_v^{\frac{\sigma_y - 1}{\sigma_y}} dv \right)^{\frac{\sigma_y}{\sigma_y - 1}}, \quad (1)$$

where σ_y is the elasticity of substitution between the varieties of the final good. These varieties may be produced in other parts of the world and imported. The price index P_y of this good is represented by equation 2:

$$P_y = \left(\int_0^1 p_v^{1 - \sigma_y} dv \right)^{\frac{1}{1 - \sigma_y}} \quad (2)$$

A consumer's labor income is entirely spent on these goods as there are no savings. Consumers maximize their utility subject to a budget constraint, where their expenditure equals their wage income. While consumers have identical consumption preferences they do not receive the same labor income as they can work in three different occupations: computer science (L_n), other occupations that require college degrees (G) and non-college occupations (H).

Furthermore, workers in the US can either be native workers (denoted by a subscript n) or foreign workers (denoted by a subscript F). High-skill immigration flows in one direction from

⁷For notational convenience we drop the country subscripts for now while noting that the values of variables and parameters can differ across countries.

India to the US and is restricted to computer scientists who come into the US on H-1B visas. Computer science H-1Bs $L_{F,us}$ then make up the remaining part of the US workforce.

We outline the details of the labor-supply decisions in subsection 2.2, where we discuss how workers in each country choose their field of college-majors and occupations over time. The decision of whether to attend college or not is made outside this model which means that the supply of non college graduates \bar{H} is exogenous, and so is the total supply of native college graduates $(\bar{L}_n + \bar{G})$. 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 .

Within occupations, we assume workers have identical abilities for production, so every worker in a particular country-occupation pair earns the same wage. In the US, the size of the labor force in the economy is $\bar{H}_{us} + \bar{L}_{n,us} + \bar{G}_{us} + L_{F,us}$ and total income m can be written as the sum of the labor income for the different types of workers as in equation 3:

$$m_{us} = w_{\ell,us}(L_{n,us} + L_{F,us}) + w_{g,us}G_{us} + w_{h,us}\bar{H}_{us} , \quad (3)$$

where $w_{\ell,us}$ is the wage paid to computer scientists, $w_{g,us}$ the wage earned by college graduate non computer scientists and $w_{h,us}$ is the wage paid to non college graduates.

As the wage differential between the US and India is very large, Indian computer scientists are always willing to come and work in the US. 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.

In India, on the other hand, there are two types of computer scientists. Those that return from the US R_{in} after the expiration of their H-1Bs earn a wage $w_{r,in}$, and those natives N_{in} that never migrated to the US, earn a wage $w_{n,in}$. Therefore, in India, the size of the labor force is $\bar{H}_{in} + \bar{N}_{in} + \bar{G}_{in} + \bar{R}_{in}$, and the total income in the economy is:

$$m_{in} = w_{n,in}N_{in} + w_{r,in}R_{in} + w_{g,in}G_{in} + w_{h,in}\bar{H}_{in} , \quad (4)$$

2.1.2 Final Goods Production

Each firm in the final goods sector has a Cobb Douglas constant returns to scale technology over intermediate inputs from the IT sector $C_{v,y}$ and the labor aggregate x , and draws a productivity level $z_{v,y}$:

$$y_v = z_{v,y}C_{v,y}^\gamma x_{v,y}^{1-\gamma} \quad (5)$$

The IT good is an input in final goods production, and innovation in IT can increase productivity in the entire economy. Following the framework introduced by [Dornbusch et al. \(1977\)](#) and [Eaton and Kortum \(2002\)](#), each country will have a different level of efficiency in producing each variety, denoted by $z_{v,y}$. The final goods sector employs three types of labor denoted by subscript y . $x_{v,y}$ is a labor aggregate of non college graduates $h_{v,y}$ and an aggregate of college graduates $q_{v,y}$:

$$x_{v,y} = \left[\alpha h_{v,y}^{\frac{\tau-1}{\tau}} + (1 - \alpha) q_{v,y}^{\frac{\tau-1}{\tau}} \right]^{\frac{\tau}{\tau-1}} \quad (6)$$

Using a nested CES format, the aggregate of college graduates $q_{v,y}$ can be represented by:

$$q_{v,y} = \left[\delta \ell_{v,y}^{\frac{\lambda-1}{\lambda}} + (1 - \delta) g_{v,y}^{\frac{\lambda-1}{\lambda}} \right]^{\frac{\lambda}{\lambda-1}}, \quad (7)$$

where $\ell_{v,y}$ is the number of computer scientists hired in the final goods sector, and $g_{v,y}$ is the number of non computer scientists hired in the final goods sector. Both sectors have the same elasticity of substitution between college and non college graduates (τ) and between computer scientists and non-CS college graduates (λ).

As immigration increases the size of the CS workforce, demand will rise for workers in complementary occupations, raising their wages. This may induce native CS workers to switch to other occupations, mitigating negative wage impacts. At the same time, skill-biased technical change will shift the values of δ over time.

In India, firms pay different wages to native CS workers and the return migrants. The $\ell_{v,y}$ computer science labor in India is an aggregate over the native $n_{v,y}$ and return migrants $r_{v,y}$:

$$\ell_{v,y} = \left[\Psi n_{v,y}^{\frac{\epsilon-1}{\epsilon}} + (1 - \Psi) r_{v,y}^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}}, \quad (8)$$

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 derive the aggregate labor demand for each worker.

2.1.3 Production in the IT sector

For each IT variety j we assume that there are infinitely small firms with constant returns to scale technology willing to produce the good. US-owned firms producing and exporting from India count towards Indian production and exports, and the same is true for Indian-owned firms located in the US. A US firm that outsources production to India may then import this

good to the US, which becomes an intermediate input in the US final good. Firms in the final goods sector have preferences over the different types of IT goods c_j , such that:

$$C_y = \left(\int_0^1 c_j^{\frac{\sigma_c-1}{\sigma_c}} dj \right)^{\frac{\sigma_c}{\sigma_c-1}} \quad (9)$$

Since these varieties may be produced in other parts of the world and imported, restricting immigration to the US may affect growth in the US IT sector and lead to certain varieties being produced in other countries. At the same time, more migration raises the prospect of migrating from India; this prospect, coupled with return migration to India increases the size of the Indian CS workforce, potentially shifting some production from the US to India.

The price index in IT can be represented by:

$$P_c = \left(\int_0^1 p_j^{1-\sigma_c} dj \right)^{\frac{1}{1-\sigma_c}} \quad (10)$$

In order to capture the contribution of the different types of labor, the IT firm has a CES technology in the labor aggregate as in equation 11:

$$c_j = z_{j,c} \left[(\delta + \Delta) \ell_{j,c}^{\frac{\lambda-1}{\lambda}} + (1 - \delta - \Delta) g_{j,c}^{\frac{\lambda-1}{\lambda}} \right]^{\frac{\lambda}{\lambda-1}}, \quad (11)$$

where $\ell_{j,c}$ is the number of CS workers and $g_{j,c}$ the non-CS college graduates employed by firm j in the IT sector. Here λ is the elasticity of substitution between the CS workers and non-CS college graduates and $\delta + \Delta$ is the distributional parameter of the CES function. We impose $\Delta > 0$ to indicate that the IT sector is more intensive in computer scientists than the final goods sector.

In India, we assume that native and return migrant CS workers are not perfect substitutes as return migrants may have a different set of skills:

$$\ell_{j,c,in} = \left[\Psi n_{j,c}^{\frac{\epsilon-1}{\epsilon}} + (1 - \Psi) r_{j,c}^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}}, \quad (12)$$

where $n_{j,c}$ is the number of CS workers that never went abroad and $r_{j,c}$ the number of return migrant CS workers employed by firm j . Here ϵ is the elasticity of substitution between the native CS workers and return migrants.

2.1.4 International Trade

We model the World economy as a set of three countries indexed by k (United States, India and the rest of the World) with preferences and production as described in sub-sections 2.1-2.1.3. Although our model will focus mainly on India and the US we still incorporate the rest of the World (RoW) to capture that both India and the US compete in the world market and have the option of buying and selling products to a third producer. While workers in RoW produce and consume both Final and IT goods we simplify the analysis by assuming workers in RoW cannot migrate and that workers in India and the US cannot migrate to RoW. As the focus of this paper is not the labor market in RoW we avoid modeling the occupational distribution of its workers and assume output in both sectors is produced with a single type of worker that can freely move across sectors.

All three countries will trade both goods following the standard framework of [Eaton and Kortum \(2002\)](#) where each country will have a comparative advantage in producing some of the varieties of each good. We assume that country k 's efficiency in producing good j in sector s is the realization of the random variable Z_k^s , drawn independently for each j from a distribution $F_{s,k}(z)$. We assume that the productivity $z_{j,s,k}$ comes from the Frechet (Type II extreme value) distribution:

$$F_{s,k}(z) = e^{-T_{s,k}z^{-\theta}}, \quad (13)$$

where $\theta > 1$ reflects the variation within the distribution. Higher $T_{s,k}$ increases the likelihood of drawing a higher efficiency for good j and can be interpreted as the technology level for each country-sector pair. This means that if the US has a higher $T_{s,k}$, the US will be more efficient at producing varieties in sector s on average, but India and RoW will be more efficient at producing some of the varieties in sector s .

Consumers in each country will buy each variety from the lowest price producer. If a consumer in country k was to buy the good from country b they would need to pay an iceberg-trade cost, modeled as a share of the final good that gets lost when moving the good from k to b . Given each variety is produced in a perfectly competitive market, the price of a good produced in country k and sold in country b can be written as marginal cost of production in each sector s ξ_k^s times the iceberg trade cost $d_{k,b}$ divided by the variety-specific productivity in country k , $z_{s,k}$ as shown in equation 14:

$$p_{j,k,b}^s = \frac{d_{k,b} \times \xi_k^s(w_{\ell,k}, w_{g,k}, w_{h,k})}{z_{j,s,k}}, \quad (14)$$

This framework allows us to capture the possibility of firms from country b outsourcing production to country k reflected by more imports in country b from country k . All else equal, a

country becomes a more attractive provider of the good whenever one of three things happen: an increase in the technology of k (that allows for better draws of $z_{s,k}$), a decrease in the trade costs $d_{k,b}$ or a decrease in labor costs in k . Such features of our model will be relevant to capture the empirical patterns shown in the data, as shown in Figure 2c, while the US was the predominant exporter of IT goods for most of the 1990s, India takes over soon thereafter as technology in India increases with respect to the US.

Importantly, we include the possibility of directed technological change (Acemoglu, 1998). Since production in IT is heavily reliant on technology, this is an important driver of how technology spreads to India. Computer scientists in both countries are innovators and increase the technological productivity in the IT sector. This can potentially raise wages on average, and mitigate the depression in CS wage growth due to immigration. Since the IT output is an intermediate input into the final goods sector, technological advances can increase the productivity of other sectors of the economy as well.

The innovation potential in India depends on the number of CS workers. The ‘brain drain’ of CS workers leaving for the US is countered by the ‘brain gain’ of return migrants coupled with workers acquiring CS skills with the prospect of migrating. Workers that migrate from India to the US acquire human capital in the form of skills and technologies, and when they return they bring this knowledge with them. This spread of technology makes the Indian IT sector more productive, and over time the leading exporter of IT goods.⁸ To capture this feature we model the productivity in the IT sector in country k to be a function of the total number of CS IT workers in country k :

$$T_{c,k} = T(L_{c,k}) \text{ for } k = \{us, in\} \quad (15)$$

2.2 The Supply of Workers in India and the US

The labor supply side of the model is related to Bound et al. (2015) who model the US labor market for computer scientists. We extend this model in various ways, and incorporate the decisions made by students and workers in India, including the potential to migrate to the US. College graduates in the US and India make two types of decisions along their career in order to maximize the expected present value of their life time utility. At age 20, individuals in college choose the field of study that influences their initial occupation after graduation, and from age 22 to 65, workers choose between working as a computer scientist or in another occupation. Individuals have rational, forward looking behavior and make studying and working decisions based on the information available at each period. Indian workers are assumed to always want

⁸We build on a growing contemporary literature on technological diffusion and directed technological change within the Ricardian trade model framework (Alvarez et al., 2013; Dasgupta, 2012; Kerr, 2013b; Perla et al., 2015; Somale, 2014)

to migrate to the US and pay a migration cost if they get to migrate. The fraction of migrants that return from the US always work as computer scientists.

2.2.1 Field of Study Decision

At age 20, an individual i draws idiosyncratic taste shocks for studying computer science or another field: $\eta_{i,k}^c$ and $\eta_{i,k}^o$, respectively (where $k = \{in, us\}$ indexes the Indian students in India and US students in the US). This student also has expectations about the prospects of starting a career in each occupation after graduation (age 22), which have a values $V_{22,k}^c$ and $V_{22,k}^o$ respectively. With this information, an individual chooses between pursuing computer sciences or a different choice of major at the undergraduate level.

The utility of a student is modeled as a linear function of the taste shocks and career prospects in each sector. There is also a taste attractiveness parameter $\zeta_{o,k}$ for studying a different field from computer science and individuals discount their future with an annual discount factor β . With these assumptions, the field of study decision for $k = \{in, us\}$ is represented by:

$$\max\{\beta^2\mathbb{E}_t V_{22,k}^c + \eta_{i,k}^c, \beta^2\mathbb{E}_t V_{22,k}^o + \zeta_{o,k} + \eta_{i,k}^o\} \quad (16)$$

It is assumed that $\eta_{i,k}^c$ and $\eta_{i,k}^o$ are independently and identically distributed and for $e = \{c, o\}$, can be defined as $\eta_{i,k}^e = \sigma_{0,k} v_{i,k}^e$, where $\sigma_{0,k}$ is a scale parameter and $v_{i,k}^e$ is distributed as a standard Type I Extreme Value distribution. This distributional assumption is common to dynamic discrete choice models (Rust, 1987) and it is convenient because it allows the decisions of agents to be smoothed out, a desired property that will be used in the characterization of the equilibrium of the model.

In Appendix A we outline the probabilities of graduating with a specific major. The important parameter for how studying choices of workers are sensitive to different career prospects is the standard deviation of taste shocks. Small values of $\sigma_{0,k}$ imply that small changes in career prospects can produce big variations in the number of students graduating with a computer science degree.

2.2.2 Occupational Choice

The field of study determines if an individual enters the labor market as either a computer scientist or with a different occupation. However, individuals can choose to switch occupations along their careers. Specifically, at the beginning of each period, individuals between ages 22 and 65 choose to work in CS or another type of job in order to maximize the expected present

value of their lifetime utility. We will first present the equations for the US and later explain how we incorporate the possibility of migration in India.

A feature of the model is that switching occupations is costly for the worker. A justification for this assumption is that workers have occupational-specific human capital that cannot be transferred (Kambourov and Manovskii, 2009). It is assumed that the cost to switch occupations is a quadratic function of a worker's age. Note that this assumption implies that it becomes increasingly harder for workers to switch occupations as they get older. Additionally, there is no general human capital accumulation and wages do not vary with the age of a worker.

In the equations below, the value functions for working as a computer scientist and working in other college occupations are represented. It is assumed that workers have linear utility from wages, taste shocks and career prospects. Furthermore, wages must be totally consumed in that same year and workers cannot save or borrow. The Bellman equations of worker i at age a between 22 and 64 at time t if he starts the period as a computer scientist or other occupation are respectively:

$$V_{t,a,k}^c = \max\{w_{t,\ell,k} + \beta\mathbb{E}_t V_{t+1,a+1,k}^c + \varepsilon_{i,t,k}^c, w_{t,g,k} - \chi_k(a) + \beta\mathbb{E}_t V_{t+1,a+1,k}^o + \varepsilon_{i,t,k}^o + \zeta_{1,k}\} \quad (17)$$

$$V_{t,a,k}^o = \max\{w_{t,\ell,k} - \chi_k(a) + \beta\mathbb{E}_t V_{t+1,a+1,k}^c + \varepsilon_{i,t,k}^c, w_{t,g,k} + \beta\mathbb{E}_t V_{t+1,a+1,k}^o + \varepsilon_{i,t,k}^o + \zeta_{1,k}\} \quad (18)$$

where $\chi_k(a) = \chi_{0,k} + \chi_{1,k}a + \chi_{2,k}a^2$, is the monetary cost of switching occupation for an age a worker, and $\zeta_{1,k}$ is the taste attractiveness parameter for not working as a computer scientist. In the model, all workers retire at age 65 and their retirement benefits do not depend on their career choices. As a consequence, workers at age 65 face the same decision problem but, without consideration for the future. The current wage in computer science $w_{t,\ell,k}$ and in the other occupation $w_{t,g,k}$ is exogenous and perfectly anticipated by the workers.

As in the college-major decision problem, idiosyncratic taste shocks play an important role in the working decisions of an individual. Once more, it is assumed that taste shocks are independently and identically distributed and for $e = \{c, o\}$ can be defined as $\varepsilon_{i,t,k}^e = \sigma_{1,k}v_{i,t,k}^e$ where $\sigma_{1,k}$ is a scale parameter and $v_{i,t,k}^e$ is distributed as a standard Type I Extreme Value distribution.

For India, whenever workers choose to become computer scientists they have the possibility to migrate to the US. We assume that all workers in India who choose computer science will be willing to migrate if they are given the choice. While this assumption ignores the possibility of heterogeneous migration preferences, as long as there is a large wage premium in the US

with respect to India and the H-1B cap remains small relative to the total number of computer scientists in India, it is a reasonable simplification to assume that there will always be workers who want to migrate to the US.⁹

At the beginning of each period, the Indian workers decide whether to work as computer scientists or in other occupations, without knowing whether they will get to migrate if they become computer scientists. Therefore, they make their decision based on the *expected wage*, by weighting the wage of computer scientists in India $w_{t,n,in}$ and in the US $w_{t,\ell,us}$ with the probability of migrating $q_{t,us}^m$, as in equation 19.

$$w_{t,\ell,in} = q_{t,us}^m w_{t,\ell,us} + (1 - q_{t,us}^m) w_{t,n,in} \quad (19)$$

Here, the probability of getting a US job is determined by the fraction of Indian computer science workers that are recruited to work in the US every year (determined by the H-1B cap $h1b_t$) and the number of computer scientists in India that year.:

$$q_{t,us}^m = \frac{h1b_t}{h1b_t + L_{n,t,in}} \quad (20)$$

Once the workers choose their occupation conditional on the expected wage, a share $q_{t,us}^m$ of all computer scientists in India will migrate to the US and the rest will remain in India and work as computer scientists during that period. Their value function is then similar to the US but we incorporate the probability of migration as in equation 21:

$$V_{t,a,k}^c = \max\{w_{t,\ell,in} + q_{t,us}^m \bar{\omega}_t + (1 - q_{t,us}^m) \beta \mathbb{E}_t V_{t+1,a+1,k}^c + \varepsilon_{i,t,k}^c, w_{t,g,k} - \chi_k(a) + \beta \mathbb{E}_t V_{t+1,a+1,k}^o + \varepsilon_{i,t,k}^o + \zeta_{1,k}\} \quad (21)$$

where $\bar{\omega}_t$ is the continuation value of moving to the US. After the 6-year limit on the H-1B visa, firms that wish to hold on to a worker must sponsor them for a green-card. This is an administratively and monetarily costly process, and once the worker receives the green-card she is free to switch workers or work for multiple employers. We assume that the number of workers who return are a fixed fraction of the number of H-1B visas that expire that year. This fraction is represented by the parameter ϱ . The full value of migration is as in equation 22. Since H-1B workers are tied to their sponsoring employer, we assume that if a worker migrates they can only work as computer scientists in the US and they only work as computer scientists

⁹Notice that we are implicitly assuming that migrating CS have similar skills to the ones that remain. Given the large number of H-1B applications, the lottery winners are identical to lottery losers. Furthermore, CS immigrants perform a wide variety of tasks across the CS wage distribution. Last, in our NSS data CS workers have consistently slightly lower variance in wages than similar occupation groups like doctors and professors, suggesting not a very wide distribution of skills.

if they return to India.

$$\bar{\omega}_t = \sum_{x=t}^{t+5} \beta^{x-t} w_{x,\ell,us} + \varrho \sum_{x=t+6}^T \beta^{x-t} w_{x,r,in} + (1 - \varrho) \sum_{x=t+6}^T \beta^{x-t} w_{x,\ell,us} \quad (22)$$

In Appendix A we discuss the probabilities of switching occupations, the value function iteration, and the corresponding size of the workforce for different types of workers.

2.3 Equilibrium

Equilibrium in each period can be defined as a set of prices and wages $(P_{t,c,k}, P_{t,y,k}, w_{t,\ell,k}, w_{t,n,k}, w_{t,r,k}, w_{t,g,k}, w_{t,h,k})$, quantities of output and labor $(C_{t,y,k}, Y_{t,k}, L_{t,n,us}, L_{t,F,us}, R_{t,in}, G_{t,k}, H_{t,k})$, and the level of technology $(T_{t,k}^s)$ such that:¹⁰

- Consumers in the US, India and the rest of the world, maximize utility by choosing $Y_{t,k}$ taking prices as given.
- College graduates in the US and India choose their field of major and occupations taking wages as given and forming expectations .
- Firms in both the IT sector and the final goods sector maximize profits taking wages and prices as given.
- Trade between the three countries is balanced.
- Output and labor markets clear.

Given the Frechet distribution assumption we can aggregate across varieties and write the probability of country b buying goods of sector s from country k as in equation 23:

$$\pi_{t,k,b}^s = \frac{T_{t,k}^s (d_{t,k,b}^s \xi_{t,k}^s)^{-\theta}}{\sum_{k'} T_{t,k'}^s (d_{t,k',b}^s \xi_{t,k'}^s)^{-\theta}} \quad (23)$$

Using equation 23 we have that total income from sector Y in country k has to be equal to the sales to each of the markets as in equation 24.

$$m_{t,y,k} = \sum_b \pi_{t,k,b}^y m_{t,b} \quad (24)$$

where $m_{t,b}$ is total labor income of country b and $m_{t,y,k}$ is total income earned by sector Y in country k . Similarly for the IT sector, we have that total income earned by the sector has to be

¹⁰Note that we've introduced a t subscript to each of the variables to denote that there is a different equilibrium for each time period.

equal to the the total sales of intermediate IT good sold to each country as in equation 25

$$m_{t,c,k} = \sum_b \pi_{t,k,b}^c \gamma_{t,b} m_{t,y,b} \quad (25)$$

Finally, labor income $m_{t,k}$ in country k has to equal total labor payments from the Y and C sectors.

$$(1 - \gamma_k) m_{t,y,k} + m_{t,c,k} = m_{t,k} \quad (26)$$

Labor markets clear as long as total demand for each occupation in country k equals the total supply of labor for that given occupation. Non-college workers' supply is fixed at \bar{H}_k in both countries. The supply of return migrant computer scientists in India is determined by the H-1B cap and the number of workers that migrate to the US and return according to probability of return ϱ . Native college graduates in both countries face the decision of whether to work as computer scientists or in some other occupation that requires a college degree. This decision 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 (16-22) and a stochastic process $A_{t,k}$ through which we characterize the expectations of workers with respect to future career prospects.

A unique equilibrium is pinned down each period by an aggregate labor demand curve in each country for native computer scientists relative to other college graduates that is derived from the production side of the model. Even though these labor demand curve from the two sectors have no closed form solution we will express it as in equation 27-28, a setup that will prove to be useful for the calculations in the following sections.

$$\frac{L_{n,t,k}}{G_{t,k}} = A_{t,k} + \Upsilon_k \left(\frac{w_{t,k}}{s_{t,k}} \right) \text{ for } k = \{US\} \quad (27)$$

$$\frac{N_{t,k}}{G_{t,k}} = A_{t,k} + \Upsilon_k \left(\frac{w_{n,t,k}}{s_{t,k}} \right) \text{ for } k = \{IN\} , \quad (28)$$

where $\Upsilon_k(\cdot)$ is a baseline relative demand curve that depends on the relative wage. $A_{t,k}$ 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 moves the relative demand curve for natives, every period differently for each country. For US workers, the relative inflow of foreign workers $\frac{L_{t,F,us}}{G_{t,us}}$ shifts in the relative demand curve for natives. Whereas, for Indian workers, the relative prospects of foreign jobs, $\frac{L_{t,F}}{G_{t,in}}$ shifts out the relative demand curve every year. $A_{t,k}$ is assumed to follow

a stationary AR(1) process with high persistence such that:

$$A_{t,k} = 0.999A_{t-1,k} + 0.001\bar{A}_k + \nu_{t,k} \quad (29)$$

where \bar{A}_k is the steady state value of $A_{t,k}$ and $\nu_{t,k}$ is an i.i.d. shock.¹¹

The equilibrium in the labor market can be expressed by a mapping from the state variables: $s = \{\mathbf{L}_{t,k}^{\text{grad}}, \mathbf{L}_{t-1,n,k}^{22}, \dots, \mathbf{L}_{t-1,n,k}^{64}, \mathbf{G}_{t-1,k}^{22}, \dots, \mathbf{G}_{t-1,k}^{64}, \mathbf{A}_{t-1,k}\}$ and exogenous productivity shock $\nu_{t,k}$ to the values of $L_{t,n,k}$, $w_{t,\ell,k}$, $w_{t,n,k}$, $G_{t,k}$, $w_{t,g,k}$ and \mathbf{V}_t , the vector of career prospects at different occupations for different ages, that satisfies the system of equations 16-22 as well as each period's relative demand curve.

3 Calibration

We calibrate the parameters of the model using data from labor force surveys, trade flows, and national accounts from both India and the US. For the product market we need to calibrate: τ , λ , γ_{us} , γ_{in} , γ_W , ϵ , σ_c , σ_y , θ , $h1b_t$, ρ , $\alpha_{y,us}$, $\alpha_{y,in}$, δ_{us} , δ_{in} , Δ_{us} , Δ_{in} , Ψ , $\bar{L}_{n,us}$, \bar{G}_{us} , \bar{H}_{us} , \bar{N}_{in} , \bar{R}_{in} , \bar{G}_{in} and \bar{H}_{in} . Additionally, there are the technology parameters $T_{s,k}$ and asymmetric trade costs $d_{k,b}^s$ that vary across countries of origin k and destination b , and the good that is traded s . For the labor supply of college graduates we have 8 parameters: $\sigma_{0,k}$, $\zeta_{0,k}$, $\sigma_{1,k}$, $\zeta_{1,k}$, $\chi_{0,k}$, $\chi_{1,k}$, $\chi_{2,k}$, and β for $k = \{us, in\}$. India has an additional parameter – the cost of migrating κ .

We follow a sequential approach in order to back out all the parameters of the model. As a first step we take the labor supply of computer scientists, non-CS college graduates and non college graduates as given and calibrate the parameters of the product market in order to match certain features of the data. Once we have our product market parameters we derive a demand curve for computer scientists relative to non-CS college graduates, for every year. Calibration of these parameters and the demand curve are summarized in subsection 3.1. In a second step, we use the shifts in the relative demand curve to calibrate the labor supply parameters and trace out the labor supply curve as explained in subsection 3.2. Finally, we use all calibrated parameters to run our counterfactual simulations.

3.1 Product Market Calibration

We calibrate the model each year between 1994-2010 and present a summary of all calibrated parameters for selected years in Table 4. A detailed summary of all our data sources can be found in Appendix B.

¹¹We assume workers consider both the technological progress from the IT boom as well as the flow of migrants from India to the US to be a series of highly persistent shocks.

3.1.1 Production Function Parameters

We set the elasticity of substitution between different factors to be time invariant and the same across all countries and sectors in our model. We calibrate the elasticity of substitution between college and non college graduates, $\tau = 1.7$ based on an average of different papers that estimate that parameter such as [Katz and Murphy \(1992\)](#), [Card and Lemieux \(2001\)](#) and [Goldin and Katz \(2007\)](#).¹² For the elasticity of substitution between computer scientists and non-CS college graduates we set $\lambda = 2$ which is within the estimates of [Ryoo and Rosen \(2004\)](#); they estimate the elasticity of substitution between engineers and other college graduates to be between 1.2 and 2.2. In the case of India we also need to calibrate the substitution between computer scientists who never worked abroad and those who return from the US. We would expect this elasticity to be greater than the elasticity between CS and non-CS graduates. The scant literature on return migrants find that in other contexts, those who emigrated for labor reasons and return home earn a wage premium relative to those that never migrated ([Barrett and O’Connell, 2001](#); [Hazans, 2008](#); [Reinhold and Thom, 2013](#)). In our steady state year, we match the average premium of 15% across papers in this literature, which corresponds with a value of $\epsilon = 30$. In [Appendix C.4](#), we show that our results are qualitatively similar as we vary both ϵ and λ .

For the substitution between varieties of IT in each country, we follow [Bernard et al. \(2003\)](#) who estimate the elasticity of substitution across US plants to be 3.79 and set $\sigma_s = 4$ for $s = \{y, c\}$. Finally, we also calibrate the Frechet dispersion parameter $\theta = 8.28$ using the [Eaton and Kortum \(2002\)](#) preferred value. In [Appendix C.4](#), we vary this parameter to $\theta = 4.2$, a value preferred by [Simonovska and Waugh \(2014\)](#).

We calibrate the rest of the parameters in the production function separately by country and year in order to capture the differential changes in technology that are going on in the US and India during our period of analysis.

The Cobb Douglas parameters γ_k represent the share of income from the final goods sector spent on varieties of the IT sector. We calibrate the parameters for $k = \{us, in\}$ using the share of IT GDP to total GDP in each country and get values: $\gamma_{us} = 0.007$ and $\gamma_{in} = 0.002$ in 1994. By calibrating these parameters every year we want to capture the changes in demand for IT varieties as an input into the final good production, and we can see that while it is increasing for both countries, it shows a larger increase for India over this period.

For the demand of IT goods from the Rest of the World W we use exports and GDP data from the OECD to first calculate the imports of IT products from the US and India as a share of

¹²We replicate [Card and Lemieux \(2001\)](#) using the India data and estimate an elasticity of complementarity of 0.55. This corresponds to $\tau = 1.8$, and is statistically indistinguishable from 1.7. These papers estimate the overall substitution between college and non college graduates, while our parameter is sector specific. However, when calculating the overall substitution between college and non college graduates our estimates are indistinguishable from our assigned value of τ .

the GDP from the rest of the world and calibrate γ_W . We then calculate the relative GDP of the rest of the world with respect to the combined GDP of US and India to match the size of the rest of the world with respect to the US and India.

The final goods production function distributional parameter $\alpha_{y,k}$ is calibrated in India and the US such that it matches the share of expenditures from the final goods sector in non college graduates. More specifically, from the March CPS for the US and the NSS data for India, we calculate the share of expenditures on non college graduates $\vartheta_{y,k}$ and the number of college and non college graduates in the final goods industry $\bar{H}_{y,k}$, $\bar{Q}_{y,k}$. We calibrate the parameter to be 0.47 and 0.48 for the US and India respectively, in 1994 using equation 30:

$$\vartheta_{y,k} = \frac{\alpha_{y,k} \bar{H}_{y,k}}{\alpha_{y,k} \bar{H}_{y,k} + (1 - \alpha_{y,k}) \bar{Q}_{y,k}} \quad (30)$$

Importantly, in Table 4 it is clear that $\alpha_{y,k}$ decreases over time, capturing how skill-biased technological change shifts production to college graduate occupations over time.

The distributional parameter between CS and non-CS college graduates δ_k is calibrated so that it matches the relative wages between computer scientists and non-CS college graduates observed in the data. We calibrate values of δ to be 0.186 in the US and 0.133 in India in 1994. This parameter increases over time capturing how shifts in skill-biased technology increase the labor share of CS workers.

The additional distributional parameter in the IT sector Δ_k captures the extra intensity of CS in the IT sector. We calibrate Δ_k such that it matches the share of expenditures of the IT sector in computer scientists in the US for 1994 and get a value close to 0.2. For simplicity we use that value for both US and India throughout the period. Finally, for India we assign a value of 0.5 for Ψ , the distributional parameter between CS that never migrated to the US and CS that return from the US.

3.1.2 Labor quantities

We calculate the number of each type of worker for each country. For the US, we use the March CPS data to get the number of computer scientists, non-CS college graduates and non-college graduates each year to match the shares of employment in each occupation. For tractability, we normalize the total population in 1994 to be 100 and then let the population grow at the same rate that the economically active population grows in the data. We use the CPS-ORG data to find the share of foreign computer scientists that are Indian and use that to calculate our foreign computer scientists measure. All foreigners who are not Indian computer scientists are considered native workers for the current purposes of our study.

We use data from the United States Citizenship and Immigration Services (USCIS) to calculate

the number of Indian CS entering the US each year: $h1b_t$. According to [Lee \(2016\)](#), the OECD estimates that $\rho = 23.5\%$ of high-skill immigrants in the US return to their home countries after a 6-year period so we can write the law of motion for foreign CS in the US as in equation 31:

$$L_{F,t+1,US} = L_{F,t,US} + h1b_t - \rho h1b_{t-6} \quad (31)$$

For India we follow a slightly different approach. We use the National Sample Survey (NSS) to get the share of each occupation group in each year and we use World Bank data to get at total active population for each year. Multiplying the shares by the total population we get the total employment under each occupation. We then normalize the total size of the population in India every year to make it's relative size with respect to the US match the data.

The NSS does not provide information that allows us to distinguish between computer scientists that never migrated to the US and those that are return migrants. To tackle this issue we create the series of return migrants based on the Indian computer scientists that are working in the US since 1980. We use the 1980 and 1990 US censuses to calculate, on average, how much has the Indian CS population in the US increased every year. From the average yearly increase between 1980-1994 we assume that each year, ρ fraction of the average migrants return to India and create the series as the cumulative of those that go back in 1980 up until those that go back in 1994.

Once we get our initial stock for 1994, every year we assume that the number of return migrants evolves according to equation 32:

$$R_{t+1,IN} = R_{t,IN} + \rho h1b_{t-6} \quad (32)$$

For the workforce of the rest of the World we use data on the size of the total labor force from the World Bank for 57 countries for which trade and GDP data are available. Given that there is no sufficient data available of the number of computer scientists and college graduates in RoW we assume they produce with a single type of labor.

An underlying assumption we use for calibrating labor quantities is that the number of effective units of labor provided by each worker is the same across countries, implying that if an Indian worker migrates to the US they produce the same than a US worker. If the Indian worker were to remain in India, they produce as much as the Indian worker that would never migrate. Thus, the wage differential from migrating, is merely a function of the 'place-premium' attributable to the US for having more skill-biased capital and better technology. While these assumption are strong, we believe them to be reasonable. [Clemens \(2013\)](#) finds that H-1B lottery winners earn far more than non-winners despite being observationally equivalent – the premium, similar to

our estimates, is therefore due to location and not because of unobservable differences between the workers. Given that H-1Bs have to get paid at least the same wage as native workers, the difference between wages in the US and India, in our model, is explained mostly through the availability of better technology in each country and not because of differences in efficiency of labor.

A summary of the calibrated employment can be found in Table 5.

3.1.3 Productivity levels and trade costs

To calibrate the productivity levels for each country-sector pair $T_{s,k}$ and bilateral trade costs by country pair and sector $d_{k,b}^s$ we use trade data to calibrate the parameters such that we match the observed trade flows every year. We follow the approach of Eaton and Kortum (2002) and Levchenko and Zhang (2016) by using the gravity equations of the model to estimate trade costs and technology parameters. As a first step we use equation 23 and take the ratio between the probability of country b buying from country k and the probability of country b buying from itself which yields the gravity equation 33.

$$\frac{\pi_{t,k,b}^s}{\pi_{t,b,b}^s} = \frac{EX_{t,k,b}^s}{EX_{t,b,b}^s} = \frac{T_{t,k}^s (d_{t,k,b}^s \xi_{t,k}^s)^{-\theta}}{T_{t,b}^s (d_{t,b,b}^s \xi_{t,b}^s)^{-\theta}} \quad (33)$$

Where $EX_{t,k,b}$ is the value of expenditures that country b has on products from country k in sector s at time t . We parametrize the trade costs as in equation 34. Following Levchenko and Zhang (2016) we define log of trade costs as a function of distance ($dist_{k,b}$), an indicator on whether the two countries share a border $border_{k,b}$, an indicator on whether the two countries belong to a currency union $CU_{t,k,b}$ and an indicator for participating in a regional trade agreement $RTA_{t,k,b}$. We also allow the trade costs to be affected by an exporter fixed effect $exp_{t,k}$ and an error term $v_{t,k,b}$.

$$\log(d_{t,k,b}^s) = dist_{k,b} + border_{k,b} + CU_{t,k,b} + RTA_{t,k,b} + exp_{t,k}^s + v_{t,k,b}^s \quad (34)$$

Using data on bilateral trade flows and domestic consumption by sector and year for the US, India and a series of 57 countries we use equation 33 to back out the trade costs and a term that combines the technology level and the unit cost of production $T_{t,k}^s (\xi_{t,k}^s)^{-\theta}$. We use this term as a parameter in the model, which allows us to separately calculate the unit costs $\xi_{t,k}^s$ and the technology level $T_{t,k}^s$. In Appendix C.1 we provide more detail on how we estimate the parameters for trade costs and technology and specify some further assumptions we make for estimation.

In Section 2.1.4, equation 14 we mentioned that the level of technology of the IT sector depended

on the number of computer scientists working in IT without specifying any functional form on this relationship. One advantage of the calibration procedure we use, is that we can calibrate the $T_{t,k}^s$ in equilibrium so our estimate will already capture the baseline level of technology plus any endogenous effect that affects the overall level of technology. In our counterfactuals, we change the number of foreign computer scientists that are in the US and India which presumably will affect the level of technology. To get to this, we calibrate the elasticity of TFP with respect to the number of computer scientists by using the estimates of [Peri et al. \(2015b\)](#) who estimate a 1% increase in total STEM workforce in the US would increase average TFP by 0.27%.¹³ In our counterfactual simulations we calibrate the $T_{t,k}^s$ to be consistent with the expected changes in TFP based on the change in the number of computer scientists working in the IT sector in each country between the real and the counterfactual. In our setup, TFP can be written as in equation 35:

$$TFP_{t,k}^c = T_{t,k}^c \left[1 + \sum_{b \neq k} \left(\frac{T_{t,b}^c \xi_{t,b}^c}{T_{t,k}^c \xi_{t,k}^c} \right)^{-\theta} (d_{t,k,b}^c)^{-\theta} \right] \quad (35)$$

The $T_{t,k}^c$ under the counterfactual (denoted by subscript *cf*) will be consistent with the equation:

$$\frac{TFP_{t,k,cf}^c}{TFP_{t,k,real}^c} - 1 = 0.27 \times \left(\frac{L_{t,k,cf}^c}{L_{t,k,real}^c} - 1 \right) \quad (36)$$

Implicitly, we are assuming that the endogenous productivity growth happens through computer scientists working in the IT sector. This is consistent with the work of [Jorgenson and Ho \(2016\)](#) and [Byrne et al. \(2013\)](#) who estimate that IT producing industries contributed more than 50% of the aggregate productivity growth in the US between 1995-2014. At the same time, [Peri et al. \(2015a\)](#) estimates that foreign STEM workers alone, contributed between 30% and 50% of the aggregate productivity growth between 1990-2010. As most foreign STEM workers come to work as computer scientists, it is reasonable to assume that overall, IT is a predominant driving force for productivity growth.

3.2 Calibrating Labor Supply

While we model our product market to be static, our labor supply side is dynamic, so we use the calibrated parameters of the product market to trace out the parameters of the supply curve. Every year, the labor demand curve for the US and India shifts, due to changes in technology and production function parameters. We assume such innovation shocks are driven by exogenous

¹³In our earlier work, [Bound, Khanna, and Morales \(2016\)](#) we use an elasticity of 0.23 that we measure by studying how the price of IT goods change with changes in the CS workforce.

skill-biased and sector-biased technological progress that move the relative demand curve for computer scientists during our period. Such exogenous shifts in labor demand allow us to identify the underlying labor supply parameters. In Appendix C.2 we explain in detail how we derive the innovation shocks and in this section we focus on the calibration of the labor supply.

On the labor supply side of the model, we have eight parameters that need to be calibrated for the US- $\{\sigma_{0,k}, \zeta_{0,k}, \sigma_{1,k}, \zeta_{1,k}, \chi_{0,k}, \chi_{1,k}, \chi_{2,k}, \beta\}$. For India we have one additional parameter given the migration cost κ . Of these, we pick the annual discount rate to be $\beta = 0.9$ for both countries, and calibrate the other parameters to match the data. In our model we assume the total quantities of non-college graduates $\bar{H}_{t,k}$, native college graduates $\overline{(L_n + G)}_{t,k}$, foreign computer scientists $\bar{L}_{F,t}$ and return migrants R_t are determined outside the model.

In the way we set-up the model, changes in enrollment, 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, enrollment 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 match data on wages, employment and age-shares in the US context, we use the March Current Population Survey (CPS). To match enrollment in CS degrees in the US, we use the Integrated Postsecondary Education Data System (IPEDS).

For India, to match wages, employment and age shares we use the largest and most comprehensive nationally representative labor force survey, called the National Sample Survey (NSS). For enrollment in engineering degrees we use yearly counts from the Ministry of Human Resources and Development. Details of the sample used in all these datasets and specific variable definitions can be found in Appendix B.¹⁴

We simultaneously match wages, employment and enrollment in three equally spaced years 1994, 2001 and 2010. We also match the share of computer science workers that are young (between 22 and 40) for the year 2010; for India we also match age shares in 1994 as we have an extra parameter.¹⁵ The series we use from the data are as follows:¹⁶

¹⁴For the CPS, 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](#)). For both the NSS and the CPS, we smooth the raw data over three-year moving averages as follows: $X_{t,smooth} = \frac{1}{3}(X_{t-1,raw} + X_{t,raw} + X_{t+1,raw})$

¹⁵Given 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.

¹⁶We have an exactly identified system as we use ten data moments to recover ten parameters -

1. $\frac{L_{n,t,k}}{G_{t,k}} = \frac{\text{Computer scientists}}{\text{Non-CS college educated workers}}$ for $t = \{1994, 2001, 2010\}$
2. $\frac{w_{t,\ell k}}{w_{t,g,k}} = \frac{\text{Median weekly wages for computer scientists}}{\text{Median weekly wages for non-CS college educated}}$ for $t = \{1994, 2001, 2010\}$
3. $\frac{q_{t+2,k}^{cs}}{q_{t+2,k}^o} = \frac{\text{Computer science/Engineering college degrees awarded (lagged 2 years)}}{\text{non-CS college degrees awarded (lagged 2 years)}}$ for $t = \{1994, 2001, 2010\}$
4. $age_{t,k}^{22,40} = \frac{\text{Computer scientists with age between 22 and 40}}{\text{CS}^{22,40} + \text{CS}^{41,65}}$ for $t = \{1994, 2010\}$

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 enrollment data should help identify the taste parameters for field of major decisions ($\sigma_{0,k}$ and $\zeta_{0,k}$), whereas the relative employment data should help pin down the occupation specific tastes ($\sigma_{1,k}$ and $\zeta_{1,k}$). The age shares in computer science employment together with enrollment and employment help identify the occupation switching cost parameters that depend on age ($\chi_{0,k}$, $\chi_{1,k}$ and $\chi_{2,k}$).

3.2.1 Labor Supply Calibration Results

Figure 6 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 data we use for these series. We match three equally spaced years (1994, 2001 and 2010) for employment, wages and enrollment, and the remaining years plotted are an out of sample test of our method. The years in between 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.

The employment series in Figures 6a and 6b fit well at the start and end of the period, but it misses some years in between. In India, the wage series fits well, particularly towards the end and the start of the series (Figure 6d), whereas in the US we do a better job of matching the second half of the 1990s (Figure 6c). Lastly, the enrollment series can be seen in Figures 6e and 6f. In India, we match the rapid increase in enrollment relatively well till the second half of the 2000s, whereas in the US we match both the enrollment rise only during the 1990s and the fall in the 2000s, while missing some years in between.

Table 6 presents the values of the calibrated parameters for India and the US. On average, we can see that in the US there is a mean taste for not working or studying in CS occupations,

$\{\sigma_{0,k}, \zeta_{0,k}, \sigma_{1,k}, \zeta_{1,k}, \chi_{0,k}, \chi_{1,k}, \chi_{2,k}\}$ and three implied values of technology in the years we match the wage/employment data $\{Z_{94}, Z_{01}, Z_{10}\}$. For India, we have an additional parameter κ , and use a eleventh data moment.

but this is the other way around in India where there is a greater dispersion in occupational tastes. In both countries, however, the sector switching costs are convex with age.

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.

3.3 Computing the Equilibrium

Once we calibrate the parameters of the product and labor market we compute the dynamic equilibrium of the model. We consider 1994 as our steady state year, and compute the equilibrium for that year such that the relative wage between computer scientists and other college graduates in both countries clears the product market and is consistent with the relative labor supply decisions of college graduates in the steady state. For the years between 1995-2010, there are shocks that move the equilibrium from the steady state driven by the change in the product market parameters that capture the technological progress, via the skill and sector-biased technical change experienced by both countries. For each year post-1994, the model computes the equilibrium relative wage that equalizes the relative number of computer scientists demanded by the firms with the relative number of workers that are able to work as computer scientists during that period taking into account workers dynamic horizon and rational expectations for future periods. The enrollment decision in computer science majors responds with a two year lag, so when the market wage increases, supply will not completely adjust in the same period as it would in the steady state. This implies that even though the labor supply curve may be inelastic in the short run, it is relatively more elastic in the longer term.

4 Endogenous Variables and Model Fit

In this section we study the evolution of the endogenous variables in our model over time, and evaluate how well it matches our data. In order to evaluate the fit of our model we compare our simulated results with features from the data as out of sample tests. In the calibration exercise we explicitly match certain data points or trends, whereas here we discuss how well our model matches the data on items we do not explicitly calibrate. Figures 3-4 show that we match fairly well some of the key aspects that we are trying to capture.

As can be seen in Figure 3, cross-country differences in wages for the different types of workers, and IT production closely match the data. While we never explicitly match the wages for CS and non-CS college graduates, we can see in Figures 3a and 3b that the model does fairly well

in predicting the trends and level differences between the wages in the US and India for these type of workers. In Figure 3a the CS ‘place premium’ in our model closely matches the data, and quasi-experimental results in the literature that show a 6-fold increase in wages for H-1B lottery winners (Clemens, 2013). Similarly, in Figure 3b we show the non-CS college graduate wage premium between the US and India is line with the data. We do not plot the non-college graduate wage as we are explicitly matching that series in our calibration exercise.

Figure 3d shows that the model does a good job predicting the levels and the trend in the share of IT output of the US in total IT production. As we can see, over time India captures more of the IT world market share, although we do predict India to catch up at a faster rate than what we observe in the data. The overall trend in our model and the data, however, indicates that India erodes the US comparative advantage in IT production and becomes a major player in the export market. Much of the increased role played by India is also exports to the US: in Figure 3c we show that the share of US IT consumption imported from India in our model, closely matches the data, and rises sharply in the mid-2000s.

In Figure 4 we study the within-country evolution of wages and employment over time, for both the US and India. Figures 4a and 4b show that our final model does a good job in matching the equilibrium quantities of computer scientists to non-CS college graduates, within each country. CS employment rises rapidly in the US since the 1990s, whereas the spurt in Indian CS employment begins in the second half of the 2000s, when CS wages also start rising rapidly (Figure 4d). While CS employment grows in the US, the wages are relatively flat (Figure 4c), and in our counterfactual exercise we test whether this growth is muted due to immigration. As can be seen by Figures 4c and 4d, our model closely fits these wage trends in the data as well.

5 Counterfactual Exercises

In order to evaluate the impact of the H-1B program on US and Indian economy we conduct a counterfactual exercise where we prohibit Indian workers from entering the US on an H-1B visa. Those workers who may have been granted visas to the US are forced to work in India. In our steady-state year, 1994, workers migrate on H-1Bs, but thereafter there is an unexpected restriction to migration; a shock that workers, firms and students know will persist. From the year 1995 through 2010, the stock of H-1B migrants is kept constant at the 1994 value: in Figure 5a we capture the nature of the counterfactual exercise.

Using the calibrated parameters and the given set-up we can trace out what happens to all endogenous variables between 1994 and 2010. We describe the regime where Indians are allowed to enter the US on H-1B visas as “with migration,” and the counterfactual regime as “without migration.” For instance, in Figure 5b we present one set of results for this exercise, where we

plot the percentage change in incomes due to the H-1B program.¹⁷ The combined incomes of the US and India are higher under the H-1B, primarily driven by increases in the income of Indian natives, including the H-1B migrants themselves.¹⁸

To understand how the dynamic process works we use Figures 5c and 5d. Figure 5c studies how US CS workers switch to other occupations for every extra H-1B migrant. The switching may occur if CS immigration depresses CS wage growth and raises non-CS (complementary occupation) wages. In the early years this switching is small, as the labor supply curve is inelastic, but over time fewer US students choose CS degrees and this makes labor supply more elastic in the longer run. The increase in labor supply elasticity over time is a feature unique to dynamic models and may explain why the reduced form literature on contemporaneous labor supply adjustments find no response to immigration. Similarly, Figure 5d studies how each additional migrant induces switching from non-CS to CS occupations in India. More migration raises the probability of the high-paying US job, but over time as more CS workers join the market, it lowers the wage premium and future switching to CS occupations.

5.1 Employment and Wages

In the top half of Table 7 we see how the labor market is affected when moving from the restricted immigration regime to the one with the H-1B program. The opening up of immigration possibilities to the US increased the size of the CS workforce in India by as much 34% in 1995. While this is a large increase, it is important to keep in mind that the base is small in 1995, and over time in the long-run, by 2010 the increase in the total CS workforce is 21%. The US CS wage in the data and our model is about 9 times that of the India CS wage in 1995 (Figure 3a). The prospect of, therefore, migrating to the US and earning such a high wage leads students to enroll in CS degrees and workers to switch into CS occupations in India. Employment in the Indian IT sector (CS and non-CS combined) is also higher by about 7.2% in 1995, and 4.75% in 2010.

In the US, on the other hand, native employment in CS is lower in a world where they allow Indian CS workers to enter on H-1Bs. When Indian CS workers enter the US on H-1B visas, this tends to lower the relative CS to non-CS wage hurting close substitutes like native CS workers and potentially benefiting complements like native non-CS college graduates. This tends to encourage native CS workers to switch into non-CS college graduate occupations. In the early years, in 1995, US-born CS employment is lower by about 0.1%, but this steady declines to about 9% in 2010. Total US employment in CS is, however, higher under the H-1B regime by about 3% in 2010.

¹⁷That is, for variable X in year t we plot $\frac{X_{with\ migration,t} - X_{without,t}}{X_{without,t}}$.

¹⁸The income pattern for Indian natives is not smooth as discrete jumps in the H-1B cap have big impacts on their incomes.

These employment shifts are accompanied with changes in wages for each of these groups. In India, the drastic increase in the CS workforce leads to an initial fall in the CS wage by as much as 13.9% in 1995. However, a larger CS workforce also leads to more productivity in the IT sector, raising wages for all workers and mitigating the negative effect for CS workers over time. By the end of the period, in 2010, CS wages in India are lower by 10.6%.

Wages for other workers in the Indian economy will be higher when there are more CS workers because of three reasons. First, other workers are complements in production, and as college graduates choose CS over other occupations, they decrease the total number of other college graduates and therefore increase their wages. More importantly, CS workers are innovators and raise productivity in the IT sector. Many of the H-1B workers are trained in the US and acquire technology that they bring back to India with them, also raising productivity in the Indian IT sector. Since the IT sector output is an intermediate good into the final sector, this raises productivity in the entire economy, raising all wages. The wages for non-CS workers in the Indian economy are higher by between 1.12% and 0.31% in 2010 under the H-1B regime.

In the US, on the other hand, there are very mild negative effects on real wages for college graduate workers, but increases in real wages for non graduates. This not only captures the effect of labor-market crowd out, but also the fact that output prices in the open economy may change. Furthermore, under the H-1B regime, the IT sector grows in India and production shifts away from the US potentially having a negative impact on workers. Even though CS workers are the worst affected, their wages only fall at most by 1.5% in 2010. As workers switch into non-CS work, their earnings dip by at most 0.14% in 2010. The least worse off are the non graduates as their real wages in 2010 are higher by 0.24%.

5.2 Incomes, Output and Prices

In Table 7 we also look at how the IT sector and total income evolves in the US and India when moving from the H-1B regime to the restricted immigration one. The H-1B regime incentivizes students and workers in India to switch to CS occupations, growing the IT sector in India. In 1995, the quantity of IT sector output is higher by as much as 6%, and at the end of this period it is about 5% higher under the H-1B regime. Since we model the IT sector output as an intermediate input into final goods production, we are introducing a degree of complementarity in production. So an increasing CS workforce, and therefore increasing IT productivity, may have ambiguous effects on total IT sector employment.

Total income and total IT output in both countries combined is higher under the H-1B regime. The gains from immigration are large in this context, with the combined income of the US and India being higher by about 0.36%, or about \$17.3 billion. Total IT output rises steadily under the H-1B regime to about 0.45% in 2010.

As IT output rises, production shifts to India. In the data, we see that over time India takes over as the major exporter of IT. Under the H-1B regime, due to the large wage premium in the US, Indian students and workers switch to CS occupations and degrees raising the size of the CS workforce. This increasing CS workforce increases productivity in the Indian IT sector. Furthermore, those who return from the US bring with them technical knowhow also increasing productivity and growing the Indian IT sector. Under the H-1B regime, therefore, in 2010 the share of world IT output for the US is lower by about 1.2%. The shift in production to India, does hurt the US IT sector. By the end of this period, in 2010, US IT sector output is lower by 0.77% and the income of US natives is lower by 0.07% even though overall incomes in the US (including migrants) are higher by 0.37% or \$16.6 billion.

5.3 The Welfare of Workers

Migration leads to distributional gains and losses in the welfare of different types of workers in each economy. In Table 8 we also split up workers by whether they were always in a specific occupation or switched occupations. This distinction is important given the heterogeneity in preferences for different occupations. Even though the CS wage may be higher than the non-CS wage, the marginal CS worker is indifferent between CS and non-CS jobs. As the CS wage falls, the first workers to switch to non-CS jobs are unaffected in terms of utility even though they may have a large wage drop. As more workers get pushed into other occupations they experience utility losses that are not equal in magnitude to their income losses. This is also why the welfare impacts on the average worker reported at the bottom of Table 8 are different from the income changes for average worker in Table 7.

For workers in the US economy, CS workers and workers that switch from CS to non-CS occupations bear the brunt of the losses. Workers that were always non-CS graduates gain in the early years as the demand for complements rise, but by 2010 their welfare is also lower as more and more CS workers switch into non-CS jobs and drive down their wage. Non college graduates in the US gain throughout the period, benefiting from lower prices and technological spillovers. Overall, the average US worker is better by about 0.01% in 2010.

In the US workforce, the major gains from migration accrue to the new migrants that are now earning wages that are many times higher. Those that migrated before we restrict migration in 1994 receive the same welfare loss as US born CS workers.

For workers in India, once again, there are significant differences in who gains and who is hurt. CS workers and those that switch into CS occupations are hurt by lower wages. Indeed, those that switch with the prospect of migrating but do not end up migrating are the most detrimentally affected. Non-CS college graduates are better off as not only have workers switched out of non-CS jobs and raised wages, but also because there are more CS workers it raises the

demand for non-CS workers. Return migrants are worse off under the H-1B regime as they compete with more and more return migrants, whereas non college graduates are better off due to lower prices and technological upgrades. On average, the native Indian worker is better off by about 1.25%. The combined welfare of US and Indian workers is higher by 0.28%.

5.4 Migration Restrictions Beginning in Later Periods

In our baseline results we start our counterfactual experiment from 1995 onward, as 1994 is the first year of our data and the steady state in our model. However, from a policy point of view, an important question may be what are the impacts of migration on incomes if we started the migration restriction in later years. The economies of both India and the US change over time: trade costs, skill biased technology, and the size of the IT sector in each country are all different in later years. For instance, once the Indian IT sector is already developed, and trade costs are lower, restricting migration from India to the US may just lead to more CS workers and IT production in India.

In Table 9 we study the impact of H-1B driven CS migration by performing different counterfactual experiments: we allow migration between 1994 and 2003 and restrict it 2004 onward. We then do the same by restricting migration only from 2007 onward. We show the impact on incomes in the year right after the change, and then in the last year of our data, 2010. In these new scenarios, migration always raises the incomes for both the average US worker and the average Indian worker. In 2010, the income gains to Indian natives is about 1.46%, rather than 1.98% in the baseline. The result that migration has a positive effect on US native income when starting the counterfactual in 2004 or 2007 can be explained with the dynamic feature of our model. The number of CS that migrate in later years is bigger than those migrating in 1994, so the technological spillover is larger than the one experienced in 1995. As US workers take time adjusting, they do not switch to other occupations immediately, so the US captures a larger share of the spillover in the early years after the policy change.

5.5 Robustness to Parameter Values

We test how robust our results are to various parameter values. The endogenous technology parameter that we calibrate to have a value of 0.27 is important for our results. In Table 10 we show our main results as we vary the parameter value between 0 (no endogenous technology) and 0.4. H-1B driven migration has the same impact on US incomes as we vary this parameter. The reason for this is that while the a larger technology parameter means a higher spillover from CS in the US, this effect is mitigated by native CS workers switching to other occupations in the US. Indian incomes however, benefit a lot more from H-1B driven migration when the value is high. This is because there is a substantial increase in CS employment in India, and

particularly in the IT sector, that raises overall productivity in India via endogenous technical change. H-1B driven migration leads to a shift in IT production from the US to India and this shift is greater for larger values of the parameter. At the same time, better production technology also lowers IT good prices further benefiting consumers.

In Appendix C.4 we discuss the sensitivity of our results to varying the three elasticities that we take from the literature. Our results are qualitatively similar to our baseline results, but some outcomes vary with the values of these elasticities in a manner that we would expect.

5.6 Model Specifications

We also test the importance of certain modeling features in our analysis, allowing us to also determine which features of the model drive certain results.

5.6.1 Occupational Choice

One crucial feature of our model is that students and workers switch occupations based on the expected wages in these occupations. In Table 11 we shut down this possibility of switching occupations to ascertain how important it was to include this feature in our model. If US-born CS workers cannot switch to other occupations when there is an increase in immigrant CS workers, then they bear the costs of even lower wages. Since CS workers can switch to other occupations, this mitigates the negative wage impacts on CS wage growth, and CS wages are only lower by 1.5% in 2010. CS wages would have lower by 6.6% if workers could not switch out into non-CS jobs. Not modeling occupation switching would have therefore overestimated the negative wage impacts on US born CS workers.

If CS workers switch to non-CS graduate jobs, this tends to lead to 0.1% lower US non-CS graduate wages. If this switching was not allowed, then US non-CS graduate wages would have risen instead by 0.4%. This is because non-CS graduates are complements in production, and demand for such workers rise when there are more immigrant computer scientists.

In India, on the other hand, CS wages would have been far higher if other workers were prohibited from switching into CS occupations. The H-1B program induces workers to switch to CS jobs ensuring that CS wages are lower by 10.6%; in the absence of this switching, CS wages would have been higher by 4.4%.

Importantly, the occupation switching is what allows production to shift from the US to India, as more and more Indian workers switch to CS jobs. In the absence of this switching, US IT output would have actually been higher and Indian IT output would have been lower under the H-1B program – a reversal of our main result. US incomes would be higher under the H-1B program as IT production doesn't shift to India and there are a lot more CS workers in the

US that innovate producing technological spillovers. In a world with restricted occupational movement, world incomes would be lower. These drastic changes show why it is so important to model occupation and major choice, and the possibility of choosing jobs when affected by technological and migration shocks.

5.6.2 Return Migration

Including return migration in our model has two countervailing effects on India. On the one hand, return migrants bring acquired skills and technical knowhow and enlarge the size of the CS workforce in India. On the other hand, the likelihood of returning home to lower wages in India, lowers the returns from migrating in the first place. These lower expected returns from migrating inhibit the accumulation of CS skills for Indian students and workers, and restrict the size of the CS workforce in India. The overall outcomes of these countervailing impacts on the Indian workforce affect the US as well – if Indian IT output grows, US IT production may fall.

In Table 12 we study what the impact of migration under the H-1B program would look like in a world without return migration. CS employment in India increases more when there is H-1B migration, since the lifetime returns to migrating are now higher in the absence of returning to lower wages in India. At the same time, workers in the US switch more to non-CS occupations as no return migrations means that there are more CS workers in the US.

When going from a scenario of no migration to H-1B migration, world incomes increase even more than before, driven by the benefits to migrants and also by more CS employment in India. Like before, IT production shifts away from the US and to India, but this shift is larger in a world with no return migration. In models that ignore return migration, therefore, the impacts (both positive and negative) of H-1B driven migration are larger for most outcomes of interest.

5.6.3 Brain-Drain, Brain-Gain and the Location of IT Production

The impacts of migration on the Indian economy depend on whether the effects of brain drain outweigh the effects of brain gain or not. As CS workers leave for the US, they take with them skills and innovation potential that could have potentially benefited the Indian economy. Brain gain, on the other hand, arises because the prospect of migrating raises the expected wage returns from being a CS worker, and induces skill accumulation in India.

For the US economy, the impact of migration determines the location of IT sector production, an outcome that is ambiguous. Migration allows for more CS workers to enter the country and tends to increase US IT production. However, the prospect of migrating abroad enlarges the

CS workforce in India and shifts IT production from the US to India. To distinguish these mechanisms we tweak our model and once again study the impacts of CS migration from India to the US in Table 13.

To determine the importance of modeling how the prospect of migrating abroad induces human capital accumulation in India and a shift in IT production from the US to India, we first re-do our baseline analysis by artificially inhibiting Indian students and workers from responding to US wages. When Indian nationals make occupation and major choices they perceive the probability of migrating abroad to be 0, even though they might end up migrating. In the second column of Table 13 we present these results.

If the labor supply decisions in India do not respond to the prospect of migrating abroad the CS workforce in India falls by 3.6%, a brain-drain that lowers overall Indian output by 0.2% and Indian IT production by 1%. Since brain-gain is restricted, there is very little shift in IT production from the US to India. Instead, migrants enlarge the size of the US IT sector and increase IT output in the US by 0.7%. It is therefore important to model the endogenous human capital accumulation in response to migration potential, not doing so would reverse many of our results.

In a different exercise we allow Indian workers to respond to the possibility of migrating and accumulate skills, but restrict migration itself. Under this specification we shut down the possibility of brain-drain but still allow for brain-gain in India. These results are presented in the last column of Table 13. The prospect of migrating and earning a high wage in the US raises CS employment in India substantially by 27.5%, which in turn raises Indian IT production and overall output by more than before. Since migration does not actually take place in this scenario, only 0.1% of US born CS workers switch to other occupations while US IT output falls by 1.5%. This fall in US IT output is large because there are no immigrant CS to enlarge the CS workforce. Overall world incomes rise by only 0.1%, much less than before.

5.6.4 The Role of Trade

As India and the US compete for the IT market in their own countries and across the world, trade costs play a role in determining where IT varieties are produced. In Table 14 we double the size of all the cross-country asymmetric trade costs, and measure the impact of CS migration once again. While almost all our results are similar to before, the one crucial difference is IT output in India and the US. When trade costs are high, the growth in the Indian IT sector is inhibited and output increases by only 0.3%, in contrast to a 5.2% increase with the original estimated trade costs. As a result of less IT growth in India, the US IT sector actually expands when there is more immigration. US IT output would have risen by 0.4%, when in the original scenario it fell by 0.8% under the H-1B program.

6 Discussion

India experienced a dramatic expansion in IT employment and output in the 1990s and early 2000s. Many factors contributed to this boom but, our work suggests that, surprisingly, policies from halfway around the world played a critical role. We study how US immigration policy, combined with high wages and technical expertise in the US, helped enable the IT boom in India. To do this, we describe the IT boom in the US and India with the help of a general equilibrium model. In our model, the prospect of high wages in the US incentivized students and workers in India to choose CS degrees and occupations. Those returning from the US after the expiration of their H-1Bs also contributed to the growing Indian workforce. These movements increased overall IT sector productivity in India and shifted the production of IT goods away from the US.

In this paper, we are explicitly testing the explanatory power of certain particular mechanisms by which US policy and conditions may have stimulated growth in the Indian IT sector. We do this by specifically focusing on four features of the US in this period that created important incentives and constraints for Indian students and workers. First, technological innovations and changing consumer preferences generated strong demand for IT workers in the US. Second, and not unrelated, the wage differential between the US and India was large, especially for IT workers. Third, US immigration policy, as embodied by the H-1B visa program, strongly favored skilled migrants. Finally, H-1B visas only last 3-6 years, obligating many migrant workers to return to India with accumulated human capital and technical knowhow. Together, these features help spread the boom across the world from the US to India.

The H-1B program has significant distributional consequences, where workers that are close substitutes are adversely affected while others benefit. These distributional effects have been at the forefront of academic discussion (Borjas, 1999; Peri and Sparber, 2011) and political debates. Importantly, certain countries may benefit more than others under such migration. In this paper we find that the overall gains outweigh the losses as the combined incomes of the US and India rise under the H-1B program by about 0.36% or about \$17.3 billion. This net gain is consistent with a long literature reviewed in Clemens (2011).¹⁹

The gains, however, are mostly driven by the development of the Indian IT sector. In a world with North-South trade, it is possible for developing countries to specialize in less productive sectors, hindering economic growth (Matsuyama, 1992). Contrarily, we find that US immigration policy, coupled with the US tech boom, helped develop the Indian IT sector. This transformation in India boosted IT exports and raised average incomes. The prospect of migrating to the US was a considerable driver of this phenomenon and led to a ‘brain-gain’ that

¹⁹Specifically, see Klein and Ventura (2007); Moses and Letnes (2004); van der Mensbrugghe and Roland-Holst (2009); Walmsley and Winters (2005). Some numbers are larger: Iregui (2005) shows that movement of skilled labor can increase world GDP by between 6-11%.

outweighed the negative impacts of ‘brain-drain’ (Dinkleman and Mariotti, 2016; Stark, 2004; Stark et al., 1997).

One somewhat striking result is that as production shifts to India, US IT output actually falls. A driving feature of this result is that an increase in the size of the Indian CS workforce increases the relative productivity of India’s IT sector. Such reductions in US IT output have been discussed by a rich literature on the economics of trade and migration. Krugman (1979); Vernon (1966) describe a North-South general equilibrium trade model where the North initially has a monopoly over new products given its technological superiority and rate of innovation. The South catches due to technological diffusion and over time starts exporting to the North the very same products the North used to export. As the rate of technological diffusion increases, or the rate of innovation in the North declines, living standards will actually fall in the North. With quality differentiation in products, Flam and Helpman (1987) generate richer trade dynamics, but also show that technical progress in the South brings about a decline in the North’s wage rate. Given certain rates of technical change, workers in the North may be harmed as production moves abroad (Acemoglu et al., 2015). Therefore, as Samuelson (2004) notes, such technical progress in the South erodes the US comparative advantage and can permanently lower per capita incomes in the US.

The labor economics literature has also emphasized these channels. For instance, Johnson and Stafford (1993) show how the effect of foreign competition from abroad lowers aggregate real incomes in the US. In fact, Freeman (2006a) focuses on the global job market for high-tech workers and argues that the growth in such labor abroad adversely affects US industry and workers. In this analysis, immigration can help maintain the US’s lead by attracting overseas talent. However, the analysis does not account for the effect of immigration on incentives to invest in India and the role of return migration, which we show to be important determinants of the shift in production abroad. Davis and Weinstein (2002) show how in a Ricardian trade framework, such as ours, a country that experiences immigration due to technological superiority always loses from such migration through a deterioration in the terms of trade. Free mobility will tend to equalize wages across countries and, therefore, hurt workers in the country with superior technology. They estimate that in 1998, the losses to US natives alone were about 0.8% of GDP, and about 0.88% of GDP for the economy as a whole including immigrants. While our numbers are considerably smaller – 0.07% of GDP by 2010 – we are only focusing on high-skill immigration from India.

Our results, therefore, quantitatively confirm many of the theoretical results in the literature. Even though migration increases the welfare of the average US worker and the average Indian worker, these averages hide significant distributional changes for different types of workers in each country.

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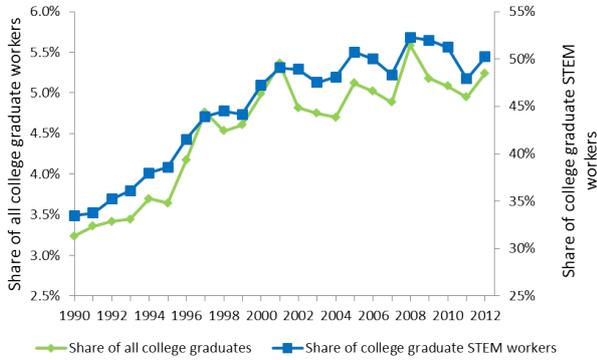
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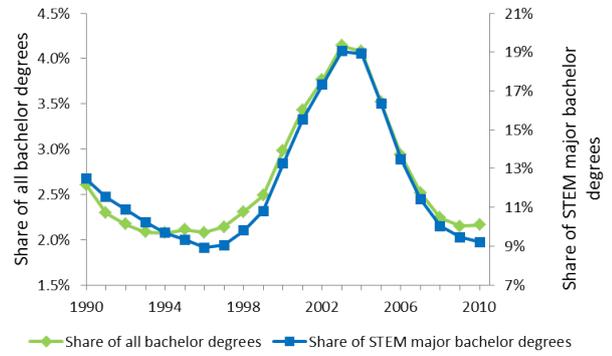
7 Tables and Figures

Figure 1: Descriptive: High-Skill Immigration and the IT Boom

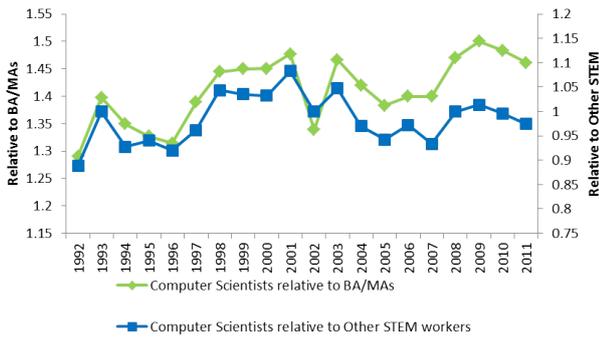
(a) Fraction of Computer Scientists in US Workforce



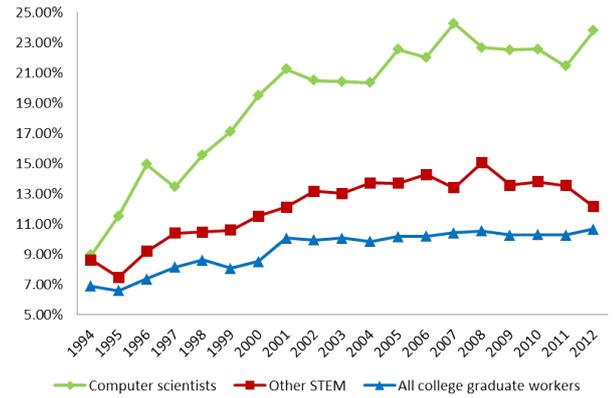
(b) Computer Science Fraction of Bachelor Degrees in US



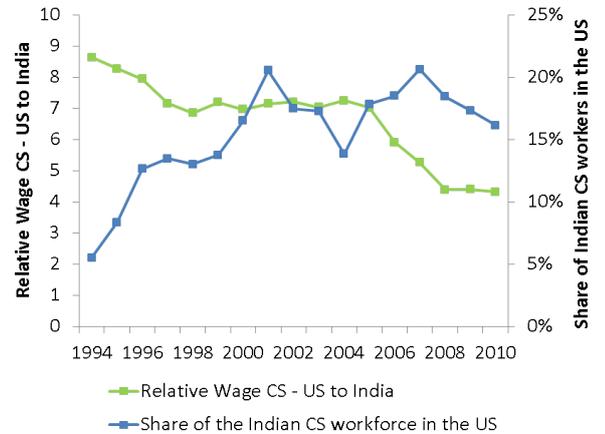
(c) Earnings of Computer Scientists Relative to Other groups



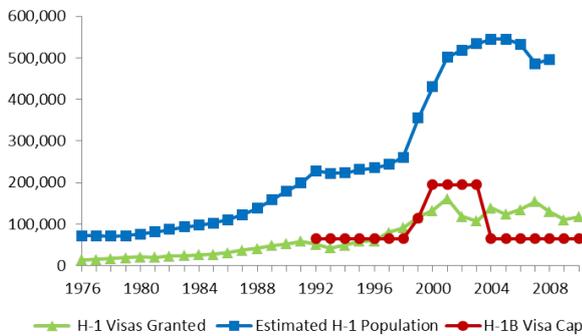
(d) Immigrants as Fraction of Workers by Occupation



(f) CS Wage Differential and Share of Indian CS in US



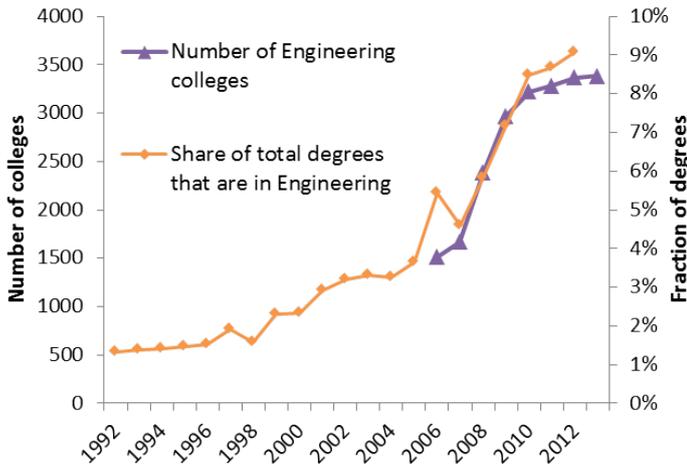
(e) H-1 Visas



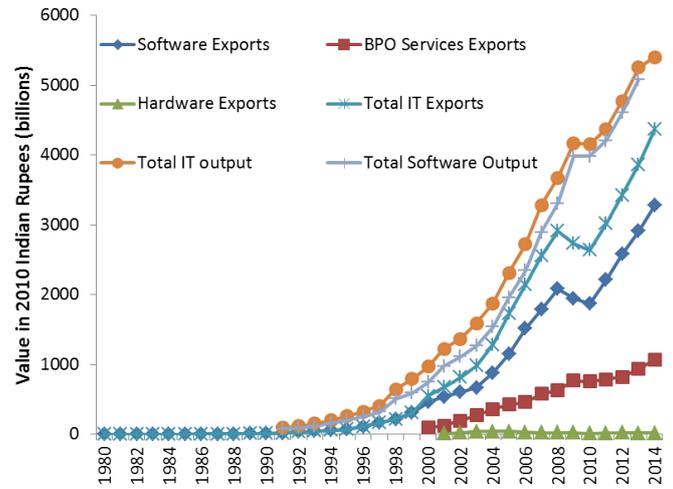
Sources: Figure 1a, 1c and 1d March Current Population Survey (CPS). Figure 1b is from IPEDS (The Integrated Postsecondary Education Data System). Figure 1e author's calculations updating Lowell (2000). Figure 1f are based on author's calculations using CPS and the National Sample Survey (NSS) of India.

Figure 2: Descriptive: High-Skill Immigration and the IT Boom

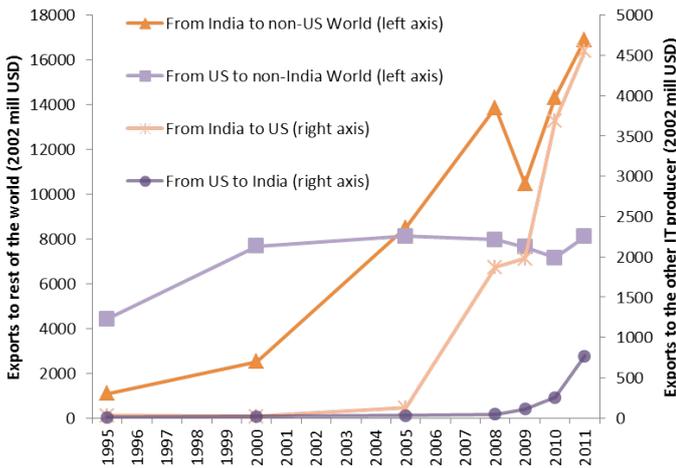
(a) India: Growth in Engineering in the Education Sector



(b) Growth in the Indian IT sector



(c) IT Exports Over Time



(d) Fraction of US Computer Scientists by Country

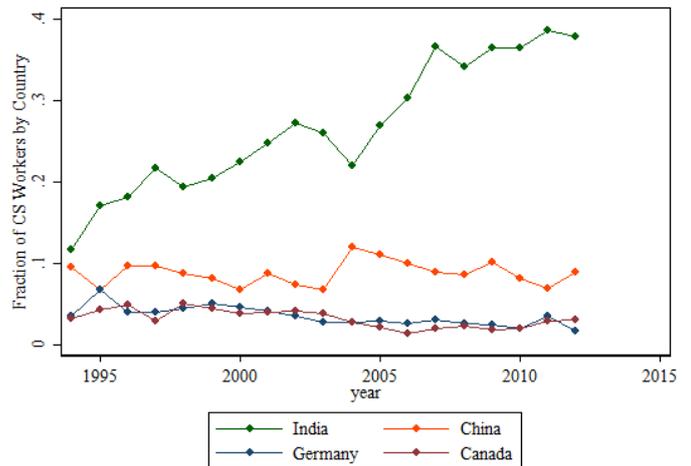
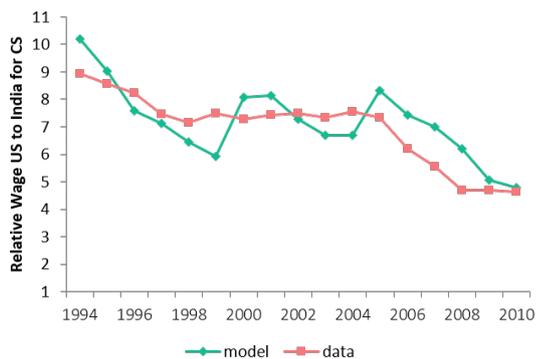


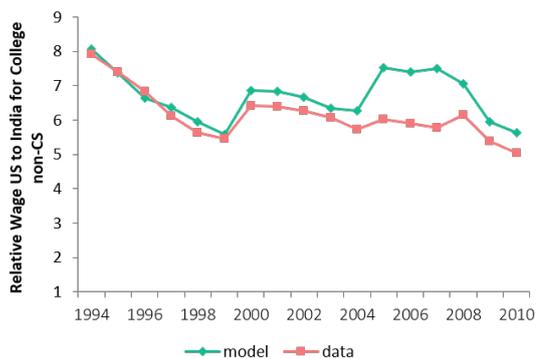
Figure 2a source: Degrees come from a combination of sources – Ministry of Human Resources and Development, the National Association of Software and Service Companies (NASSCOM) and the All India Council for Technical Education (AICTE); missing years are interpolated. Number of universities is from Ministry of Human Resources and Development. Figure 2b source: Electronic and Information Technology Annual Reports, Indian Department of Electronics reports, National Association of Software and Service Companies (NASSCOM). Much of this data has been collated and standardized by the Center for Development Informatics at the University of Manchester, UK. Figure 2c source: OECD Trade in Value Added statistics for the “C72: Computer and Related Activities” industry. The data is only available for 1995, 2000, 2005 and 2008-2011. Figure 2d source: Current Population Survey – Outgoing Rotation Group Survey. Fraction of US CS workers by Country of Birth (variable ‘penatvty’ in CPS-ORG).

Figure 3: Model Fit: Relative Wages and Production Between the US and India

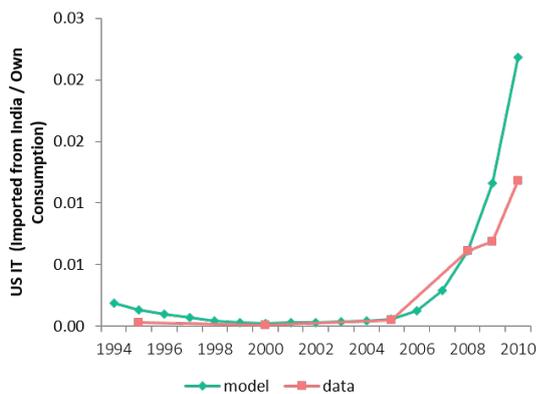
(a) Relative Wage for Computer Scientists: US to India



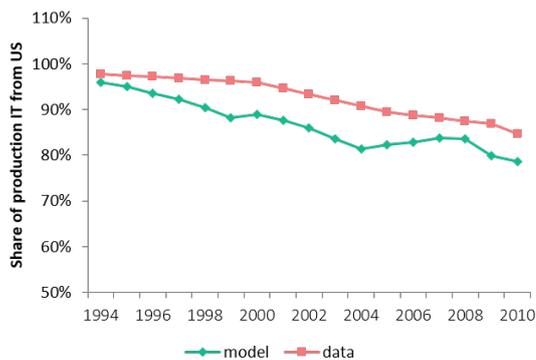
(b) Relative Wage for non-CS College Graduates: US to India



(c) US IT: Imported from India over produced at home

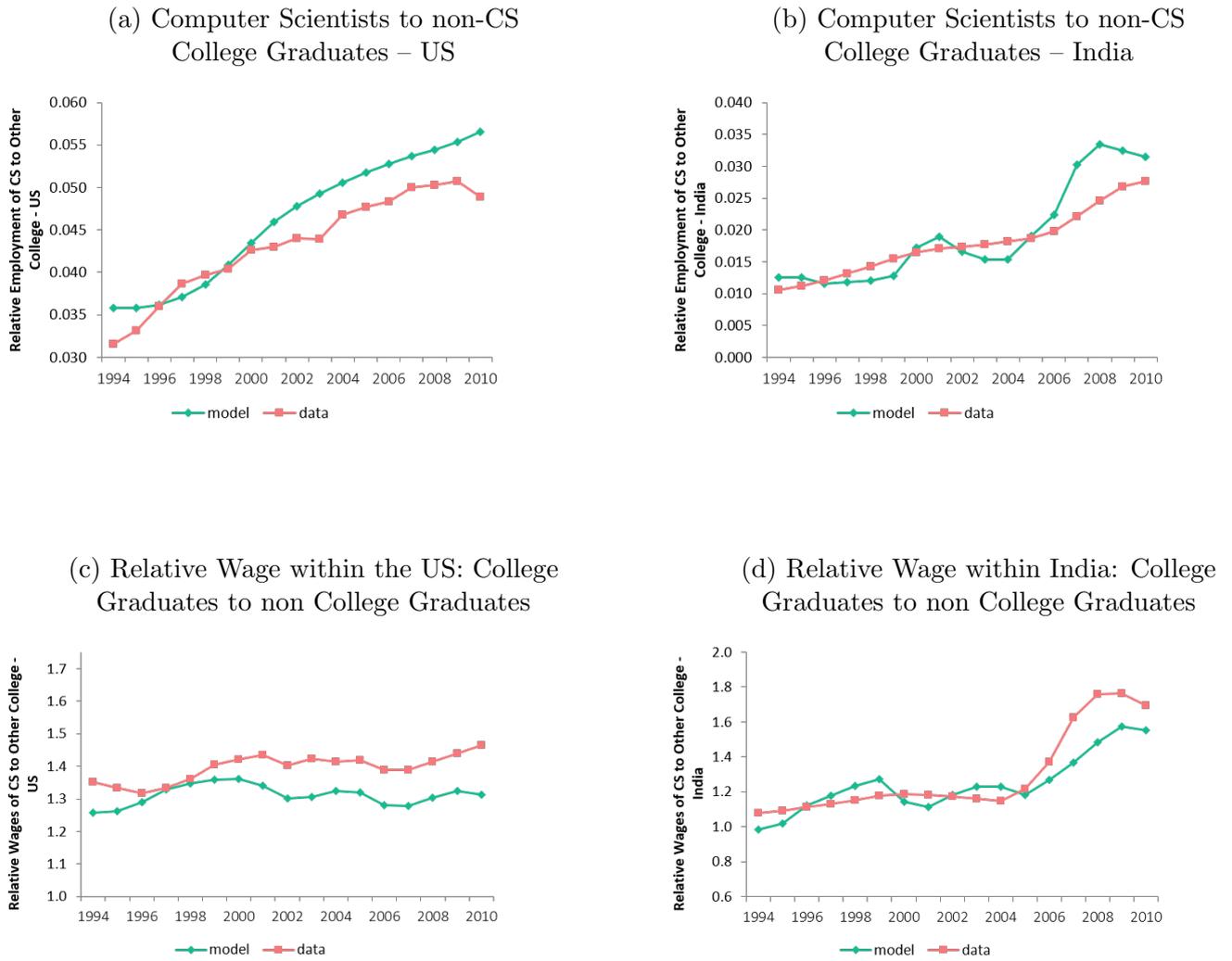


(d) Share of US production in IT



Figures plot the simulated model output and the actual data for the endogenous variables of interest. Top panels show the relative wages for various occupations between the US and India. Bottom panel shows the US's share in IT production and the fraction imported from India relative to produced in the US. For data sources please refer to Data Appendix B

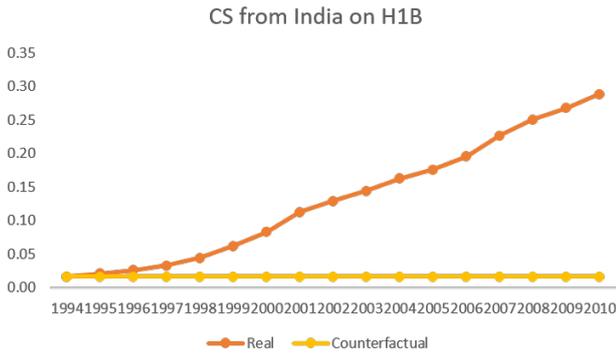
Figure 4: Model Fit: Relative Wages and Employment (CS / non CS graduates) by Country



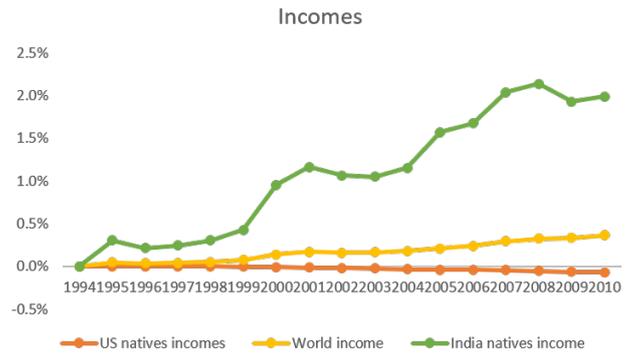
Figures plot the simulated model output and the actual data for the endogenous variables of interest. Top panels show relative wages, bottom panels show relative employment within the US and within India. For data sources please refer to Data Appendix B

Figure 5: Counterfactual Exercise: The Effect of H-1B migration

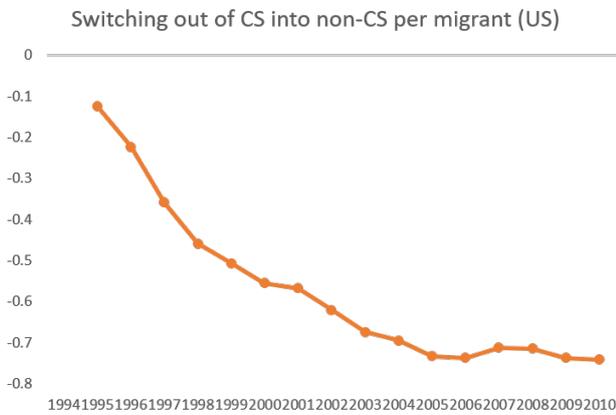
(a) Restricting Migration in the Counterfactual



(b) The Impact of H-1B Migration on Incomes



(c) Worker Switching in the US



(d) Worker Switching in India

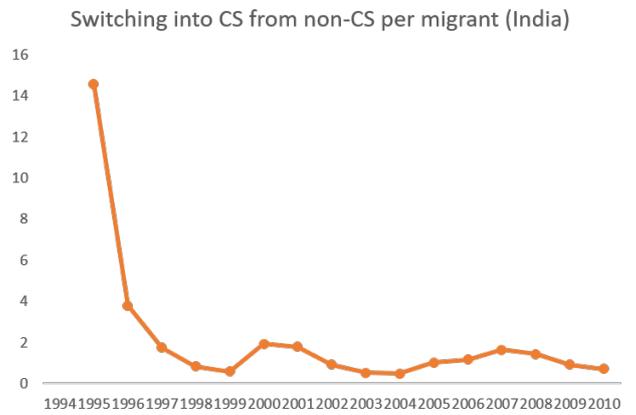


Figure 5a explains the nature of the counterfactual exercise – while in the real scenario migration continues under the H-1B program, the stock of migrants are restricted to be the same as in 1994 for the counterfactual. Figure 5b plots the difference between the impact of H-1B driven migration on incomes in the US, India and the combined income of the two countries. Figure 5c studies how US-born CS workers switch to other occupations for every extra migrant – in the early years this switching is small, but over time fewer US students choose CS degrees and this makes labor supply elastic in the longer run. Figure 5d studies how each additional migrant induces switching to CS occupations in India – more migration raises the probability of the high-paying US job, but over time lowers the wage premium.

Table 1: Number of H-1Bs by Firm (Approved)

2013 Rank	Company	Headquarters	Primary Employment Base	2012	2013
1	Infosys	India	India	5600	6298
2	Tata Consultancy Services	India	India	7469	6258
3	Cognizant	USA	India	9281	5186
4	Accenture Inc	Bahamas	India	4037	3346
5	Wipro	India	India	4304	2644
6	HCL Technologies Ltd	India	India	2070	1766
7	IBM(India, Private Ltd.)	USA	India	1846	1624
8	Mahindra Satyam	India	India	1963	1589
9	Larsen & Toubro Infotech	India	India	1832	1580
10	Deloitte	USA	US	1668	1491
11	IGATE(Patni)	USA and India	India	1260	1157

Source: Author's calculations using USCIS reports. The last two columns indicate the number of H-1B visas that were approved for each year.

Table 2: 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 B). 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 3: Location of Highest Degree by Type of Worker for those on Temporary Work Visas

Location of Highest Degree	All Workers			IT Workers		
	Abroad	US	Total	Abroad	US	Total
Bachelor's Highest degree	599,500	35,604	635,104	132,600	12,744	145,344
Percentage	94%	6%		91%	9%	
Master's Highest degree	207,964	61,751	269,715	68,301	22,003	90,303
Percentage	77%	23%		76%	24%	

Source: National Survey of College Graduates (2010). Sample of foreign-born workers working in the US on temporary work visas in 2010.

Table 4: Product Market Parameters

Time invariant parameters				
τ	1.7	ϵ	30	
λ	2	Ψ	0.5	
σ_y	4	ϱ	0.230	
σ_c	4	Δ_{us}	0.2	
θ	8.28	Δ_{in}	0.2	
Time varying parameters				
	1995	2000	2005	2010
$\frac{T_{c,in}}{T_{c,us}}$	0.126	0.151	0.166	0.268
$\frac{T_{y,in}}{T_{y,us}^c}$	0.077	0.091	0.083	0.118
δ_{us}	0.187	0.214	0.230	0.239
δ_{in}	0.137	0.164	0.172	0.267
$\alpha_{y,us}$	0.474	0.442	0.416	0.406
$\alpha_{y,in}$	0.466	0.434	0.415	0.411
γ_{us}	0.008	0.015	0.013	0.017
γ_{in}	0.003	0.010	0.015	0.016
γ_w	0.008	0.012	0.012	0.012
$h1b$	0.006	0.022	0.018	0.026

Time invariant parameters: τ : Elasticity of substitution between college and non college graduates; λ : Elasticity of substitution between CS and non-CS college graduates; σ_y, σ_c : Elasticity of substitution between varieties in sectors Y and C ; θ : Dispersion parameter of Frechet distribution; ϵ : elasticity of substitution between CS that never migrated to the US and CS that return from the US; Ψ : distributional parameter of CS aggregate in India; ϱ : return rate to India and Δ_k : Extra CS intensity of IT sector compared to Final Goods Sector.

Time varying parameters: $\frac{T_{s,in}}{T_{s,us}}$ Relative technology parameter between India and US δ_k : Distributional parameter of CS on both sectors. $\alpha_{y,k}$: Distributional parameter of non college graduates in Final goods sector; γ_k : Cobb-Douglas parameter of IT goods in Final goods sector; $h1b$: H-1B cap in the US

Table 5: Normalized Labor Quantities

	1995	2000	2005	2010
$L_{n,US}$	0.83	1.23	1.53	1.74
$L_{F,US}$	0.02	0.06	0.10	0.15
G_{US}	25.78	30.16	32.81	36.25
H_{US}	74.69	80.02	80.44	76.06
Total US	101.3	111.5	114.9	114.2
$L_{n,IN}$	0.23	0.42	0.57	0.89
R_{IN}	0.004	0.010	0.019	0.044
G_{IN}	20.6	25.9	31.7	33.7
H_{IN}	291.8	319.6	361.0	365.1
Total India	312.6	345.9	393.3	399.7
Total RoW	1202.6	1294.0	1362.0	1423.4

US population in 1994 is normalized to 100. India and US populations grow at the rate observed in the data. We use the March CPS and the National Sample Survey to match the shares of each occupation to those observed in the data every year.

Table 6: Labor Supply Calibrated Parameters

	US	India
σ_0 Std dev of study-area taste shocks	0.38	1.59
σ_1 Std dev of occupation taste shocks	0.47	3.39
ζ_0 Mean taste for not studying CS	3.24	-1.67
ζ_1 Mean taste for not working in CS	1.17	-0.24
χ_0 Sector switching cost (constant)	3.11	11.04
χ_1 Sector switching cost (linear in age)	1.08	-1.81
χ_2 Sector switching cost (quadratic in age)	0.06	0.11
κ Migration cost		39.28

In the calibration exercise, the years 1997, 2002 and 2007 were used to match the data for employment, wages and enrollment. In the US, wage and employment data come from the March CPS, whereas enrollment data is from IPEDS. In India, wage and employment data come from the NSS, whereas enrollment data is from HRD Ministry. See Appendix B for more details.

Table 7: The Impact of H-1B Driven Migration of Computer Scientists from India to the US

	1995	2000	2005	2010
Employment				
US natives in CS	-0.1%	-2.7%	-6.5%	-9.1%
India non-migrants in CS	34.6%	37.6%	34.9%	21.4%
Total CS in US	0.44%	2.17%	2.33%	3.14%
India IT sector	7.20%	2.78%	1.12%	4.75%
US IT sector	-0.15%	0.37%	0.45%	-0.36%
Wages in the US				
CS	-0.23%	-1.04%	-1.07%	-1.48%
Non CS graduates	0.00%	-0.01%	-0.08%	-0.14%
Non graduates	0.01%	0.07%	0.14%	0.24%
Wages in India				
Non migrant CS	-13.86%	-15.91%	-15.47%	-10.63%
Return migrants	-14.25%	-18.86%	-20.16%	-18.20%
Non CS graduates	0.45%	0.70%	0.64%	1.12%
Non Graduates	0.24%	0.30%	0.13%	0.31%
Output and Incomes				
World income	0.04%	0.14%	0.21%	0.36%
World IT output	0.12%	0.41%	0.25%	0.45%
Share of IT Output by US	-0.30%	-0.22%	-0.07%	-1.22%
US				
US natives income	0.00%	-0.01%	-0.04%	-0.07%
US Income (including migrants)	0.01%	0.11%	0.23%	0.37%
US IT output	-0.18%	0.20%	0.18%	-0.77%
India				
India income (including migrants)	0.30%	0.95%	1.57%	1.98%
India domestic income	0.25%	0.29%	0.09%	0.32%
India IT output	6.27%	2.17%	0.58%	5.24%
Prices				
US IT price	-0.11%	-0.82%	-0.90%	-1.00%
India IT price	-8.98%	-9.32%	-8.88%	-7.44%

Percent difference on main outcomes when we go from a scenario with no migration (counterfactual) to a scenario with migration (real). In the counterfactual, the H-1B stock is held constant to the 1994 level.

Table 8: Impact of Migration on the Welfare of Workers

Workers in the US	Fraction of Workforce	Welfare Change Due to H-1B Migration			
	2010	1995	2000	2005	2010
Always CS	1.77%	-0.2%	-1.0%	-1.1%	-1.5%
Switch from CS to non-CS grad	0.18%	-0.1%	-0.5%	-0.6%	-0.8%
Always non-CS graduates	31.21%	0.0%	0.0%	-0.1%	-0.1%
Non college graduates	66.59%	0.0%	0.1%	0.1%	0.2%
Immigrants arrived after 1994	0.24%	564.9%	466.1%	518.7%	282.8%
Immigrants before 1994	0.01%	-0.2%	-1.0%	-1.1%	-1.5%
Workers in India					
Always CS	0.22%	-14.1%	-16.1%	-15.5%	-10.9%
Switch from non-CS grad to CS	0.05%	-8.8%	-16.2%	-21.1%	-21.5%
Always non-CS graduates	8.38%	0.2%	0.5%	0.6%	0.8%
Returners that migrated pre-94	0.00%	-14.4%	-19.0%	-20.2%	-18.4%
Return Migrants	0.01%	-1.2%	-4.9%	-5.2%	-0.9%
Non college graduates	91.33%	0.0%	0.1%	0.1%	0.0%
Total Welfare					
Welfare of US natives		0.00%	0.01%	0.01%	0.01%
Welfare of Indian natives		0.06%	0.54%	1.23%	1.25%
Total welfare		0.01%	0.10%	0.22%	0.28%

Percent difference on welfare of workers when we go from a scenario with no migration (counterfactual) to a scenario with migration (real). In the counterfactual, the H-1B stock is held constant to the 1994 level. “Fraction of Workforce” is percentage of domestic workforce (including immigrants) in the country.

Table 9: Counterfactuals Beginning in Different Periods

	Baseline: Restrict from 1995 onward		Restricting Migration from 2004 onward		Restricting Migration from 2007 onward	
	Year 1	2010	Year 1	2010	Year 1	2010
US natives income	0.00%	-0.07%	0.28%	0.08%	0.35%	0.08%
India native income	0.30%	1.98%	0.21%	1.46%	0.57%	1.24%
World income	0.04%	0.36%	0.27%	0.37%	0.39%	0.33%

Percent difference on welfare of workers when we go from a scenario with no migration (counterfactual) to a scenario with migration (real). “Restricting Migration from 2004” has a counterfactual where between 1994 and 2003 immigration is allowed under the H-1B program, but is thereafter stopped. “Restricting Migration from 2007” performs the same procedure for 2007 onwards.’

Table 10: Impact of Migration: Sensitivity analysis for endogenous technology parameter - 2010

	No spillover elasticity=0	Baseline spillover elasticity=0.27	Large spillover elasticity=0.4
US Income (including migrants)	0.4%	0.4%	0.4%
US natives income	-0.1%	-0.1%	-0.1%
India income (including migrants)	1.7%	2.0%	2.2%
India domestic income	0.0%	0.3%	0.5%
US IT output	0.2%	-0.8%	-1.3%
India IT output	0.9%	5.2%	7.8%
US IT price	-0.6%	-1.0%	-1.0%
India IT price	-1.6%	-7.4%	-10.8%
CS employment India	21.0%	21.4%	21.6%
CS employment US	-9.0%	-9.1%	-9.1%
US Wages CS	-1.4%	-1.5%	-1.5%
US Wages India	-11.1%	-10.6%	-10.3%

Percent difference when we go from a scenario with no immigration (counterfactual) to a scenario with immigration (real). No immigration means setting the H-1B cap to 0 from 1995 onwards.

Table 11: Impact of Migration: Scenario with Fixed Supply by Occupation - 2010

	Baseline	Fixed supply		Baseline	Fixed supply
Wages US			Wages India		
CS	-1.5%	-6.6%	Non migrant CS	-10.6%	4.4%
Non CS graduates	-0.1%	0.4%	Return migrants	-18.2%	-6.0%
Non graduates	0.2%	0.3%	Non CS graduates	1.1%	-3.3%
			Non graduates	0.3%	-2.3%
Native CS Employment					
US	-9.1%	0.0%	India	21.4%	-23.2%
Income and Output					
US Income (including migrants)	0.4%	0.6%	India income (including migrants)	2.0%	-1.0%
US natives income	-0.1%	0.1%	India domestic income	0.3%	-2.8%
US IT output	-0.8%	14.1%	India IT output	5.2%	-31.2%
World income	0.4%	-0.1%			

We show the percent difference on main outcomes when we go from a scenario with no immigration (counterfactual) to a scenario with immigration (real). No immigration means setting the H-1B cap to 0 from 1995 onwards. We set each occupation category to the value observed in the data for that year.

Table 12: Impact of Migration: Scenario with no return migration to India - 2010

	Baseline	No return migrants
CS employment India	21.4%	43.2%
CS employment US	-9.1%	-10.3%
World income	0.36%	0.44%
US Income (including migrants)	0.37%	0.44%
US natives income	-0.07%	-0.08%
India domestic income	0.32%	0.47%
India income (including migrants)	1.98%	2.40%
US IT output	-0.8%	-1.2%
India IT output	5.2%	7.8%

Percent difference when we go from a scenario with no immigration (counterfactual) to a scenario with immigration (real). We set return rate to zero for both real and counterfactual scenarios

Table 13: Impact of Migration: Brain drain vs. Brain Gain - 2010

	Baseline	Migration but no reallocation	No migration but reallocation
CS employment India	21.4%	-3.6%	27.5%
CS employment US	-9.1%	-9.0%	-0.1%
World income	0.4%	0.3%	0.1%
US Income (including migrants)	0.4%	0.4%	0.0%
US natives income	-0.1%	-0.1%	0.0%
India income (including migrants)	2.0%	1.5%	0.5%
India domestic income	0.3%	-0.2%	0.5%
US IT output	-0.8%	0.7%	-1.5%
India IT output	5.2%	-1.0%	6.6%

Percent difference when we go from a scenario with no immigration (counterfactual) to a scenario with immigration (real). The “Migration but no reallocation” means that we still allow for migration into the US, but Indian workers do not consider the possibility of migrating when they make their occupation and college decisions. The “No migration but reallocation” bans migration to the US, but workers still consider the expected wage between India and the US to choose occupations and majors.

Table 14: Impact of Migration: Scenario with double trade costs - 2010

	Baseline trade costs	Double trade costs		Baseline trade costs	Double trade costs
CS employment India	21.4%	20.8%	World income	0.4%	0.4%
CS employment US	-9.1%	-9.0%			
US IT output	-0.8%	0.4%	US Income (including migrants)	0.4%	0.4%
India IT output	5.2%	0.3%	US natives income	-0.1%	-0.1%
US IT price	-1.0%	-1.3%	India income (including migrants)	2.0%	1.9%
India IT price	-7.4%	-6.7%	India domestic income	0.3%	0.3%

We show the percent difference on main outcomes when we go from a scenario with no immigration (counterfactual) to a scenario with immigration (real). No immigration means setting the H-1B cap to 0 from 1995 onwards. In both real and counterfactual we set the trade costs between all countries and sectors to double than in the baseline specification. Trade costs within country are 1.

A Additional Model Details for Labor Supply

In this section we provide further details on the dynamic labor supply model. Given the assumption of idiosyncratic taste shocks being distributed Type I Extreme Value, it follows that the probability of a worker *graduating* with a computer science degree can be written in logistic form:

$$q_{t,k}^c = [1 + \exp(-(\beta^2 \mathbb{E}_{t-2}[V_{22,k}^c - V_{22,k}^o] - \zeta_{o,k})/\sigma_{0,k})]^{-1} \quad (37)$$

The next step to characterize the supply of young computer scientists is to map the graduating probability described above to employment. Defining $M_{t,k}^a$ as the exogenous number of college graduates with age a in time period t , the number of recent graduates with a computer science degree in year t is represented by $L_{t,k}^{grad} = q_{t,k}^c M_{t,k}^{22}$ for $k = \{in, us\}$.

For the occupational decision we follow a similar procedure. In the next few equations we detail the occupational switching probabilities, the value function iteration and equilibrium labor supply by age cohort for US workers. The equations are similar for students and workers in India, but include the migration prospects as well. Since taste shocks $v_{i,k}^e$ are also distributed Type I Extreme Value we can define $q_{t,a,k}^{e,e'}$ as the probability that a worker at age a between 22 and 64 moves from occupation e to occupation e' , it follows from the error distribution assumption that the migration probabilities can be represented as:

$$q_{t,a,k}^{oc} = [1 + \exp(-(w_{t,\ell,k} - w_{t,g,k} - \chi_k(a) - \zeta_{1,k} + \beta \mathbb{E}_t[V_{t+1,a+1,k}^c - V_{t+1,a+1,k}^o])/\sigma_{1,k})]^{-1} \quad (38)$$

$$q_{t,a,k}^{co} = [1 + \exp(-(w_{t,g,k} - w_{t,\ell,k} - \chi(a) + \zeta_{1,k} + \beta \mathbb{E}_t[V_{t+1,a+1,k}^o - V_{t+1,a+1,k}^c])/\sigma_{1,k})]^{-1} \quad (39)$$

and the occupational migration probabilities of workers at age 65 are the same without discounting future career prospects. Note that the switching probabilities depend upon both the current wage differential and expected future career prospects at each occupation. The standard deviation of the taste shocks, the sector attractiveness constant and the cost of switching occupations will effect the extent to which changes in relative career prospects affect the movement of US residents across fields.

A feature of dynamic models with forward looking individuals is that working decisions depend upon the equilibrium distribution of career prospects. As in the dynamic choice literature with extreme value errors (Rust, 1987), one can use the properties of the idiosyncratic taste shocks distribution to simplify the expressions for the expected values of career prospects. As a result, 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:

$$\begin{aligned} \mathbb{E}_t V_{t+1,a+1,k}^c &= \sigma_{1,k} \mathbb{E}_t [\varpi + \ln\{\exp((w_{t+1,\ell,k} + \beta \mathbb{E}_{t+1} V_{t+2,a+2,k}^c)/\sigma_{1,k}) + \\ &\quad \exp((w_{t+1,g,k} - \chi_k(a) + \zeta_{1,k} + \beta \mathbb{E}_{t+1} V_{t+2,a+2,k}^o)/\sigma_{1,k})\}] \end{aligned} \quad (40)$$

$$\mathbb{E}_t V_{t+1,a+1,k}^o = \sigma_{1,k} \mathbb{E}_t [\varpi + \ln\{exp((s_{t+1,k} + \zeta_{1,k} + \beta \mathbb{E}_{t+1} V_{t+2,a+2,k}^o) / \sigma_{1,k}) + exp((w_{t+1,k} - \chi_k(a) + \beta \mathbb{E}_{t+1} V_{t+2,a+2,k}^c) / \sigma_{1,k})\}] \quad (41)$$

where $\varpi \cong 0.577$ is the Euler's constant and the expectations are taken with respect to future taste shocks. Workers at age 65 face the same expected values but don't discount the future.

In transferring the occupational migration probabilities to employment, the first step is to determine the CS supply of recent college graduates. After leaving college, individuals can start their careers in the occupation correspondent to their field of study with no cost. However, we also allow workers at age 22 to pay the switching costs and get their first job in an occupation different from their field of study. As a consequence, the number of computer scientists at age 22 is a function of the number of recent graduates with a computer science degree and the migration probabilities:

$$L_{t,n,k}^{22} = (1 - q_{t,22,k}^{co}) L_{t,k}^{grad} + q_{t,22,k}^{oc} [(L_{t,n,k}^{22} + G_{t,k}^{22}) - L_{t,k}^{grad}] \quad (42)$$

$$G_{t,k}^{22} = (1 - q_{t,22,k}^{o,cs}) [(L_{t,n,k}^{22} + G_{t,k}^{22}) - L_{t,k}^{grad}] + q_{t,22,k}^{cs,o} L_{t,k}^{grad} \quad (43)$$

where $L_{t,k}^{grad}$ is the number of recent graduates with a computer science degree, and $(L_{t,n,k}^{22} + G_{t,k}^{22}) - L_{t,k}^{grad}$ is the number of college graduates with any other degree. In the same way, the supply of native computer scientists at age a from 23-65 is a function of past employment in each occupation and the occupational migration probabilities:

$$L_{t,n,k}^a = (1 - q_{t,a,k}^{co}) L_{t-1,n,k}^{a-1} + q_{t,a,k}^{oc} [G_{t-1,k}^{a-1}] \quad (44)$$

$$G_{t,k}^a = (1 - q_{t,a,k}^{o,cs}) G_{t-1,k}^{a-1} + q_{t,a,k}^{cs,o} [L_{t-1,n,k}^{a-1}] \quad (45)$$

where $G_{t,k}^a$ is the number of workers at age a working in the residual sector and $L_{n,t,k}^a$ is the number of native CS workers at age a .

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

$$L_{t,n,k} = \sum_{a=22}^{a=65} L_{t,n,k}^a \quad (46)$$

$$G_{t,k} = \sum_{a=22}^{a=65} G_{t,k}^a \quad (47)$$

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.

B Details of the Data Used

B.1 US Data

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 `qinlongj` 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 and the crosswalk given the categories 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: “064 Computer systems analysts and scientists” and “229 Computer programmers”. For the years 2000-2 the CPS-ORG reports codes using both the 1990 Census definition and the 2000 Census definition. This allows us to create a crosswalk where we weight the 2000 occupational codes by the 2 occupational categories in the 1990 Census.

College enrollment 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 engineers as the number of degrees awarded in these fields lagged by 2 years. For 1994 and 1995, enrollment in electrical engineering was not available by native and foreign students but only shown together with all engineering degrees. We impute the data for these two years by looking at the average growth in electrical engineering for 1996-2002.

In some 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, mathe-

maticians 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 "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.

B.2 Trade Data

Information on Imports, Exports and Rest of the World consumption of IT products from the US and India come from the OECD Trade in Value Added statistics. We use gross exports, gross imports and total GDP data for the "C72: Computer and Related Activities" industry in addition to aggregate numbers by country across all industries. The data is only available for 1995, 2000, 2005 and 2008-2011 so we interpolate the missing years.

B.3 India Data

Data on earnings, employment in different occupations and sectors, and age-shares in each occupation comes from the National Sample Survey (NSS). We use the Employment and Unemployment labor force surveys that come between rounds 50 through 66. These rounds cover 1994 through 2010 with gaps in between, for which we interpolate the macro moments.

NSS is a nationally representative survey used by many researchers studying India. It is the largest household survey in the country, asks questions on weekly activities for up to five different occupations per person, and records earnings during the week for each individual in the household. Computer scientists are defined as "systems analysts, programmers, and electrical and electronic engineers" based on the 3-digit National Occupational Codes (NOC). We use the earnings data for the primary occupation only. The IT sector is restricted to be "software" (code 892 in the National Industrial Classification).

There are various sources for education data, the most comprehensive of which is the Ministry of Human Resources and Development that records number of degrees and universities by type of degree (for example, engineering degrees). We combine this with reports from the All India Council for Technical Education (AICTE) and the National Association of Software and Service Companies (NASSCOM) to also look at the growth in Masters for Computer Application (MCA) degrees.

To get total IT output (and export numbers which we corroborate with our exports data), we use data from the Electronic and Information Technology Annual Reports, and the Indian Department

of Electronics reports. Much of this data has been collated and standardized by the Center for Development Informatics at the University of Manchester, UK. The remaining data for summary tabs and graphs are from National Association of Software and Service Companies (NASSCOM).

C Calibration details

C.1 Gravity equation parameters

To get our estimates for trade costs and technology we take logs of equation 33 and get equation 48 which can be estimated by OLS and will allow us to back out the trade costs and a term that combines the technology level and the unit cost of production $T_{t,k}^s(\xi_{t,k}^s)^{-\theta}$. We ran a separate equation for each sector and year to capture the differential evolution in technology and trade costs over time. We also assume trade costs are equal to 1 if the country is buying from itself, so trade costs only arise due to international trade.

$$\log\left(\frac{EX_{t,k,b}^s}{EX_{t,b,b}^s}\right) = \underbrace{\log\left((T_{t,k}^s(\xi_{t,k}^s)^{-\theta}) - \theta exp_{t,k}\right)}_{\text{Exporter fixed effect}} - \underbrace{\log\left((T_{t,b}^s(\xi_{t,b}^s))^{-\theta}\right)}_{\text{Importer fixed effect}} - \theta(dist_{k,b} + border_{k,b} + CU_{t,k,b} + RTA_{t,k,b} + v_{t,k,b}) \quad (48)$$

The distance variable $dist_{k,b}$ is a group of 6 indicator variables that take the value of 1 if the distance between k and b falls within each of the following intervals measured in miles: $[0, 350]$, $[350, 750]$, $[750, 1500]$, $[1500, 3000]$, $[3000, 6000]$, $[6000, \text{maximum}]$, and 0 otherwise.

We estimate equation 48 separately by sectors Y and C . Distance, currency union and regional trade agreement data comes from CEPII gravity database and data on industry specific trade flows and GDP from the OECD. We run the regression separately for years 1995, 2000, 2005 and 2010 as those are the only years we have good data on trade flows for the IT sector for a large number of countries. For the years in between we interpolate. From the estimates of equation 48 we can back out the trade costs conditional on our preferred value of θ . The fixed effects represent a convolution of the relative technology levels and unit costs of a country. To estimate them, we drop the fixed effect for the US and interpret the estimate for each country as the relative technology levels and unit costs between a country k and the US and get the estimate $\hat{\Xi}_{t,k,us}^s = \left(\frac{T_{t,k}^s \xi_{t,k}^s}{T_{t,us}^s \xi_{t,us}^s}\right)^{-\theta}$.

When computing our general equilibrium model we feed the estimated expressions for $\hat{\Xi}_{t,k,b}^s$ together with our preferred value of θ and total labor quantities for each occupation. This allows the model to endogenously calculate the wages based on the labor market clearing conditions and pin down the unit costs, which in turn allows us to back out the level of technology relative to the the US. We assume the technology level for the US is 1 for both sectors. For RoW we get estimates for 57 countries while our model just has a single 3rd country. We calculate a weighted average of trade costs and $\hat{\Xi}_{t,k}^s$

based on country-sector GDP to get to the average trade costs and $\hat{\Xi}_{t,k,b}^s$ in RoW we will feed into the model.

While this procedure allows us to choose the trade costs and technology levels such that we match the trade flows between India, the US and RoW, we particularly want to additionally match the relative level of wages between the US and India, which reflects the productivity differences between the two countries. To do so, we forgo matching $\hat{\Xi}_{t,k,b}^s$ between US and India and instead calibrate the relative level of technology between the two countries by matching the relative wages observed for non-college graduates and adjusted by PPP. By doing this, we do no longer explicitly match the trade flows in the Y sector between India and US but we do match the relative wage for non-college graduates in the two countries.

C.2 Labor demand

Once we calibrate all the product market parameters and the relative productivity process we proceed to derive the labor demand curve for our baseline year 1994. As the notation is slightly different, we first describe the process for the US and then describe the differences of deriving the relative labor demand for India. Since our demand curve has no closed form solution we approximate it through the following process: we change the relative quantity of computer scientists to non-CS college graduates ($\frac{\bar{L}_{us}}{\bar{G}_{us}}$) leaving the total quantity of college graduates and all other parameters fixed and calculate, for each $\frac{\bar{L}_{us}}{\bar{G}_{us}}$ what is the relative wage $\frac{w_{l,us}}{w_{g,us}}$ predicted by the model.

We calculate the relative wages for relative labor quantities between 0.03-0.055 in order to capture the shape of the demand curve across the relative labor values we observe in the data during our period. We then run a regression of relative quantities of CS to non-CS college graduates on a quadratic of predicted relative wages.²⁰ This allows us to express the demand curve as in equation 49:

$$\frac{\hat{L}_{us}}{\hat{G}_{us}} = \hat{f}\left(\frac{w_{l,us}}{w_{g,us}}\right) \quad (49)$$

Where $\hat{f}(\cdot)$ are the estimated coefficients of the relative labor demand curve for the baseline year 1994. We can then calculate the relative labor demand shifter for years 1995-2010 as in equation 50, by calculating the difference between the relative labor quantities observed in the data and the predicted ones using equation 49 and the relative wage in each period.

$$\Lambda_{t,US} = \frac{L_{t,us}}{G_{t,us}} - \hat{f}\left(\frac{w_{t,l,us}}{w_{t,g,us}}\right) \quad (50)$$

The calculated Λ_t represent the relative demand shifters for all workers in the US and picks up the occupational-biased technological change that occurred during the period which shifts labor demand towards a more intensive use of computer scientists. Innovation shocks that drive the tech-boom disproportionately increase the demand for CS workers, and this is captured by Λ_t .

²⁰We experiment with higher order polynomials and our results do not change.

In the case of the US, we want to use the shifts in labor demand to trace out the relative supply curve of native computer scientists to non-CS college graduates. However, the Λ_t represent the shifts in the total relative labor demand which includes foreign computer scientists. To calculate the shifts for US natives we assume foreign workers are marginally more productive (or are willing to work at marginally lower wages) than their US counterparts which means that firms first hire these foreign CS workers (subject to the H-1B cap), and 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.

Given this assumption, firms hire them first making US computer scientists experience the shifts $Z_{t,k}$ of a residual labor demand such as in equation 51:

$$Z_{t,us} = \Lambda_{t,us} - \frac{L_{t,F,us}}{G_{t,us}} \quad (51)$$

We assume $Z_{t,us}$ follows an AR(1) process as in equation 29, so we can use the calculated $Z_{t,us}$ from the data and calculate the $\nu_{t,US}$ for every year as the unexpected shocks the native US college graduates face.

For India the process is almost identical. The key difference is that we just focus on the relative demand curve of CS workers that never migrate with respect to non-CS college graduates $\frac{L_{n,IN}}{G_{US}}$, taking the number of return migrant CS, $\bar{R}_{t,in}$, as given. We calculate the predicted relative wages by the model for relative labor quantities between 0.001-0.03 to cover the range of values observed in the data. The process follows as it does in the US, by fitting a second order polynomial to get a closed form solution of the relative labor demand curve and calculate the aggregate demand shifts $\Lambda_{t,IN}$ in a similar fashion to equation 50. This gives us shocks to the relative demand curve of Indian firms. To get to the shocks that Indian workers experience, we add the possibility that Indian workers have of migrating into the US. This enters equation 52 as an additional shock to the relative labor demand experienced by workers.

$$Z_{t,in} = \Lambda_{t,in} + \frac{L_{F,t,us}}{G_{t,in}} \quad (52)$$

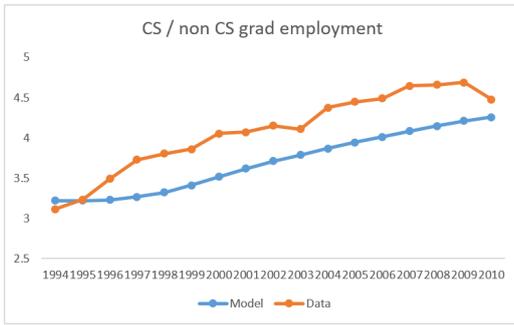
Once again, assuming $Z_{t,in}$ follows an AR(1) process and using the values of $Z_{t,in}$ from the data we can get the shocks $\nu_{t,in}$ that Indian college graduates face.

C.3 Labor Supply Calibration

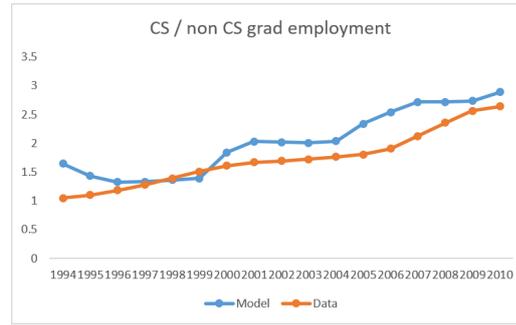
In figure 6 we show how well our labor supply parameters match the moments observed in the data.

Figure 6: Calibration: India and US Labor Supply

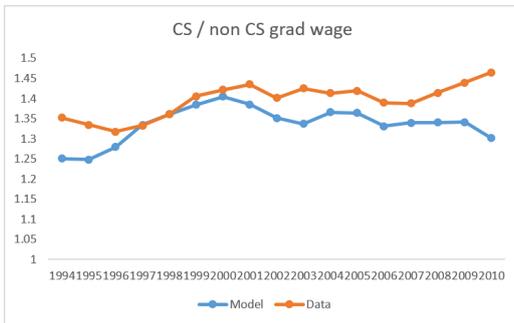
(a) Relative Labor Supply – US



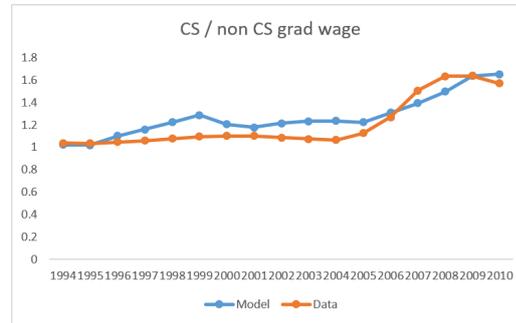
(b) Relative Labor Supply – India



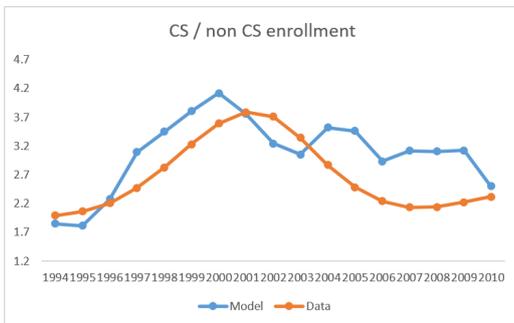
(c) Relative Wages – US



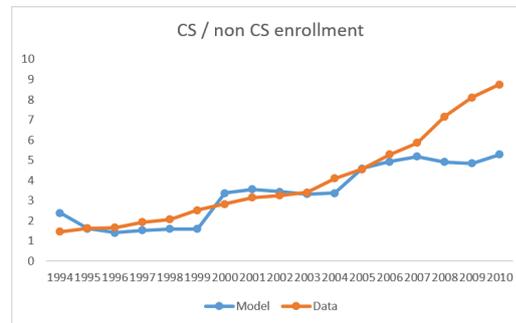
(d) Relative Wages – India



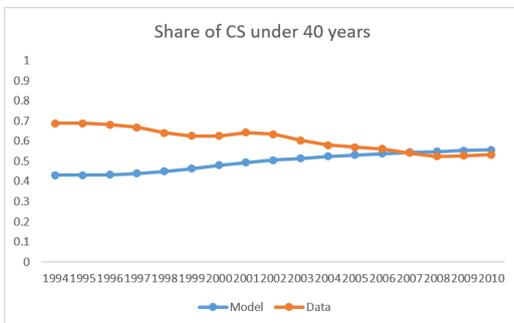
(e) Relative Enrollment – US



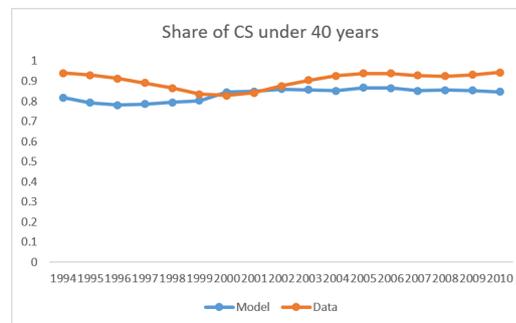
(f) Relative Enrollment – India



(g) Fraction Young CS – US



(h) Fraction Young CS – India



The years 1994, 2001 and 2010 were used to match the data for employment, wages and enrollment, and 2010 was used to match age shares. The years in between are an out-of-sample test. In the US, wage and employment data are from the March CPS, and enrollment data is from IPEDS. In India, wage and employment data are from the NSS, whereas enrollment data is from HRD Ministry. See Appendix B for details.

C.4 Sensitivity to Key Elasticities

In our calibration we rely on the literature to calibrate three key elasticities: the elasticity of substitution between CS and other college graduates λ , the elasticity of substitution between return migrants and native CS in India ϵ and the trade elasticity θ . In table 15 we run our counterfactual for different values of these parameters, to evaluate how sensitive our conclusions are to alternative values. While the magnitude of the effects change, our conclusions are qualitatively robust to the parameter choices.

When we try a larger substitution between other college graduates and CS (parameter λ), we see that employment in India and the US respond more to migration with US workers moving away from CS and Indian workers getting more into CS. Wages for CS also decrease more in both countries as employers find it easier to substitute between the two types of labor. US natives lose less from migration, as the difference between wages in CS and Other is smaller when λ is larger. Overall a larger value of λ increases World income, as it becomes easier for workers to switch between occupations and for employers to substitute across inputs when migration is allowed.

When we try a lower value of the elasticity of substitution between return migrants and non-return CS, we see that India gains more from immigration. Return migrant CS become more necessary for production than in the baseline scenario, and migration increases the stock of return-migrants in the economy, allowing for IT production to expand by 15.71% in India as opposed to 5.24% in the baseline. Wages for return migrants CS decrease by 75.5% when substitution is low compared to 18.2% in the baseline, due to the wage levels in the counterfactual being much higher when substitution is low.

The trade elasticity θ is also the parameter that summarizes the variance in the Frechet distribution where firms draw their productivities. We use the preferred value of Eaton and Kortum (2002) of 8.28 but in table 15 we use the proposed value of Simonovska and Waugh (2014) of 4.2. Intuitively, a higher value of θ would increase the gains of trade as it becomes more likely that there are differences in productivity across varieties drawn by each country. We see that the effects of migration tend to be smaller when the trade elasticity is higher, which is intuitive as the IT sector without migration is larger than in the baseline scenario. Even without migration, we still observe high levels of trade and a large Indian IT sector when trade is more important. The growth in CS employment in India is much smaller given workers would switch to CS even without migration.

Table 15: Impact of CS Migration from India: Sensitivity to key elasticities - 2010

	Baseline	Sensitivity λ	Sensitivity ϵ	Sensitivity θ
	$\lambda = 2, \epsilon = 30,$ $\theta = 8.28$	$\lambda = 3, \epsilon = 30,$ $\theta = 8.28$	$\lambda = 2, \epsilon = 2,$ $\theta = 8.28$	$\lambda = 2, \epsilon = 30,$ $\theta = 4.2$
Employment				
CS employment India	21.36%	76.89%	62.45%	2.75%
CS employment US	-9.05%	-24.72%	-9.11%	-9.13%
Wages in the US				
CS	-1.48%	-4.29%	-1.59%	-1.45%
non CS graduates	-0.14%	-0.14%	-0.16%	-0.14%
non graduates	0.24%	0.30%	0.25%	0.23%
Wages in India				
Non migrant CS	-10.63%	-17.46%	-20.70%	-3.07%
Return migrants	-18.20%	-23.42%	-75.52%	-11.78%
non CS graduates	1.12%	2.12%	2.13%	0.63%
non graduates	0.31%	0.94%	0.96%	0.01%
Output and Incomes				
World income	0.36%	0.52%	0.53%	0.29%
US				
US natives income	-0.07%	-0.02%	-0.08%	-0.08%
US Income (including migrants)	0.37%	0.41%	0.36%	0.37%
US IT output	-0.77%	-3.52%	-2.61%	-0.67%
India				
India income (including migrants)	1.98%	2.56%	2.84%	1.53%
India domestic income	0.32%	0.96%	1.15%	0.00%
India IT output	5.24%	17.28%	15.71%	4.53%

Percent difference when we go from a scenario with no immigration (counterfactual) to a scenario with immigration (real). No immigration means setting the H-1B cap to 0 from 1995 onwards. In each column we change the value of one of the parameters with respect to the baseline, leaving the other parameters as in the baseline. λ is the elasticity of substitution between CS and non-CS college graduates, ϵ is the elasticity of substitution between return migrants and non-migrant CS workers in India θ is the trade elasticity.