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

Gaurav Khanna, Nicolas Morales

Abstract

We study how US immigration policy and the Internet boom affected not just the US, but also led to a tech boom in India. Students and workers in India acquired computer science skills to join the rapidly growing US IT industry. As the number of US visas was capped, many remained in India, enabling the growth of an Indian IT sector that eventually surpassed the US in IT exports. We leverage variation in immigration quotas and US demand for migrants to show that India experienced a "brain gain" when the probability of migrating to the US was higher. Using detailed data on higher education, alumni networks, and work histories of high-skill workers, we show that changes in the US H-1B cap induced changes in fields of study, and occupation choice in India. We then build and estimate a quantitative model incorporating migration, heterogeneous abilities, trade, innovation, and dynamic occupation choice in both countries. We find that high-skill migration raised the average welfare of workers in each country, but had distributional consequences. The H-1B program induced Indians to switch to computer science occupations, and helped drive the shift in IT production from the US to India. We show that accounting for endogenous skill acquisition is key for quantifying the gains from migration.

KEYWORDS
High-skill migration, H-1Bs, India, computer scientists, IT sector, brain gain

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1 Introduction

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 sending and receiving countries. For instance, immigration can attract global talent and lead to production growth in receiving countries, but migration-induced technological catch-up may contrarily shift production to the sending country. The sending country may experience brain drain as human capital departs, or experience brain gain as the opportunity to migrate induces skill acquisition. We resolve these ambiguities by modeling and estimating the long-term welfare consequences of high-skill migration to the US, and examine how the combination of the US IT boom and US immigration policies led to a boom halfway across the world in India.

We evaluate the role played by US immigration policy in the shift of IT production from the US to India. We start by presenting a series of facts that describe how changes in US immigration policy and shocks to US labor demand affected the education and occupation choices of Indian college graduates. We build and estimate a quantitative model that incorporates migration, heterogeneous abilities, trade, and dynamic occupational choices of forward-looking workers and students in both countries. In counterfactual exercises that restrict the migration of Indian workers, our results indicate that the H-1B program and the tech boom had a powerful impact on IT sectors in both countries. US high-skill immigration policy facilitated the spread of the US-led boom to India, and by the mid-2000s India became the major exporter of software. Despite various distributional effects, we find that, on average, workers in each country are better off due to immigration.

As a first step, in Section 2, we use descriptive trends and background information to describe our narrative and ground our model. Innovation rapidly caused an expansion in the US IT sector in the early 1990s (Bound et al., 2015; Clemens, 2013; Kerr, 2013; Peri et al., 2015; Peri and Sparber, 2011). Indian workers and students responded to these booms and migration opportunities by accumulating computer science skills valuable 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, helping production shift from the US to the lower-wage destination of India. This educated workforce in India enabled the Indian IT sector to grow rapidly, where India became a major producer of software, eroding the US dominance in IT exports.

We proceed by showing well-identified evidence supporting the underlying driving force behind our hypothesis: labor demand shocks in the US affected human capital accumulation in India. In Section 3, we introduce new detailed annual data on India's higher education sector taken from various government reports, and data on work and education histories of high-skill workers all over the world taken from the universe of LinkedIn profiles. Our event study designs show that when the propensity to migrate to the US increased, there was a meaningful response in major and occupational choice in populations that had stronger migrant connections to the US.

We then estimate specifications with major and occupational choice in India as the outcome, and demand from the US as the explanatory variable, conditional on high-dimensional fixed effects. We derive variation in US demand for migrants from changes in the H-1B visa cap, and demand for non-Indian migrants. Changes to the cap were plausibly independent from unobserved shocks to supply-side worker preferences and occupation-specific demand shocks from local industry in India. We expect these immigration policy shocks to have larger impacts in schools-by-fields of study, and region-occupation pairs with larger alumni networks in the US.

We estimate a positive, quantitatively significant response to US demand shocks in both the choice of major and the choice of occupation in India. This represents a 'brain gain' driven by immigration prospects. We control for a wide array of fixed effects that absorb potential confounding factors. For instance, state-by-major-by-year fixed effects control for local demand shocks for particular fields of study. We obtain data from other destination countries and highlight the lack of occupation-specific correlated demand for Indian migrants. A variety of different sources of variation and specifications consistently point to our posited 'brain gain' hypothesis.

Motivated by these facts, the primary substance of our paper is the GE model outlined in Section 4, which contains three crucial features. First, we model dynamic labor supply decisions and how they respond to changes in immigration policy (Colas, 2019; Monras, 2020). Students in both countries have heterogeneous abilities and preferences, and make forward-looking decisions on choosing their college major given their expected future earnings in different occupations. After graduation, workers choose every year to either continue working in their current occupation or switch occupations (paying a cost), given the labor demand shocks and their expected future benefits in each occupation.

Indian computer scientists (henceforth, CS) incorporate the possibility of migration when making their occupational and major decisions (Clemens, 2013). As such, workers choose their occupation considering the *expected* value of working as CS, observing both the wages in India and the US. We allow for workers with higher ability in CS, to have higher migration probabilities. While choosing occupations, workers have uncertainty over the migration cap, as well as whether they will be selected to migrate to the US. Such uncertainty opens up the possibility of brain gain in India, driven by the prospect of migration. Once in the US, Indian CS can choose to return to India, which is a second channel through which India can experience brain gain (via 'brain circulation').

Second, we model how firms hire both local and foreign workers, across different occupation-skill groups. As migration increases the size of the US CS workforce, firms demand more workers in complementary occupations, such as managerial positions (Peri and Sparber, 2011). At the same time, skill-biased technical change shifts labor demand in favor of high-skill occupations, while computer scientists, both domestic and foreign, are innovators and increase the overall IT productivity in both countries (Kerr and Lincoln, 2010; Peri et al., 2015). We allow for immigrants and natives to be imperfect substitutes in production (Burstein et al., 2020). With return migration, some Indian CS working in the US return to India with specialized skills that are complementary to local CS skills in India. Our final feature captures trade between India, the US, and the rest of the world. The IT sector produces a continuum of varieties, the productivities of which differ across countries. The products are traded between countries as in the canonical Eaton and Kortum (2002) framework. Restricting immigration, or rapid growth in the Indian IT sector can shift production across borders. Since the final output uses software as an intermediate input in production, an expansion in IT raises productivity in the rest of the economy. Consumers benefit from lower prices, while both countries compete for global markets. The potential to trade helps drive India's growth, as workers switch to the high-innovation IT sector. At the same time, in both countries, immigration-wage impacts are muted by trade as resources shift across sectors (Ventura, 1997), and tradable sectors can absorb labor supply shocks (Burstein et al., 2020). Our model generates 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 acquire skills valued in the US, and return migrants also improve local production. Similarly, the impact on the US IT sector is theoretically unknown: 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, eroding the US's market share.

To discipline the model and resolve these theoretical ambiguities, we use a combination of estimation and calibration techniques. The parameters in our major and occupational choice model jointly determine a key elasticity for our results: the dynamic labor supply elasticity. This plays a crucial role in the occupational response of Indian and US college graduates when immigration policy in the US changes. We estimate this elasticity by minimizing the distance between a series of targeted moments and their empirical counterparts using data from 1995-2010. Given the dynamic nature of labor supply decisions, the long-run labor supply curve is more elastic than the short-term labor supply curve (as students choose different majors over time), implying that reduced-form estimates of contemporaneous responses to immigration changes in some other work may not pick up the entirety of the labor supply adjustments.

Intuitively, the production side helps us determine the exogenous innovation shocks that shift the labor demand curve for computer scientists, allowing us to trace out the dynamic labor supply curve. We rely on methods from trade to estimate trade costs and technology parameters. We use instrumental variables, leveraging variation in US immigration policy and migrant-supply shocks, to measure the innovation response (captured by patenting) to industry-level CS flows, and find results consistent with previous work (Kerr and Lincoln, 2010; Khanna and Lee, 2018; Peri et al., 2015).

Methodologically, our approach is similar to recent developments in the migration literature that combine reduced-form identification with structural models to make meaningful statements about welfare (Lagakos et al., 2023), and general equilibrium effects (Brinatti and Guo, 2024; Brinatti and Morales, 2023; Colas, 2019; Llull, 2018). Given the complexity of the model, it is important to do validation exercises. In Section 5.4, we evaluate how well our model captures the Indian CS employment response to immigration estimated in the data. To causally identify such response, we use nationally representative datasets for the US and India, and construct an instrument that interacts the changes in US migrant demand over time with pre-period region-occupation exposure in India to migration to the US. We find that when the number of migrants to the US from a given region-occupation pair increases by 1%, local employment in that occupation in India increases by 0.56%. Our model, which does not explicitly target this moment, predicts a similar response of 0.59%. Both in the model and the data, the supply response in India is driven by young workers.

In Section 6, we conduct counterfactual exercises to study the impact of a more restrictive immigration policy on both the US and Indian IT sectors by restricting H-1B migration to only half the number of Indian migrants over the 1995-2010 period. 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, increasing the size of the non-migrant Indian CS workforce. However, the migration led native US CS workers to switch to non-CS occupations, which led to a 3.89% drop in the native US CS workforce in 2010.

An increase in the size of the Indian CS workforce due to the H-1B program also led to an increase in India's IT sector productivity. Under the H-1B program, IT production grows more in India than in the US – US IT output is 1% higher, and Indian IT output 25% higher in 2010. The production shift to India, however, hurts some US workers, most notably US-born computer scientists. World IT output increases, the US-India combined welfare is higher by 0.15%, and the average worker in each country is better off in a world with skilled migration. The net H-1B welfare gains to US workers are about $13,031 per migrant, and gains to Indian non-migrants are about $1,119 per migrant.

We highlight important mechanisms and show the quantitative relevance of our modeling decisions. We show that dynamic endogenous labor supply decisions are important for a quantitative exercise on migration. Ignoring occupational choice in both countries would predict welfare gains of immigration for the US that are 40% larger than our baseline and predicts India would experience welfare losses driven by brain drain. We describe the consequences of not allowing for brain drain, brain gain, and return migration, to understand the contributions of each. We also show that trade amplifies the welfare gains for India and sightly mitigates the gains for the US, as IT production and innovation relocates from the US to India when migration is higher.

Our paper is innovative in four main ways. First, we contribute to the literature that uses quantitative models to understand the general equilibrium consequences of immigration (Brinatti and Guo, 2024; Brinatti and Morales, 2023; Burstein et al., 2020; Caliendo et al., 2021; Colas, 2019; Desmet et al., 2018; di Giovanni et al., 2015; Ghose, 2024; Llull, 2018; Monras, 2020; Morales, 2023). We contribute by considering how migration-driven incentives to invest in human capital facilitate the corresponding growth in production for both sending and receiving countries. We show that incorporating uncertainty in migration when making occupational choices substantially alters the global gains from migration.

Second, we address the debate between 'brain drain' and 'brain gain' (Abarcar and Theoharides, 2024; Agrawal et al., 2011; Beine et al., 2001; Dinkleman and Mariotti, 2016; Easterly and Nyarko, 2009; Shrestha, 2016; Stark et al., 1997). While many worry about the large number of educated Indians emigrating, we show how better-paid jobs abroad incentivize students to choose certain majors and supply a skilled workforce to Indian firms. Migrants who return with newly acquired skills and technical knowhow help develop the IT sector at home, contributing to the brain gain, and facilitating growth in exports and innovation (Bahar and Rapoport, 2018; Prato, 2024).

Third, we delve deeper into the role of migration and trade between developed and developing economies to either help or hinder structural transformation. On the one hand, North-South trade may hinder structural transformation as developing economies specialize in less productive sectors (Matsuyama, 1992) and migration may help developed economies maintain their comparative advantage by attracting global talent (Freeman, 2006b; Rybczynski, 1955). On the other hand, technological diffusion through trade and migration can help developing countries catch up with developed ones (Acemoglu et al., 2015; Davis and Weinstein, 2002; Krugman, 1979). By proposing a new mechanism through which immigration affects production, we provide novel evidence to understand major 'big push' sectoral transformations to high-skill production in emerging economies (Lagakos and Waugh, 2013; Lewis, 1954; Murphy et al., 1989).

Lastly, our paper addresses crucial issues raised by the labor literature on the impacts of high-skill immigrants on the US economy. Several papers quantify the costs and benefits of high-skill immigration for the US (Borjas, 1999; Bound et al., 2016; Dimmock et al., 2022; Doran et al., 2022; Freeman, 2006b; Glennon, 2023; Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Mahajan et al., 2024) but abstract away from the role played by migrants' home-countries. In our current paper, we incorporate the occupational responses in India and the growth of the Indian tech sector, which greatly affects incomes in the US. To study the linkages across the countries and the feedback into the US, we model what happened on both sides of the world.

2 The Tech Boom in the US and India

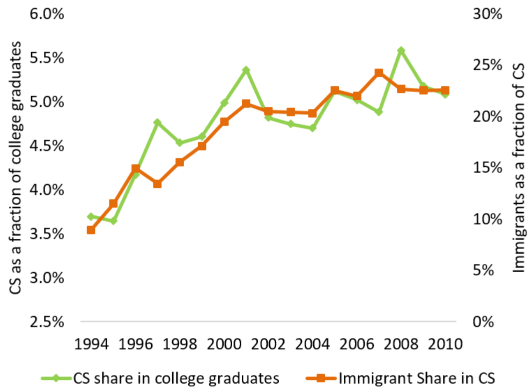
Starting in the mid-1990s, innovation in the IT sector led to an increase in demand for computer scientists (CS) in the US. As Figure 1a shows, CS employment, as a share of the college-educated workforce, rose dramatically in the second half of the 1990s. CS occupations were the fastest growing occupations in the second half of the 1990s, and were expected to remain the fastest over the next decade (BLS, 1996).

This growth was, in part, fueled by foreign-born workers (Figure 1a). In 1994, the share of foreign-born among CS was 8.9%. But by 2010 foreigners accounted for more than 20% of the CS workforce. The Immigration Act of 1990, which established the H-1B visa program for temporary workers in specialty occupations (requiring *"theoretical and practical application of a body of highly specialized knowledge in a field of human endeavor"*), played an important role in this growth.

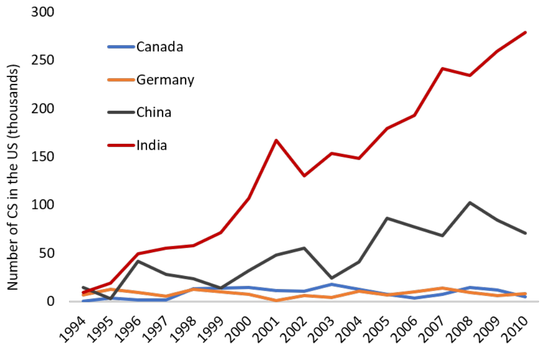
By the time the IT boom started in the mid-1990s, the 65,000 Congressional-set H-1B cap had

Figure 1: High-Skill Immigration and the IT Boom

(a) Immigrant Computer Scientists in US Workforce



(b) Foreign-born CS workers in the US by Country



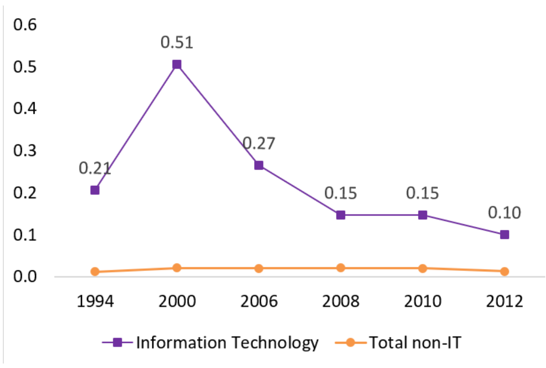
Source: March Current Population Survey (CPS). Immigrants are defined as foreign-born who migrate after the age of 18. In the left panel, we plot the number of CS as a fraction of US college graduates (left axis) and the number of immigrant CS as a fraction of total CS (right axis). In the right panel (March CPS) we restrict the sample to foreign-born workers in CS who immigrated after the age of 18. Data details are in Appendix A.1.

started binding. According to the USINS (2000), about two-thirds of all H-1B visas were awarded to computer-related occupations in 1999, and during the late 1990s, 28% of all programmer jobs went to H-1B visa holders (U.S. Department of Commerce, 2000). H-1B visas, therefore, became an important source of labor for the technology sector.

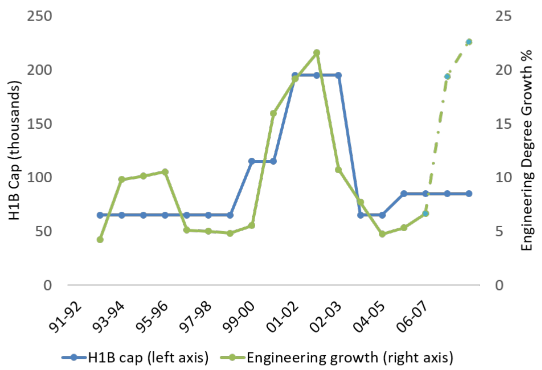
Most foreign CS came from India as shown in Figure 1b. By 2010, more than 55% of all foreign CS were born in India, while only 15% were Chinese nationals. Even as the US IT sector was growing rapidly, the Indian IT sector was comparatively small in the early years. At the turn of the century, for every two IT workers in India, there was one Indian-born migrant in the US IT sector (Figure 2a).

Figure 2: Migration Prospects and Changes in the H-1B Cap

(a) Ratio of Indian workers in US relative to India by sector.



(b) H-1B Cap and Growth in Engineering Enrollment in India



Source: The left panel calculates the ratio of Indian college graduates working in the US relative to the number of Indian college graduates working in India. We plot the ratio separately for the Information Technology (IT) sector and all other sectors except IT. The data comes from the American Community Survey for US and National Sample Survey for India. The right panel shows the H-1B cap based on USCIS reports, and the growth rate in Engineering enrollment in India, from the Ministry of Human Resources and Development. The dotted line represents Engineering enrollment growth after the Indian tech boom takes off in the mid-2000s. Data details are in Appendix A.1.

The large relative demand from US IT implied that migration prospects potentially influenced college graduates in India to choose CS to increase their chances of migrating. Given the large CS wage differentials between the US and India and the non-trivial probability of US migration, the US IT boom raised the expected returns to studying and working in an engineering/CS field in India.

As the cap was binding in most years, changes in the cap often mirrored the change in enrollment in Engineering programs in India (Figure 2b). The figure suggests that these higher (expected) returns to CS, affected the education sector in India. Commentators at that time note that since Indian programmers were "*in a domestic environment with few job opportunities, growth (in training and degrees) was also driven by larger salaries in the IT industry abroad*" (Bhatnagar, 2006). To meet the rising demand, engineering schools introduced CS-oriented degrees, and companies started training and building technical skills for the industry (Arora and Athreye, 2002).

These aspirations are reflected in a survey of those who topped the school-leaving exam between 1996-2015: 40% are in the US, 56% have an Engineering degree, and 32% of workers work in IT (Indian Express, 2020). Figure 2b suggests that this enrollment response in India closely follows the changes to the US Congress changing the H-1B cap. When the cap is raised, engineering enrollment accelerates. The growth in Engineering was positive throughout, even in the 1990s, when the Indian IT industry was underdeveloped and local computer science premiums were low. Still, the expected returns to the degree were rising because of the H-1B program. After 2007, the growth in engineering enrollment rises, as the tech boom spreads to India.

India sent top engineers during the earlier hardware boom of the 1970s and 1980s. This diaspora helped establish strong connections and a reputation for well-trained workers (Arora et al., 2001; Saxenian, 1999). Bhatnagar (2006) notes that Indians 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*" in the expanding IT sector. With the advent of the H-1B program facilitating migration, it is these occupations and regions with strong connections that saw large emigration responses, as these tech workers "*migrate to better paid jobs in other countries*" (Kumar, 2006).

Figure 3a confirms this narrative. It shows that regions increasing their CS employment were those that had larger high-skilled migrant diasporas in the US. The impacts of baseline 1990 migration exposure (the share of CS that were in the US, from each state), vary by era. Before the H-1B program (1970-1990) there did not seem to be any noticeably higher growth in Indian CS employment in regions with higher exposure (red line). Yet, in the H-1B era, we see a meaningful upward relationship between Indian CS employment growth and 1990 migration exposure (green line).

Even as Indians acquired skills that were valuable abroad, the H-1B visa was capped, and many were unable to migrate to the US. As H-1B visas are awarded for 3 to 6 years and green card queues for Indians are long, many migrants return to India after their H-1Bs expire. This meant that the highly skilled immigrant workforce was not in the US in the longer term and many joined the Indian workforce with specialized CS skills. Indian firms tapped into this skilled workforce, leading to an export-led IT boom later in India (Figure 3b).

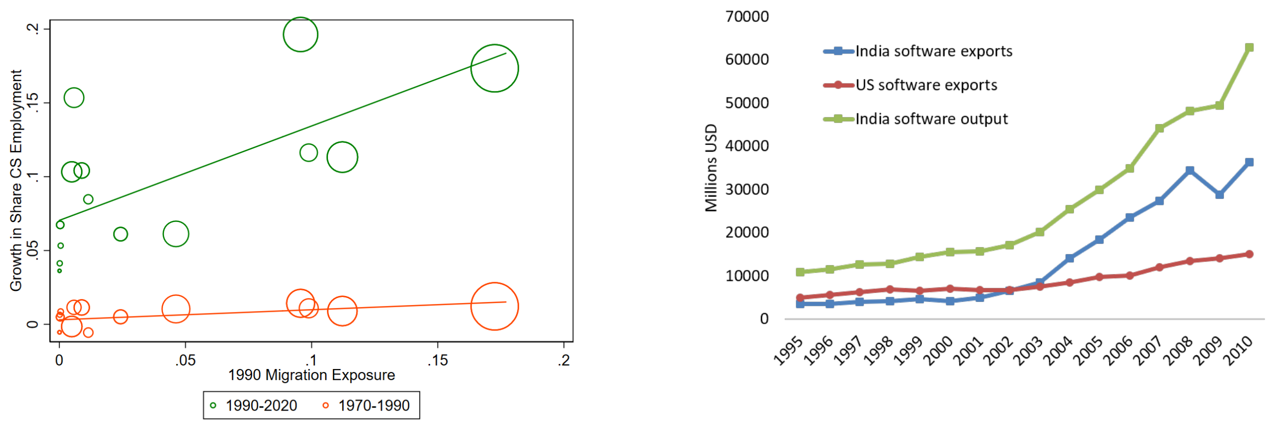
The growth in India affected the US's dominance in IT exports, as production shifted to the other side of the world. While the US was historically the largest exporter of software, in the mid-2000s, India overtook the US as the major exporter of IT products (Figure 3b). Most of the early growth was export-led: in 1995, software was only 2% of all exports, but by the turn of the century, it was 26%. Indeed, Indian IT firms were export-oriented, catering to a consumer base abroad.

In Appendix E, we explore other details on why this boom missed other countries but settled on India. India has not only had high-quality engineering schools that train potentially lower-wage, English-speaking workers, but also developed strong networks with the US during the earlier hardware boom (Bhatnagar, 2006). Our hypothesis is that this spread of the IT boom from the US to India was partly driven by the H-1B program, and we analyze how important US immigration policy was for a structural transformation half-way across the world.

Figure 3: The IT Boom Spreads to India

(a) Growth in CS Employment by Indian State's 1990 Migration Exposure

(b) Growth in the Indian IT sector and US exports



Notes: The left panel uses data from LinkedIn. The y-axis plots the growth in the share of employment in each Indian state that is in computer science (CS), in the pre-H-1B era (1970-1990), and in the post-H-1B era (1990-2020). The x-axis plots the state's 1990 migration exposure, as the share of CS migrants working in the US, that come from that state. This is based on LinkedIn profiles. The y-axis is the long difference of the change in the share of high-skill employment that is CS. The right panel uses data from National Association of Software and Service Companies (NASSCOM), and OECD Trade in Value Added Statistics for industry C72: Computer and Related Activities. It plots production and export value (in real terms) over time. Data details are in Appendix A.1.

3 Educational and Occupational Choice in India

Despite these concurrent trends, one may contend that such human capital investments in India were independent of demand shocks from the US. To support the quantitative exercise in the main part of our analysis, we first causally establish that labor demand shocks in the US did indeed lead to education and labor supply responses in India.

Estimating the education and labor supply response to demand from the US, generates three main identification challenges. First, unrelated coincident investments in Indian universities or changes to preferences among Indian college graduates may drive migration to the US, and bias our estimates.

That is, there may be an increase in certain occupations, fields-of-study, and regions over time, driven by worker preferences or education investments (that are unrelated to US demand shocks). Second, Indians may choose to migrate in occupations where job opportunities at home are low, downward biasing an OLS relationship between migration and occupational choice at home. This is a case of reverse causality: when local job opportunities are low, those with high preferences for specialized occupations migrate. The third challenge is that demand shocks in the US may be correlated with demand shocks in India or other parts of the world, confounding our estimates.

To tackle these issues we take a few concrete steps. With the help of granular data, we control for high-dimensional fixed effects that, for instance, account for changes in field-specific local demand or occupation-specific demand. We then leverage plausibly exogenous changes in the H-1B cap, or in the US demand for migrants, which are likely to be uncorrelated with unobserved confounders. We discuss other concerns, such as global shocks that affect occupational choice in India, and perform a series of checks with alternative instruments, specifications, and falsification tests that reinforce the validity of our approach.

Data: To convincingly implement these tests, we compile various sources of data. Data on Indian college enrollment by field and year, for the universe of colleges are not readily available (Sekhri, 2020). First, we digitize and code examination tables from the universe of registered colleges to obtain the number of exam-eligible, and exam-passed (in any year of enrollment) individuals by school, field of study, degree, and year. Such data is only available between 2000 and 2010. Second, we also compile aggregate data by state and field of study from the Ministry of Human Resources Development in India which is available from 1992 to 2010. Third, we obtain the universe of LinkedIn profiles across the world. This data, assembled by data provider Revelio Labs, has detailed work histories (job title, job spell, locations, and firm information), and education histories (degree, location, field of study, college name). We use these data to document which colleges and regions from India are migrants in the US coming from, and then also study the occupation choice of Indians working in India. Appendix A.2 describes the education data, while Appendix A.3 describes the LinkedIn data in detail and compares it with nationally representative data from the American Community Survey (ACS) (Amanzadeh et al., 2024). While not all migrants have a LinkedIn profile, we show that we cover over 60% of those studying computer science and engineering. In later sections, we also show results using the nationally representative National Sample Survey (NSS) from India. We augment these data with various other sources, including micro-level data from other destination countries (like the UK and Canada), patenting data, trade flows data, and the US Census and American Community Survey (ACS).

3.1 Education responses to US demand

To better describe our variation, we first begin our analysis at the state-by-time level. In Figure 4a, we split regions into four quartiles of baseline migration intensity to the US. We define migration intensity as the ratio between the number of Indian migrants in the US who graduated from a university in the state before 1990 (measured by LinkedIn) relative to the total enrollment in the state in 1992. Between 1998 and 1999, the US raised the H-1B cap, and we find that initial growth in response to the H-1B program was from the most exposed regions.[1] Yet, once the IT boom spreads to India in the mid-2000s, Engineering enrollment in other regions also grow.

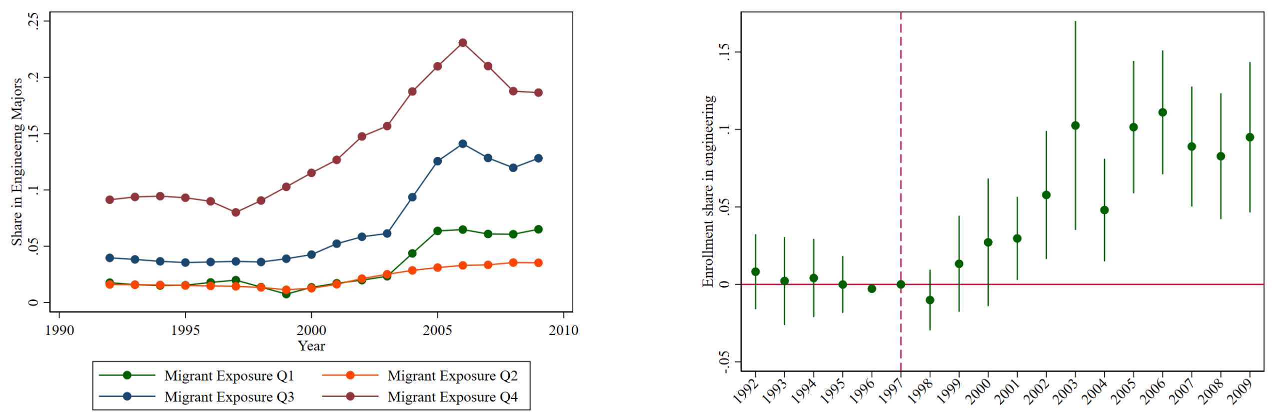
To better isolate these impacts, we estimate a regression where our outcome is the share of total enrollment that is in Engineering, by state and year. On the right-hand side, we interact a state-level measure of migration exposure (a binary variable that takes the value of one if the state had positive migration intensity in 1992) with year indicators, control for state and year fixed effects, and cluster errors at the state level. In Figure 4b, we plot the coefficients on the interaction terms between year indicators and our binary migration exposure.

The major increase in the H-1B cap was between 1998 and 1999, and in the figure we see a corresponding increase in the share of total enrollment that was in Engineering. The next major decrease in the cap was between 2003 and 2004, and we see a temporary differential fall in enrollment. Yet, as we argue, since the IT boom spreads to India, enrollment stays fairly stable thereafter, rather than falling all the way back to zero.

Figure 4: Change in Engineering Enrollment By Baseline Migration Exposure

(a) Enrollment in CS by Migration Exposure Quartile

(b) Differential Engineering Enrollment Growth by Migration Exposure



Notes: Data from LinkedIn (for migration exposure), and from the Ministry of Human Resources Development (for enrollment by major and state). The left panel splits the sample into 4 quartiles of migration exposure. The right panel estimates the differential impact of non-zero exposure over time, relative to 1997. The regression is at the state-by-year level, include state fixed effects and year fixed effects, and standard errors are clustered at the state level. While the H-1B cap was changed in various years, one big increase occurs between 1998 and 1999, and a decrease occurs between 2003 and 2004. Data details are in Appendix A.2.

We then bring in more granular data at the school-by-major-by-year level, to study whether changes in US immigration policy impacted the education choices of Indian students. Our goal is to quantify how the choice of field of study in India responds to immigration incentives from the US. Yet, a simple correlation between migrating to the US and education decisions in India may

[1] We do not have data going back to the 1980s for enrollment, else we would test if the introduction of the H-1B program also affected enrollment.

be confounded by various factors. For instance, local demand for certain skills in India may be correlated with migrant flows to the US, and this local demand may be driving education decisions. Or, individual preferences for certain majors in India may drive major choice. Subsequently, an increase in individuals with these skills will lead to more emigration to the US of such individuals. This would be a case of reverse causality.

To credibly examine the relationship between migration probabilities and education decisions in India, we obtain two new databases: First, we obtain college-by-degree-by-field-by-year level government reports on end-of-year examinations, for registered colleges and universities in India between 2000 and 2010. While reports for 2006 to 2010 are available at the school level online, we digitized reports from 2000 to 2005 obtained from Indian ministries. The final data consists of 437 colleges across 10 fields of study to create a new database of examinations. These numbers are for all years of the degree (whether they are first-year or final-year students). We take a one-year lead of this variable, as enrollment decisions may take time to affect the number of students. We show robustness to alternative lead structures.

Our second new database is data from the universe of LinkedIn profiles for Indian migrants to the US. These profiles report school, field of study, and graduation year. We use the universe of LinkedIn profiles of users who graduated from an Indian university before 2000 and eventually migrated to the US to construct school-by-field level migration exposure. We estimate the following specification using these data:

$$Ln(\mathrm{N}_{s(r)f,t+1}) = \beta_1 \Big((\text{Mig exposure}_{s(r)f}) \times Log(\text{Mig Demand}_t) \Big) + \delta_{s(r)f} + \delta_{s(r)t} + \delta_{frt} + \varepsilon_{s(r)ft} \quad (1)$$

Here, $N_{srf,t+1}$ is the number of students in school s, located in region (state) r, field of study f, and year $t+1$. We also look at the alternative outcome of number of students from s,r,f who pass their annual exams in $t+1$. The Mig Demand$_t$ is a variable that calculates migrant demand from the US. We operationalize this time-shifter in two ways. First, we use only changes in the policy-determined annual H-1B cap. Second, we use the annual number of high-skill work visas granted to non-Indians (including renewals), so as to capture the annual demand for migrants from the US.

The changes in the cap and migrant demand are likely to have bigger impacts on schools-by-majors with relatively more alumni in the US. These are schools-by-majors that will be known to US employers, and with the help of alumni network, facilitate the hiring of workers to the US. As a result, we may expect that changes in the probability of migrating would have a bigger impact on those schools-by-majors. We interact the changes in demand with a measure of Mig exposure$_{s(r)f} = \frac{\text{N grads from s(r)f before 2000 in US}}{\text{Enrollment in s(r)f in 2001}}$. We convert this to standard deviation units.

Despite the fact that we derive variation from the cap changes, we iteratively control for various fixed effects, to account for various possible confounders. These include school-by-field fixed effects $\delta_{s(r)f}$, school-by-time fixed effects $\delta_{s(r)t}$, and field-by-region-by-time fixed effects δ_{frt}. This is a fully saturated model, that accounts for changes in local demand for certain majors over time, baseline

Table 1: The Effect of the H-1B cap on Enrollment in Majors

	Log(Enrolled)				Log(Passed Exams)			
Migration Exposure X Log(H-1B Cap)	0.174***	0.121***			0.172***	0.125***		
	(0.0639)	(0.0447)			(0.0643)	(0.0348)		
Migration Exposure X Log(Non-Indians)			0.139***	0.0976***			0.139***	0.102***
			(0.0494)	(0.0343)			(0.0489)	(0.0258)
Observations	8,421	7,649	8,421	7,649	8,421	7,649	8,421	7,649
R-squared	0.914	0.950	0.914	0.950	0.874	0.920	0.874	0.920
School-by-Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field-by-Year FE	Yes	No	Yes	No	Yes	No	Yes	No
State-by-Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Field-State-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
School-Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Enrollment is the number of students eligible to appear for an examination in school s, located in state r, studying in field f, and year $t+1$. Passed exams is the number of students passing the examinations in school s, located in state r, studying in field f, and year $t+1$. Migration exposure is defined as the number of pre-2000 graduates from school s and field f working in the US, divided by the total enrollment at school s and field f in year 2000. The H-1B cap is the annual policy-determined cap. Non-Indians is the number of high-skill work visas granted (including renewals) to workers from all other countries in the world, excluding India. Data for the migration exposure are from the universe of LinkedIn users that studied in India, and work in the US. Data on examinations are from annual Indian Government reports. Data details are in Appendix A.2. Standard errors clustered at the school level. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

links at the school-field level, and growth in enrollment at specific universities, among other things.

Table 1 shows that, even with a stringent fixed-effects specification, increases in the H-1B cap, lead to differential increases in enrollment in schools-by-fields that had stronger links to the US. In Appendix Table B1, we show robustness to alternative lead structures.

One core assumption is that the cap changes are not driven by preferences of Indian students. Figure 2b shows the changes in caps that occurred over our period of analysis, likely reflecting political bargaining in the US Congress. The cap was raised substantially with the help of a series of Acts between 1998 and 2001, signed by President Clinton. It was lowered in 2004 by President Bush, with separate provisions for those with graduate degrees from the US. Unlike other work that leverages changes in the cap to study outcomes in the US (Kerr et al., 2015; Kerr and Lincoln, 2010), we need weaker identification assumptions as our outcomes are in India. We do not expect cap changes to be associated with either shocks to supply-side preferences in India, nor with demand in India that is not from the US. All these results show that as the probability of migrating to the US increases, there is an increase in enrollment in colleges and fields that are more strongly connected to the US.

3.2 Occupational responses to US demand.

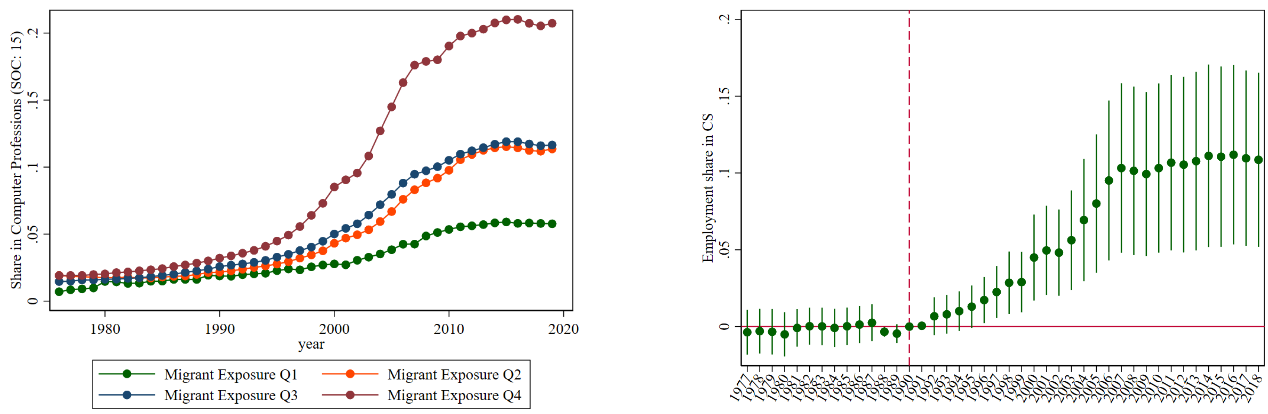
Next, we examine the occupation changes in India in response to changing US migration prospects. The advantage of the LinkedIn data is we see work histories for workers, including where and when they worked, and job titles. We classify job titles into 6-digit Standard Occupation Codes (SOC), and define CS occupations as those with the first two digits being '15.' The advantage of these data are that, we can study the pre H-1B era, and isolate the impact of the introduction of the H-1B program.

In Figure 5a, we first show trends over time at the state-by-year level, by CS migration exposure, as measured by the 1990 share of CS in the US from that state. After the H-1B program was introduced, there was steady growth in individuals choosing to be CS professionals in India, differentially so in regions with a higher baseline (pre-1990s) migration exposure.

Figure 5: Change in CS Employment By Baseline Migration Exposure

(a) CS Employment Share by Migration Exposure Quartile

(b) Differential CS Employment Growth by Migration Exposure



Notes: Data from LinkedIn. The left panel splits the sample into 4 quartiles of baseline (pre-1990) migration exposure. The right panel estimates the differential impact of above mean baseline exposure over time, relative to 1990. The regression is at the state-by-year level, and standard errors are clustered at the state level. The H-1B program was started in 1991. While the H-1B cap was changed in various years, one big increase occurred between 1998 and 1999, and a big decrease occurred in 2004. Data details are in Appendix A.3.

Figure 5b shows the analogous regression plot, with state and year fixed effects, and errors clustered at the state level. After the H-1B program was introduced, there was a steady differential growth in CS employment in exposed regions. When the H-1B cap had its largest increase in 1999, there was a slight differential jump as well. And a few years after the cap was lowered, this differential growth flattened out. Again, even though it levels out, the effects did not fall back down to zero, as the boom had spread to India by then.

Next, we put together more granular data, at the state-by-year-by-occupation level. We study whether the emigration of Indians to the US in particular occupations o induced Indians who had not yet migrated to choose such occupations. A standard immigration model that ignores endogenous occupational choice driven SOC by immigration would predict pure brain drain in India, such that a stronger US demand for migrant workers in occupation o would reduce the number of workers in India in o. Yet, with endogenous occupation choice, more demand in the US for occupation o can potentially increase the supply of occupation o in India, as workers choose occupations that may help them migrate in the future. We estimate the following specification:

$$Ln(\mathrm{N}_{ort}) = \beta_2 \left((\text{Mig exposure}_{or}) \times Log(\text{Mig Demand}_t) \right) + \delta_{or} + \delta_{rt} + \delta_{ot} + \varepsilon_{ort} \quad (2)$$

Here, N_{ort} is the number of workers working in occupation o, region (state) r, and year t. This specification is similar to before, with the exposure now being calculated at the occupation-by-region level. For the migration exposure, we take all the Indian migrants in the US by occupation, and measure their last reported work or study location (state) in India, as long as it was before 1990. We convert this into standard deviation units for ease of interpretation. The migrant demand shifters are, as before, changes in the H-1B cap, or the number of non-Indian H-1Bs (including renewals) granted.

The set of fixed effects helps account for meaningful confounders that may be associated with local demand (rather than US demand) for certain occupations, or with coincident local changes to supply and preferences (unrelated to US demand). For instance, certain regions may have a higher propensity to hire in certain occupations δ_{or}, or worker preferences for certain jobs may vary across regions δ_{or}. Certain regions may just be growing faster, either because of more local firm growth, or changes in worker preferences δ_{rt}. Similarly, overall demand for certain occupations might be changing by year δ_{ot} (e.g., other types of demand shocks for Indian CS or Indian doctors).

Like before, we assume that the exogenous variation in cap changes by the US Congress, are unlikely to be driven by occupation-specific shocks to the Indian labor market and worker preferences. Since our specification includes occupation-region, occupation-time, and region-time fixed effects, the remaining variation is primarily coming from the changes in the cap over time, reweighted by the baseline occupation migration propensities. Indeed, since the cap is not occupation-specific, we believe such variation to be more exogenous to underlying changes in occupation-specific demand. The shares capture the propensity of Indians to be differentially represented in certain occupations and regions at baseline, so these occupations are more likely to respond when faced with time-varying shocks to the propensity to migrate.

Table 2 describes the occupation response in India. Changes in migrant demand from the US (measured via the policy-set H-1B cap or the number of non-Indian H-1Bs) has a differential response to local Indian employment by baseline migration exposure. Places with stronger connections to the US before the H-1B program started, see larger increases in local employment, whenever the cap changes (either increases or decreases).

We further see that this response is stronger among younger cohorts (graduated from college in 1990 or after), than among older cohorts (graduated before 1990, before the H-1B). Indeed, the smaller response among older cohorts supports our identification assumptions, as we are unlikely to be picking up overall increases in local demand as the driving factor. We would expect the young to be more responsive to migration prospects, and older cohorts less responsive. We revisit this age heterogeneity when describing the model, and then our model validation importantly replicates our empirical brain gain elasticities by cohort.

In Section 5.4, we reproduce our main results using the nationally representative NSS survey. Finally, in Appendix Table B2, we explore the role of the changing earnings for migrants in the US. That is, we reformulate our demand shock from abroad, to take into account not only the probability of migration but also the occupation-specific wages in the US. This augments our primary specifica-

Table 2: Occupational Response in India to the H-1B Cap

	Log(Employment)					
	All	Young	Old	All	Young	Old
Migration Exposure X Log(H-1B Cap)	0.00778**	0.0187***	0.000675			
	(0.00373)	(0.00580)	(0.00204)			
Migration Exposure X Log(Non-Indian H-1Bs)				0.0524***	0.101***	0.00509**
				(0.00955)	(0.0126)	(0.00226)
Observations	283,133	89,533	45,287	234,369	77,682	35,930
R-squared	0.987	0.977	0.982	0.990	0.981	0.985
State-by-Occ FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occ-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Employment is the number of persons employed by state-occupation-year in India. We use the LinkedIn data to create retrospective work histories for all individuals, and job spells. Migration exposure is defined as the number of workers from an Indian state-and-occupation who migrated to the US before 1990. We normalize this variable into standard deviation units. The H-1B cap is the annual policy-determined cap. Non-Indians is the number of H-1Bs granted (including renewals) to workers from all other countries in the world, excluding India. Data for the migration exposure are from the universe of LinkedIn users that either ever worked or studied in India, and then work in the US. We define young and old based on year of graduation (when reported). 'Young' are workers who graduated after 1990, while 'Old' graduated before 1990 (before the H-1B program). Data details are in Appendix A.3. Standard errors clustered at the state level. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

tion above, which leveraged only baseline the share of migrating. The results in Table B2, suggest that accounting for wages does not affect our primary elasticity estimates of the labor-response with respect to the probability of migrating.

3.3 Robustness and Threats to Identification

Our identification assumptions rely on the fact that, conditional on high-dimensional fixed effects, the changes in the H-1B cap were not influenced or correlated with other confounders.

US Congress is unlikely to be influenced by the preferences of Indian students, and so such supply-side factors may be less of a concern. Since we include field-by-state-by-time, school-by-time, and school-by-field fixed effects, it would have to be that students from a particular school-by-field influence Congress over time. It is unlikely that the political wrangling in the US on the H-1B cap changes resulted from college major-choice in India. Indeed, as we intimate in Section 2 and Appendix E, the fledgling Indian IT sector was still nascent and local CS wages low, when the US innovation boom happened and drove up-skilling in India (Figure 3). Yet, in the enrollment regressions, we control for state-major-time fixed effects to absorb any such shocks.

On the demand side, one may question whether the H-1B cap changes are themselves correlated with shocks to the US economy. This does not raise identification concerns *per se*, as we do want variation from the US economy (whether business cycle changes or policy shocks, or a combination), to drive the demand from the US. Figure 2b suggests that sometimes these forces may move in opposite directions – for instance, the cap increase coincided with the 2001 dot-com bust.

One may also be concerned that demand for workers from the US is also correlated with demand for workers from other destinations (e.g., the UK or Canada), altering the interpretation of the estimated elasticity. We examine this possibility in detail in Appendix B.1, where we combine microdata from other non-US destinations, and show that the demand from firms in other parts of the world plays a negligible role. In Figures B1a and B1b, it is clear that even in 2012, when other countries have had time to develop their IT sectors, the US swamps overall demand when compared to the UK or Canada. As expected, in 2000, when only the US IT sector was developed, the scale of the difference in the demand for IT from the US was many magnitudes larger than the UK (Figure B1c).

While not a traditional shift-share, we do benefit from recent insights from the shift-share literature (Adao et al., 2019; Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020). We confirm that our specification favorably fits certain guidelines and recommendations suggested by such recent work. In incorporating occupation-by-region fixed effects, we already control for the baseline shares, and rely on the time-varying (H-1B policy) shocks for identification. And in controlling for local demand shocks, we control for local confounders. Unlike other work on migration, (Card, 2001), our outcomes and explanatory variables are based on datasets from different parts of the world, preventing mechanical biases, and necessitating weaker identification assumptions (Jaeger et al., 2018).

While the advantage of LinkedIn data is that it is high-frequency, and tracks the entire work history of cross-border migrants, it is not necessarily representative of the full population. The object of our study, however, is high-skill workers, who are on the margin of choosing between CS and non-CS occupations, and are so likely to be on LinkedIn. In Appendix A.3, we compare the data to other sources, and show that along with fairly wide coverage, summary characteristics seem to look similar to representative surveys. In excellent new work, Amanzadeh et al. (2024) argue that the LinkedIn data does a good job of representativeness, especially for high-skill migrants. We should note that, since we are not relying on new individuals joining LinkedIn every year, but rather on the full reported retrospective work history (as of 2023), we are not concerned about yearly variation in costs and incentives to be online (e.g, internet coverage).

Finally, we re-do our analysis using the nationally representative National Sample Survey (NSS). While the NSS is the largest survey done in India, representative at the state level, and has excellent information on wages and earnings, it has a two drawbacks. First, the large rounds are held approximately every five years, and so annual changes are harder to detect. Second, it does not have information on migrants to the US (unlike the LinkedIn data). In Section 5.4, we reproduce our main results using the NSS survey for local employment outcomes, but the LinkedIn data for migration exposure. We estimate the brain gain employment elasticity with respect to expected earnings in the US (i.e., local log employment as a function of log Indian migrant earnings in the US), and show that our model estimates the same elasticity by cohort, as in our empirical estimation.

4 Model

Our model consists of two main parts: in Section 4.1, we model the labor supply decisions of college graduates in both the US and India, and in Section 4.2, we discuss how goods are produced and sold to consumers in each country, and the rest of the world. In the product market, firms and consumers make static decisions each period conditional on the parameters of the model, and the availability of each type of labor in the economy. The college labor market has 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. Workers in India are uncertain on whether they will get a slot to migrate when making their occupational choices, which opens up the possibility of brain-gain. In Section 4.3, we describe the equilibrium.

4.1 The Supply of Workers in India and the US

Workers in India and the US work for a finite number of periods N and are either high-skilled (college graduates) or low-skilled (non-college graduates), denoted by $H_{t,k}$ and $L_{t,k}$ respectively, where k represents country and t time. We focus on the decision of college graduates to work as computer scientists ($CS_{t,k}$) or in some other college-graduate occupation ($G_{t,k}$). [2]

We allow for two types of decisions for college graduates. First, before joining the labor market, students choose whether to enroll in CS or non-CS fields of study, which influences their initial occupation after graduation. Second, workers choose every period between working in CS or another occupation. We group non-CS occupations together despite the heterogeneity across jobs: we capture this heterogeneity through the differences in abilities and tastes for each occupation.

Some Indian CS have the opportunity to migrate every period to work in the US as computer scientists ($CS^f_{t,k}$). The number of Indian migrants depends on the US migration policy cap each period (cap_t) and their ability to draw in CS. Once in the US, migrants can choose whether they want to stay working in the US, or return to India and work as computer scientists ($CS^r_{t,k}$) until they retire.

We assume workers in both countries have perfect foresight on the evolution of the migration cap and wages across countries and occupations. While Indian CS who never migrated know that every period, they will participate in a lottery that can give them a chance to emigrate, the key uncertainty (when making their occupation decisions) is whether they will effectively get one of the capped slots. Figure C1 summarizes the timing of the decisions each period.

We present equations for Indian workers and omit country subscripts for simplicity. The decisions for the US-born are a subset of Indian workers' decisions, as US-born only choose between CS and non-CS, but do not migrate. All supply-side parameters are country-specific.

[2] In our baseline framework, we assume that the decision to attend college is made outside the model. We consider the marginal computer scientist's main choice to be between CS and other college-graduate occupations instead of between CS and not going to college. In Section 7.3, we show that quantitatively, our results change very little when adding an endogenous college decision.

At the start of their studies, college graduates draw an ability for each occupation o, $\phi_{o,i}$ from independent Normal distributions with mean $\mu_{\phi,o}$ and variance $\sigma_{\phi,o}$, which they carry with them throughout their careers.[3] Individual i's decision problem, before joining the labor market is:

$$\max_{cs,g}\left\{\underbrace{\rho\mathbb{E}_t V^{cs}_{i,t+1}(\phi_{o,i})}_{\text{future payoff of joining as CS}} + \underbrace{\bar{F}}_{\text{education cost}} + \underbrace{\sigma_\eta \eta^{cs}_{i,t}}_{\text{preferences}},\quad \underbrace{\rho\mathbb{E}_t V^{g}_{i,t+1}(\phi_{o,i})}_{\text{future payoff of joining as non-CS}} + \underbrace{\sigma_\eta \eta^{g}_{i,t}}_{\text{preferences}}\right\} \tag{3}$$

Individuals compare the expected future payoffs of joining the labor force next period with a CS degree $V^{cs}_{i,t+1}$ with the future payoff of joining with some other college degree $V^{g}_{i,t+1}$. We set the discount factor ρ to 0.9 throughout the paper. Such choices are also affected by a fixed education cost for studying CS, $\bar{F}$, which can be positive or negative, and idiosyncratic taste shocks for studying each field: $\eta^{cs}_{i,t}$ and $\eta^{g}_{i,t}$.[4] We assume that $\eta^{cs}_{i,t}$ and $\eta^{g}_{i,t}$ are independently and identically distributed as a standard Type I Extreme Value distribution (Rust, 1987). The parameter σ_η controls the sensitivity of major and occupation choices to preference shocks. A smaller σ_η implies small changes in career prospects, generating larger variation in the number of students graduating with CS degrees. Enrolling in a CS major allows individuals to first join the labor force as CS, while non-CS majors begin their careers in non-CS occupations.

Once they join the labor market, at the start of each period, individuals choose to work in CS or another occupation to maximize the expected present value of their lifetime utility. We denote occupational choice as $o = \{cs, g\}$ in equation 4:

$$V^{o}_{i,t,a} = \max_{o}\left\{\underbrace{w^{o}_{t}\times\phi_{o,i}}_{\text{current wage}} + \underbrace{\chi(a)\times\mathbb{1}(o_t \neq o_{t-1})}_{\text{switching cost}} + \underbrace{\zeta\times\mathbb{1}(o_t = g)}_{\text{distaste for CS}} + \underbrace{\rho\mathbb{E}_t[V^{o}_{i,t+1,a+1}]}_{\text{future payoffs}} + \underbrace{\sigma_\eta\eta^{o}_{i,t}}_{\text{preferences}}\right\}, \tag{4}$$

where $V^{o}_{i,t,a}$ is the value of starting in occupation o in period t at age a. At the beginning of each period, individuals learn their period-specific preference shock and decide whether to switch occupations, taking into account their expected lifetime stream of income. ζ is the taste attractiveness parameter for not working as a computer scientist, and $\chi(a)$ is the age-dependent monetary cost of switching occupations. For simplicity, we assume switching costs are linear in age: $\chi_0 + (\chi_1 \times age)$, to capture that switching can become harder as workers get older. In the model, all workers retire after working N periods. The wage that worker i receives for working in occupations o is the wage per effective unit paid for that occupation in a given country w^{o}_{t} times the individual ability draw for that occupation.

The ability draws are constant throughout individual careers, while idiosyncratic preference shocks are drawn every period. Hence, heterogeneity in abilities will act as an additional friction,

[3]The heterogeneity in abilities in our model is similar to Dix-Carneiro (2014).

[4]The fixed cost for getting a CS major $\bar{F}$ captures the taste frictions faced by college goers that potentially deter them from choosing CS degrees despite CS having higher relative wages.

reducing occupation switching over time, while heterogeneity in preferences will induce more two-way switching after individuals take a new draw every period.

After each period of CS work in India, workers participate in a lottery to migrate and work as computer scientists from the next period onward. Since the outcome of the lottery is uncertain when making occupation decisions, the future payoff of choosing a CS occupation becomes a weighted average between the future payoffs of working in India and the future payoffs of working in the US:

$$\mathbb{E}_t[V^{cs}_{i,t+1,a+1}] = \mathbb{E}_t[\underbrace{p_{i,t+1} \times V^{cs,us}_{i,t+1,a+1}}_{\text{Payoff migrate}} + \underbrace{(1-p_{i,t+1}) \times V^{in}_{i,t+1,a+1}}_{\text{Payoff stay}}] , \tag{5}$$

where the value function of working in US, $V^{cs,us}_{i,t+1,a+1}$, is defined in equation 7. The value function of staying in India, $V^{in}_{i,t+1,a+1}$, is the same as in equation 4. The migration probability, $p_{i,t+1}$, is:

$$p_{i,t+1} = \bar{p}_{t+1} \times F(\phi_{cs,i}) , \tag{6}$$

where we parameterize the probability as a Normal distribution function $F(\phi_{cs,i})$ evaluated at individual i's ability draw in CS, and re-weighted by parameter $\bar{p}_{t+1}$. Intuitively, $F(\phi_{cs,i})$ makes more able individuals have a higher probability of migration and $\bar{p}_{t+1}$ ensures that when we add all probabilities of migration across individuals we get the current migration cap, cap_{t+1}. A simplification of our model is that Indian CS workers will always migrate for at least one period if given the chance to do so. As long as there is a large wage premium in the US, and the H-1B cap is small relative to the total number of CS in India, it is reasonable to assume that there will always be enough workers who want to migrate for at least one period.

Once in the US, Indian migrants can either choose to stay working as CS in the US until they retire or return to India, to work as a return computer scientist. The future payoff of migrating is:

$$\begin{aligned} V^{us}_{i,t+1,a+1} = \max\{ & \underbrace{w^{cs,us}_t \times \phi_{cs,i}}_{\text{wage in US}} + \underbrace{\rho\mathbb{E}_t[V^{us}_{i,t+1,a+1}]}_{\text{future payoffs}} + \underbrace{\xi^{us}_{i,t}}_{\text{preferences}} , \\ & \underbrace{w^{cs,r}_t \times \phi_{cs,i}}_{\text{wage in India}} + \underbrace{\bar{\Lambda}}_{\text{Home taste}} + \underbrace{\rho\mathbb{E}_t[V^{cs,r}_{i,t+1,a+1}]}_{\text{future payoffs}} + \underbrace{\xi^{cs,r}_{i,t}}_{\text{preferences}} \}, \end{aligned} \tag{7}$$

where $V^{cs,r}_{i,t+1,a+1}$ is the future payoff of returning to India and working as a returned CS until retirement. Parameter $\bar{\Lambda}$ represents the average preference for being at home, which also captures the stringency of the US migration system for granting green cards to Indian workers. Finally, $\xi^{x}_{i,t}$ are iid standard Type I Extreme Value distribution preference shocks that capture individual-specific tastes for working in the US and India.

For US workers, the structure of the model is identical to the one presented above with the exception of emigration. All parameters in the labor supply model will be calibrated separately for

US and Indian workers. The labor supply parameters jointly determine the dynamic elasticity of occupational choices with respect to wage: the short-run labor supply curve may be inelastic, but as more students choose majors, the long-run elasticity can be higher.

4.2 Product Market

4.2.1 The Household Problem

We close the model by specifying how consumption, production, and trade occurs. Consumers in each economy supply one unit of labor, and have the same preferences over final good Y, which has Constant Elasticity of Substitution (CES) form over different varieties $v \in [0,1]$.[5]

$$Y = \left(\int_0^1 y_v^{\frac{\iota-1}{\iota}} dv \right)^{\frac{\iota}{\iota-1}}, \tag{8}$$

where ι 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. Access to more varieties at lower prices (say, as IT production expands) raises consumer welfare.

A consumer's labor income is spent on these goods as there are no savings. Consumers maximize utility subject to a budget constraint, where expenditure equals wage income. While consumers have identical consumption preferences, they do not receive the same labor income as they work in three different occupations (CS, non-CS graduates, and non-graduates).

4.2.2 Final Goods Production

Each firm producing variety v in the final goods sector (subscript y) has Cobb Douglas constant returns to scale technology over intermediate inputs from the IT sector $C_{v,y}$, and a labor aggregate, with Cobb Douglas parameter γ. Each variety is produced with productivity $z_{v,y}$:

$$y_v = z_{v,y} C_{v,y}^{\gamma} \left(\left[\alpha (\ell_{v,y})^{\frac{\tau-1}{\tau}} + (1-\alpha)(h_{v,y})^{\frac{\tau-1}{\tau}} \right]^{\frac{\tau}{\tau-1}} \right)^{1-\gamma} \tag{9}$$

The IT good is an input in final goods production; importantly, this implies that innovation in IT can increase productivity in other sectors of the economy.[6] Following the framework introduced by Eaton and Kortum (2002), each producer has a different level of efficiency in producing each variety, denoted by $z_{v,y}$. The final goods sector employs low-skilled non-college graduates $\ell_{v,y}$, and an aggregate of high-skilled college graduates $h_{v,y}$, with an elasticity of substitution τ between them, and a distributional parameter α.

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

[5] Since the product market is static and that the structure is the same across countries, we omit country and time subscripts k and t for convenience, but all endogenous variables and parameters are time and country-specific. The production function elasticities are constant and common for both countries.

[6] A major component of US productivity growth is attributable to industries that use IT as an input (Jorgenson et al., 2017), such as financial services, motor-vehicle manufacturing, and scientific production.

tion 10, where $cs_{v,y}$ is the number of CS hired in the final goods sector, and $g_{v,y}$ is the number of non-CS graduates hired in the final goods sector. The elasticity of substitution between CS and non-CS college graduates is λ.

$$h_{v,y} = \left[\delta \left(cs_{v,y}\right)^{\frac{\lambda-1}{\lambda}} + (1-\delta)\left(g_{v,y}\right)^{\frac{\lambda-1}{\lambda}}\right]^{\frac{\lambda}{\lambda-1}} \tag{10}$$

This complementarity ensures that as the US hires more CS workers (say, from abroad), it raises the demand for non-CS occupations (like managers), tending to raise the non-CS wage. This may induce native CS workers to switch to other occupations, mitigating negative wage impacts. At the same time, skill-biased technical change towards CS workers δ, or towards college graduates $(1-\alpha)$, shift over time with the innovation boom.

In both countries, the total number of computer scientists is also a CES aggregate of two distinct types of labor. In the US, we assume CS are a composite of native-born and foreign-born CS:

$$cs_{v,y} = \left[\left(cs^n_{v,y}\right)^{\frac{\upsilon-1}{\upsilon}} + \left(cs^f_{v,y}\right)^{\frac{\upsilon-1}{\upsilon}}\right]^{\frac{\upsilon}{\upsilon-1}}, \tag{11}$$

where $cs^n_{v,y}$ and $cs^f_{v,y}$ are the number of effective units of native- and foreign-born CS, respectively. By considering imperfect substitutes, even within occupation, we follow the literature on immigration where its been documented that immigrants focus on more analytical tasks and natives tend to specialize in communication-intensive tasks (Burstein et al., 2020; Peri and Sparber, 2011).

In India, we assume CS workers are a CES aggregate of native CS (cs^n) and return CS (cs^r) as in equation 12:

$$cs_{v,y} = \left[\left(cs^n_{v,y}\right)^{\frac{\varepsilon-1}{\varepsilon}} + \left(cs^r_{v,y}\right)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}} \tag{12}$$

Native and return-migrant CS workers are not perfect substitutes, as return migrants have different sets of skills given their work history abroad. ε is the elasticity of substitution between the native CS workers and return migrants.

The first-order conditions determine the demand for intermediate IT inputs and the different types of labor in the final goods sector. Together with the demand for labor from the IT sector, we derive the aggregate labor demand for each worker.

4.2.3 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. Firms in the final goods sector have preferences over different types of IT goods c_j, such that:

$$C_y = \left(\int_0^1 c_j^{\frac{\iota-1}{\iota}} dj\right)^{\frac{\iota}{\iota-1}} \tag{13}$$

IT firms have CES technology in the labor aggregate (equation 14), where $cs_{j,c}$ is the number of CS and $g_{j,c}$ non-CS college graduates employed by IT firm j. Here λ is the elasticity of substitution between CS and non-CS college graduates, and $\delta + \Delta$ is the distributional CES parameter. $\Delta > 0$ as IT is more intensive in CS than the final goods sector. In the US, CS in the IT sector are a composite between immigrants and natives as in equation 11. For India, $cs_{j,c}$ is the CES composite between native and return computer scientists as in equation 12.

$$c_j = z_{j,c} \left[(\delta + \Delta) \left(cs_{j,c} \right)^{\frac{\lambda-1}{\lambda}} + (1 - \delta - \Delta) \left(g_{j,c} \right)^{\frac{\lambda-1}{\lambda}} \right]^{\frac{\lambda}{\lambda-1}} \tag{14}$$

4.2.4 International Trade

We model the world economy as a set of three regions: the United States, India, and the rest of the world (RoW), with preferences and production as described in Sub-sections 4.2-4.2.3. Although we focus on India and the US, we incorporate the RoW to capture how India and the US compete in the world market and how they have the option of buying and selling products to a third region. While workers in the RoW produce and consume both final goods and IT goods, we simplify the analysis by assuming they do not receive or send CS migrants.[7]

All three regions trade both goods (final and IT) following the standard framework of Eaton and Kortum (2002), where each region has 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 $F_{s,k}(z)$, where productivity $z_{j,s,k}$ is from a Frechet (Type II extreme value) distribution:

$$F_{s,k}(z) = e^{-T_{s,k} z^{-\theta}} \tag{15}$$

Here $\theta > 1$ governs the dispersion of the productivity draws across varieties. Higher $T_{s,k}$ increases the likelihood of drawing higher efficiencies for good j, and is the technology level for each country-sector pair. If the US has higher $T_{s,k}$, the US is more efficient at producing more varieties in sector s on average, even as India and the RoW will be efficient at producing certain varieties in the sector. Innovation by CS workers shifts out the distribution, raising $T_{s,k}$.

Consumers in each country buy each variety from the lowest-price producer. If a consumer in b buys from k, they pay an iceberg-trade cost $d_{b,k}$. All else equal, a country becomes a more attractive provider of the good whenever their prices are lower as a consequence of one of three things: an increase in the technology (that allows for better draws of $z_{s,k}$), a decrease in trade costs $d_{b,k}^s$, or a decrease in labor costs $(w_{\ell,k}, w_{g,k}, w_{cs,k})$.

Such features of our model will be relevant to capture the empirical patterns shown in Figure 3b: 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. Since varieties may be produced in any part of the world and imported, restricting immigration to the US may affect growth in the US IT sector and lead

[7] Figure B1 describes the relatively negligible skilled migration from India to non-US destinations. In recent years, the role of third countries might have become more important as documented by Brinatti and Guo (2024).

to certain varieties being produced in other countries. At the same time, more migration raises the prospect of migrating from India; which increases the size of the Indian CS workforce, potentially shifting some production from the US to India.

We capture the possibility of firms from country b outsourcing production to k, reflected by more exports from k to b. US-owned firms producing and exporting from India count towards Indian production and exports. The same is true for Indian-owned firms in the US.[8]

Importantly, we model 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 (Kerr and Lincoln, 2010). This can potentially raise wages on average and can mitigate the depression in CS wage growth due to immigration. Since IT output is an intermediate input into the final goods sector, technological advances can increase the productivity of other downstream sectors of the economy as well.

Innovation depends on the number of CS workers in the IT sector. The 'brain drain' of CS workers to the US is countered by the 'brain gain' of workers acquiring CS skills with the prospect of migrating. As we show later, the brain gain makes the Indian IT sector more productive and, over time, the leading exporter of IT.[9] We parametrize IT sector productivity in country k to be a function of the total number of CS IT workers in country k:

$$T_{c,k} = \bar{T}_{c,k} CS_{c,k}^{\beta} \;\; for\, k = \{us, in\}\,, \tag{16}$$

where $\bar{T}_{c,k}$ is baseline IT technology in country k, and $CS_{c,k}^{\beta}$ is the endogenous technology component. β is the elasticity of technology level to changes in CS IT workers in country k.

Brain-gain vs brain-drain: Overall, the model allows for either brain-gain or brain-drain in response to an increase in the migration cap. The net effect will depend on the quantification. On one hand, if the responsiveness of Indian CS to changes in the migration probability is high, then there will be a larger influx into the CS occupation in India relative to those who leave. On the other hand, if the responsiveness of labor supply is limited, not enough Indians will work as CS in response to an increase in the cap. The responsiveness of CS supply will depend on the supply elasticity of enrollment, the supply elasticity of occupation choice, and the supply elasticity of return migrants. In Section 5.4, we show that for our preferred calibration, India experiences a brain-gain when migration policy expands.

4.3 Equilibrium

Equilibrium in each period is a set of prices and wages ($P_{t,c,k}$, $P_{t,y,k}$, $w^{\ell}_{t,k}$, $w^{g}_{t,k}$, $w^{cs}_{t,k}$), quantities of output and labor ($C_{t,y,k}$, $Y_{t,k}$, $L_{t,k}$, $G_{t,k}$, $CS_{t,k}$), and level of technology ($T^{s}_{t,k}$) such that: (1) consumers

[8] Morales (2023) explores the implications of US high-skill immigration policy on multinational activity.

[9] Here we address a growing literature on technological diffusion and directed technological change within the Ricardian framework (Alvarez et al., 2013; Dasgupta, 2012; Kerr, 2018; Perla et al., 2021; Somale, 2021).

in all countries, maximize utility by choosing $Y_{t,k}$ taking prices as given, (2) college graduates in the US and India choose their major and occupations, taking wages as given, (3) firms in both the IT and the final goods sector maximize profits taking wages and prices as given, (4) trade between the three regions is balanced, and (5) output and labor markets clear. In Appendix C.2, we describe in detail the equilibrium equations regarding trade, occupation choice, and the price index.

5 Empirically Determining the Model's Parameters

Here we describe how we use data to determine the parameters of the model for the period 1995 to 2010. We map each period in the model as a 5-year period in the data (1995, 2000, 2005, 2010). We assume students choose their majors at age 20 and join the labor force at age 25. Then they work for 8 periods until age 65, when they retire.[10]

To make the exposition transparent, we separate this process into three building blocks of parameters: 1) product market elasticities: τ, λ, ε, ι, θ, ν and β; 2) time-varying product demand parameters: $\delta_{k,t}$, $\alpha_{t,k}$, $T^s_{k,t}$, $d^s_{k,b,t}$, $\gamma_{k,t}$, $\Delta_{t,k}$, the labor quantities and the migration cap; and finally, 3) the elasticity of labor supply of college graduates in the US and India determined by labor supply parameters: $\Theta = \{\sigma_{\eta,k}$, ζ_k, $\chi_{0,k}$, $\chi_{1,k}$, $\bar{F}_k$, $\mu_{\phi,o,k}$, $\sigma_{\phi,o,k}$ and $\bar{\Lambda}\}$ for $k = \{us, in\}$.

The solution algorithm consists of the following steps: first, we estimate product market elasticities, and set some to values estimated in the literature (Block 1). Second, we guess the labor supply elasticity parameters $\hat{\Theta}_{guess}$ and discipline the time-varying product demand parameters to match trends in wages and productivity that reflect the skill- / sector-biased technological change that occurred (Block 2). Once all product market parameters are determined, we solve for equilibrium, conditional on the labor supply parameters being $\hat{\Theta}_{guess}$. Finally, we construct a series of targeted data moments related to the labor supply. Our algorithm repeats the process iteratively, searching over the labor supply parameters until the distance between predicted and observed data moments are minimized (Block 3). In Section 5.1 - 5.3, we discuss the estimation of each block in detail.

5.1 Product Market Elasticities

As a first step, we determine the product market elasticities. We set the elasticity of substitution between college and non-college graduates, $\tau = 1.7$, based on papers that estimate the parameter (Card and Lemieux, 2001; Goldin and Katz, 2007; Katz and Murphy, 1992), and we explicitly estimate it using data from India.[11] For elasticities of substitution between CS and non-CS college graduates, we

[10]The 5-year period decision is mainly due to the NSS in India being available roughly every 5 years until 2005 and every 2 years after that. We describe in detail the US and India datasets in Appendix A.

[11]We replicate Card and Lemieux (2001) using the India data and estimate an elasticity of complementarity of 0.55 (see Table C1). 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 noncollege graduates, our estimates are indistinguishable from our assigned value of τ.

set $\lambda = 2$, which is within the estimates of Ryoo and Rosen (2004) and Burstein et al. (2019).[12] To determine the substitution elasticity between CS who never emigrated, and those who return from the US, we follow the literature on return migration. We may expect this elasticity to be greater than the elasticity between CS and non-CS graduates. In our steady-state year, we match the average premium of 15% across papers in this literature, corresponding to a value of $\varepsilon = 30$.[13] For the substitution between varieties in each country, we follow Bernard et al. (2003), who estimate the elasticity of substitution across US plants to be 3.79 and set $\iota = 4$. For the trade elasticity, we use $\theta = 8.28$, proposed by Eaton and Kortum (2002). We set the the elasticity of substitution between natives and immigrants, υ, to 10 following Burstein et al. (2020).[14]

Finally, for the elasticity of technology with respect to the number of CS working in IT, we estimate $\beta = 0.228$. As we elaborate on in Appendix C.4, we use an instrumental variable strategy together with variation in patenting across industries in the US to identify this parameter. We use an instrument that interacts the industry-specific dependence on immigrant CS workers at baseline with the US's total number of immigrant CS each year. Our instrument leverages variation in US immigration policy (like changes to the H-1B cap), sending country shocks, and the fact that immigrants are more likely to be CS. Importantly, our estimated elasticity is very close to other work.[15]

5.2 Time-varying Product Market Parameters

For a given guess of the labor supply parameters $\hat{\Theta}_{guess}$, we discipline the time-varying product demand parameters such that we match observed trends in relative wages, trade flows and production shares. A detailed summary of our data sources can be found in Appendix A. The time-varying parameters γ_k, $\alpha_{t,k}$, $\delta_{t,k}$, $\Delta_{t,k}$, $T^s_{t,k}$ and $d^s_{t,k,b}$ are calibrated separately for 1995, 2000, 2005 and 2010 for each country. Here we just mention what trends we are explicitly matching, and in Appendix C.5 we document details on the implementation.

To calibrate the Cobb Douglas parameters γ_k we match the share of income from the final goods sector spent on varieties of the IT sector for each country. The share parameter of non graduates in the production function, $\alpha_{t,k}$, is determined in both India and the US such that it matches the observed share of expenditures from the final goods sector in non-college graduates. The distributional parameter between CS and non-CS college graduates $\delta_{t,k}$ is calibrated to match within-country relative wages between CS and non-CS college graduates in the data. The additional distributional parameter in the

[12] Ryoo and Rosen (2004) estimate the elasticity of substitution between engineers and other graduates to be 1.2 - 2.2. Burstein et al. (2019) estimate an occupational elasticity of substitution between 1.81-2.1.

[13] Work on return migrants finds that in other contexts, those who emigrated for work and return home earn a wage premium relative to those who never migrate (Barrett and O'Connell, 2001; Hazans, 2008; Reinhold and Thom, 2013).

[14] When looking at educated workers, Ottaviano and Peri (2012) find an elasticity of substitution of 12.6. Burstein et al. (2020) estimate a within-occupation elasticity of 5.6 and an overall elasticity of 10.1.

[15] Peri et al. (2015) estimate a 1% increase in the US STEM workforce increased TFP by 0.27%, whereas Kerr and Lincoln (2010) find patenting elasticities that lie between 0.1 and 0.4. In our earlier work, Bound, Khanna, and Morales (2016), we estimate an elasticity of 0.23 from how the price of IT goods change with changes in the CS workforce. In recent work, Khanna and Lee (2018) we find an elasticity of 0.2 using measures of innovation derived from Schumpeterian growth. In Section 7.2, we discuss how our results change for different values of β, including when there is no spillover in India and no spillover in both countries.

IT sector $\Delta_{t,k}$ captures the extra intensity of CS in the IT sector. We calibrate $\Delta_{t,k}$ to be proportional to $\delta_{t,k}$ every period such that it matches the within-country relative share of CS between the IT and non-IT sector in 1995. To estimate the productivity levels ($T^{s}_{t,k}$) and bilateral trade costs ($d^{s}_{t,k,b}$) for each country-sector pair, we use trade data and match the observed trade flows every year. Finally, for relative technology in the non-IT sector between India and the US, we calibrate $\left(\frac{T^{y}_{t,in}}{T^{y}_{t,us}}\right)$ such that we match relative wages of non-graduates between India and the US.

We also calibrate the total quantity of college and non-college workers in each country using population statistics. We use information on new-Indian immigrants to the US to calibrate the migration cap under the real scenario.

5.3 Dynamic Labor Supply Identification

We are now ready to estimate the labor supply parameters $\hat{\Theta}$, which determine the dynamic elasticity of labor supply. Every year, the labor demand curve for the US and India shifts due to changes in technology and production function parameters as in Section 5.2. Such exogenous innovation shocks capture skill-biased and sector-biased technological progress that shift out the relative demand curve for CS. These exogenous shifts in labor demand allow us to trace out the (dynamic) labor supply curve, and identify the underlying labor supply parameters.

We use a minimum distance estimation technique (McFadden, 1984) where we identify the labor supply parameters $\hat{\Theta}$ jointly using specific moments of the data. Let the product market parameters in Sections 5.1 and 5.2 be $\hat{\Omega}$. We calculate a vector of targeted moments predicted by the model, $m(\hat{\Omega}, \hat{\Theta}_{guess})$, using parameters $\hat{\Omega}$ and labor supply guess $\hat{\Theta}_{guess}$. The algorithm searches over $\hat{\Theta}$ such that it minimizes the distance between the targeted moments predicted by the model and their empirical counterparts as in equation 17:

$$\hat{\Theta}^{*} = \min_{\Theta} \left(m(\hat{\Omega}, \Theta) - m(Data)\right)' W \left(m(\hat{\Omega}, \Theta) - m(Data)\right) \ , \tag{17}$$

where $m(Data)$ are the empirical counterparts of the targeted moments and W is the weighting matrix. $\hat{\Theta}$ is composed of fifteen parameters: the taste dispersion parameters $\sigma_{\eta,k}$, the mean tastes for non-CS occupations ζ_k, the occupation switching costs $\chi_{0,k}$, $\chi_{1,k}$, the education costs for CS $\bar{F}_k$, the ability dispersion for each occupation $\sigma_{\phi,o,k}$, and the average value of returning to India $\bar{\Lambda}$.[16]

To separately identify each parameter, we choose fifteen moments that are differentially affected by each of the parameters, such that the solution of equation 17 yields parameters that minimize the distance between the simulated and data moments. For both India and US we choose the following moments: the share of workers in CS in 1995 and 2010; the ratio between the CS share among those between 25-30 years relative to 31-60 years old in 2010; the net occupation switching rate between 1995 and 2000, and the ratio between the CS aged 45-60 years relative to 31-60 years old in 2010;

[16] We normalize the mean ability dispersion $\mu_{\phi,o,k}$ to 0 as it cannot be separately identified from mean occupation tastes ζ_k. The difference in average wages across countries will be pinned down by the difference in technology and production function parameters.

Table 3: Empirical vs. Simulated moments

	US		India	
	Data Moments	Simulated Moments	Data Moments	Simulated Moments
Share CS 1995	2.9%	2.9%	0.1%	0.1%
	[2.6%-3.2%]		[0.04%-0.12%]	
Share CS 2010	4.4%	4.4%	3.1%	3.0%
	[4.1%-4.7%]		[2.5%-3.6%]	
Transition rate 95-00	1.7%	1.7%	0.1%	0.02%
	[1.3%-2.1%]		[0.1%-0.2%]	
Ratio CS Share [25-30]/[31-60] 2010	1.06	1.00	3.72	4.22
	[0.83-1.29]		[2.3-5.1]	
Ratio CS share [45-60]/[31-60] 2010	0.86	0.84	0.19	0.07
	[0.79-0.93]		[0.06-0.31]	
Coeff Variation CS wage 1995	0.41	0.41	0.36	0.48
	[0.37-0.44]		[0.25-0.47]	
Coeff Variation Other wage 1995	0.64	0.63	0.62	0.62
	[0.63-0.65]		[0.60-0.64]	
Avg Return rate 95-10			13%	14%
			[1.7%-17%]	

Notes: Simulated method of moments results comparing empirical moments to data moments. 'Share CS' is the share of the college graduate workforce that is in CS.'Transition rate' is defined as the net occupational switching rate between CS and non-CS occupations. 'Ratio CS Share [25-30]/[31-60]' is the relative share of CS workers in age group 25-30 and those in age group 31-60. 'Ratio CS Share [45-60]/[31-60]' is the relative share of CS workers in age group 45-60 and those in age group 31-60. 'Coeff Variation' stands for the ratio of the standard deviation of wages in each occupation relative to its mean. Avg return rate is the average rate of return for Indian college graduates in the US. 95% confidence intervals for empirical moments are in parenthesis.

the standard deviation of wages in occupation in each occupation and country relative to its mean in 1995. The final moment we target is the average return rate for Indian college graduates in the US.

While our system uses all empirical moments together to simultaneously identify the parameters, there is strong intuition behind the identification of each parameter. The CS share in 1995 and 2010 help identify both, the mean taste for non-CS ζ_k and the dispersion parameter $\sigma_{\eta,k}$. A higher ζ_k will make CS less desirable and lower the average CS share. The change in the CS share between 1995 and 2010 helps identify $\sigma_{\eta,k}$, since a higher $\sigma_{\eta,k}$ means that individuals assign high weights to the idiosyncratic preference shocks they receive every period, making them less responsive to changes in the relative wage. The ratio of the CS share between those aged 25-30 relative to those 31-60 helps identify the education costs $\bar{F}_k$, since a higher ratio implies that it is easier to join CS occupations at the initial period (paying the education cost) than later by switching occupations. The net switching rate will primarily identify the switching costs $\chi_{0,k}$, since high switching costs are expected to decrease switching both in and out of CS. The ratio of the CS share between those aged 45-60 relative to those 31-60 will help identify the age-specific component of the switching rate captured by parameter $\chi_{1,k}$. The standard deviation of wages relative to its mean help identify the dispersion of abilities by occupation $\sigma_{\phi,o,k}$. Finally, the average return rate for college graduates helps pin down the average taste for returning to India $\bar{\Lambda}$. In Appendix Table C3, we corroborate that these moments are particularly responsive to their respective parameters.

We construct the fifteen data moments using predominantly the CPS and the NSS for the US and India, respectively. We consider the CS share as the total number of CS workers relative to the total number of college graduates in each country, excluding the Indian migrants from both India and US shares. For the relative CS shares between age groups, we compute the CS share for each age group and take the ratio. For the switching rate, we use net flows by cohort between 1995 and 2000, calculated by adding the absolute value of net flows across each cohort and taking the ratio with respect to the sum of the net stayers across each cohort. The coefficient of variation is calculated by computing the standard deviation and mean of wages for each occupation and country.

Finally, the average return rate is computed using the LinkedIn data. We restrict the sample to those who did their undergraduate degrees in India, have some work experience in the US, and report a location of their work experience in every position. We then calculate the average of the fraction of those present in the US in 1995, 2000, and 2005 that report a position in India five years later.[17]

The equation 17 routine minimizes the distance between simulated and empirical moments. The model is perfectly identified (fifteen data moments to identify fifteen parameters). Table 3 shows the predicted moments match the empirical data moments closely.

The estimated labor supply parameters are in Table 4. As expected, there is a positive mean taste for non-CS occupations in both countries, which explains the positive CS wage premium. Switching costs in India are higher than in the US, which capture the observed pattern that Indian workers mostly join CS through the college pipeline and have limited occupation switching throughout their careers. Age-specific switching costs, however, are higher in the US. Education costs for CS relative to 'Other' are small for both countries, but the estimates are positive for the US and negative for India. This parameter captures that conditional on the observed relative wages, studying CS is less costly than studying other occupations in the US, while its slightly more costly in India. The ability dispersion parameters are higher in both countries for the 'Other' occupation than for CS, which captures the larger degree of heterogeneity on the jobs under Other occupations. Finally, the average taste for returning home is positive, meaning that Indian workers get a positive utility premium from choosing to return.

Together, the parameters estimated in this section determine the dynamic labor supply elasticity in each country. We represent this elasticity in Figure 6, where we artificially raise the CS wage in the US or in India by 1% starting in 1995, and estimate the labor supply response over time. In the short run, labor supply is less responsive, as few shift into CS. But over the longer run, as more and more students major in CS, and more workers switch into CS, the labor supply curve becomes more elastic. Estimating this dynamic labor supply elasticity is an important contribution of our work: previous reduced-form estimates in some of the literature are often estimating a static elasticity and, as such, providing a limited picture of the long-run labor-supply response.

Short-run labor supply elasticity in the US is 3.25, while in the long-run, we estimate the US occupational elasticity to be 4.15. Ryoo and Rosen (2004) estimate the supply of engineers relative to

[17]The estimated return rate is consistent with the 5-year return rate for Indians estimated by Amanzadeh et al. (2024).

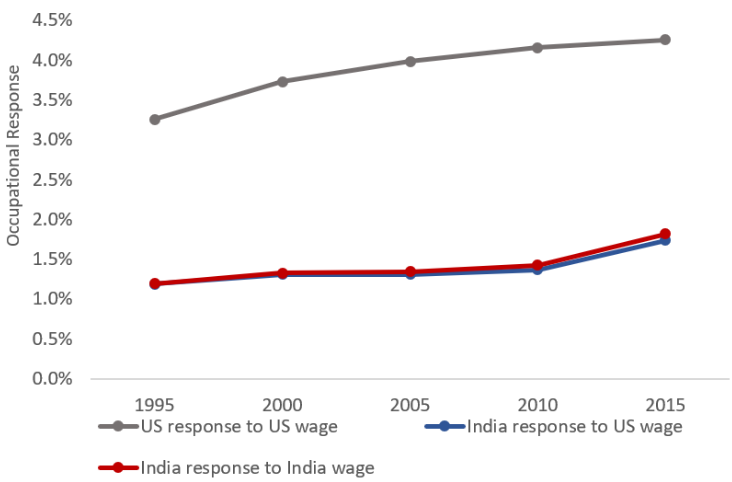
Table 4: Labor supply parameter estimates

	Parameter	US	India
Mean taste for non-CS occupations	ζ_k	0.52	0.50
		[0.47, 0.56]	[0.43, 0.56]
Preference dispersion parameter	$\sigma_{\eta,k}$	0.28	0.098
		[0.26, 0.30]	[0.09, 0.11]
Education cost for CS degrees	$\bar{F}_k$	0.033	-0.0515
		[0.030, 0.037]	[-0.056, -0.047]
Occupation switching costs	$\chi_{0,k}$	-0.42	-1.63
		[-0.46, -0.38]	[-1.82, -1.43]
Age-specific switching cost	$\chi_{1,k}$	-0.022	-0.000052
		[-0.023, -0.020]	[-0.000057, -0.000048]
Variance CS ability	$\sigma_{\phi,cs,k}$	0.435	0.37
		[0.38, 0.49]	[0.32, 0.42]
Variance Other ability	$\sigma_{\phi,oth,k}$	0.603	0.581
		[0.55, 0.65]	[0.53, 0.63]
Mean taste for home	$\bar{\Lambda}$	-	0.287
			[0.26, 0.31]

Notes: Estimated labor supply parameters based on the simulated method of moments exercise. These parameters jointly determine the short-run and long-run labor supply elasticities. 'Mean taste for non-CS' is the average preference for non-CS occupations. 'Preference dispersion' is the variance in tastes for occupations. 'Switching costs' are occupation switching costs between CS and non-CS occupations. 'Education cost for CS' is the average cost / non-preference for CS degrees. All costs and tastes in units of the numeraire (consumption basket). 'Variance CS/Other ability' is the ratio of the standard deviation of wages in that occupation relative to their mean. 'Mean taste for home' is the average preference for returning to India. Confidence intervals for parameters are calculated through a bootstrap (with replacement) using 50 repetitions.

other graduates to be between 2.5 and 4.5, which covers both our short and long-term elasticities. As shown in Figure 6, Indian college graduates respond to both changes in the US and Indian wages in a similar magnitude. Overall labor supply in India goes from 1.19% in the first year to 1.42% in 2010.

Figure 6: Dynamic occupation choice in response to wages: permanent increase in CS wage



Notes: Graphs show the dynamic labor supply response to a 1% permanent increase in the US or Indian CS wages since 1995. The short- and long-run response depend on the labor supply parameters estimated in Table 4.

5.4 Model Fit

To evaluate the fit of our model, we run two exercises and compare our simulated results with features from the data as out-of-sample tests.

First, we can compare how India's CS supply responds to increased immigration prospects in our model with empirical evidence that is un-targeted in the estimation. For the empirical evidence, we use the nationally representative National Sample Survey (NSS) in India. We need to estimate the brain gain response to expected earnings in the US. Our outcome (as in the reduced-form results of Section 3.2) is simply the number of workers in India, in state r, occupation o, and year t. Our coefficient of interest is on the Indian migrant earnings in the US term, which captures the expected returns to migrating to the US. This term increases if there are more Indian migrants in a certain occupation and/or the earnings of that occupation increases.

$$Log(\text{Emp in IN})_{rot} = \beta Log(\text{IN Migrant Earnings in US})_{rot} + \delta_{ro} + \delta_{o't} + \delta_{rt} + \gamma X_{ort} + \varepsilon_{rot} \quad (18)$$

A standard immigration model that ignores endogenous occupational choice driven by immigration would predict pure brain drain in India, $\beta < 0$, such that a stronger US demand for migrant workers in occupation o would reduce the number of workers in India in o. Yet, with endogenous occupation choice, more demand in the US for occupation o can potentially increase the supply of occupation o in India, as workers choose occupations that may help them migrate in the future, $\beta > 0$. Our goal is to estimate the elasticity of local occupational choice with respect to US demand, β. Yet, not adequately accounting for the other components will bias our estimates of β.

As before, we condition on state-by-year fixed effects, state-by-occupation fixed effects, and broad occupation-by-time fixed effects. This model controls for all factors related to local growth, time-invariant state comparative advantages in certain occupations, and other occupation-specific demand shocks. The set of fixed effects helps account for meaningful confounders that may be associated with local demand (rather than US demand) for certain occupation, or with coincident local changes to supply and preferences (unrelated to US demand). For instance, certain regions may have a higher propensity to hire in certain occupations, or worker preferences for certain jobs may vary across regions. Certain regions may just be growing faster, either because of more local firm growth, or changes in worker preferences. To further address this issue, we also control for two region-occupation-time specific demand sources in X_{ort}. The first one is a Bartik-style demand control where we interact the share of employment in an occupation-region pair that goes to a given industry in 1994 with the national level growth in employment of that industry at time t. The second one interacts the initial share of an occupation-region pair in a given industry with the share of US imports of that industry in time t that comes from India. Details on the data used for this section can be found in Appendix A.5 while details on the controls and implementation can be found in Appendix C.7.

To isolate the demand-from-abroad channel, we construct different instruments that leverage changes in US visa policy, and demand for different types of migrants by occupation. Our aim is to derive variation from either US policy changes, or from US occupational-specific demand, that are not correlated with supply-side changes in India or demand from other destinations.

$$\text{Instrument}_{ort} = \underbrace{\frac{(\text{N Indians in US})_{or,1990}}{(\text{N Indians in US})_{1990}}}_{\text{Migration Exposure}} \times \underbrace{(\text{Demand from US})_{ot}}_{\text{Time Shifter}} \tag{19}$$

Our demand shifters depend on changes to the H-1B cap, or US demand for non-Indian migrants by occupation (e.g., whether the US demands more doctors from Pakistan in that year). We assume that the exogenous variation in cap changes by the US Congress, are unlikely to be driven by occupation-specific shocks to certain specific regions of the Indian labor market and worker preferences. We describe in detail how we define these variables in Appendix C.7.

The top two panels of Table 5 show the IV-2SLS results documenting similar brain gain responses as in Section 3.2, but using the 5-yearly nationally representative NSS data. In the bottom panel, we compare our empirical results to the model-implied elasticities as a validation check.

While our model is simpler than our empirical setup (e.g., it has no regions, only CS can migrate), we can construct an analog of these elasticities for comparison. We change the H-1B cap in our model by 1% and compute the occupation choice response in India. In Table 5, we show that the labor supply elasticities to migration between the empirical exercise and the model are quite close. The model also replicates the empirical pattern where young workers are the most responsive to immigration when compared to older workers who almost do not respond to US labor migration prospects.

In Appendix C.7, we conduct three types of robustness checks. First, in Table C4, we test for baseline correlations between our migration exposure (at occupation-by-region level) measure, and various other characteristics. We find balance in 1994 characteristics from the nationally representative NSS data. Next, in Table C5, we show how the independent variable of interest, is not correlated with baseline education and labor market characteristics. Finally, in Figure C2, we check the sensitivity of our elasticity estimates to dropping one state at a time, and one occupation at a time.

Our second validation test, tests for model fit on relative wages. In the estimation exercise, we explicitly match certain data points or trends, but a key moment we do not target is the relative wage for CS and other college occupations between the US and India, which influences the decision of Indian workers to choose CS with the prospects of migrating. In Figure 7, we show that we match fairly well the level and trend relative wages across countries.

6 Counterfactual Exercises

Policymakers often debate changing the H-1B cap, and recent political debates focus on restricting the number of H-1B visas. To evaluate the impact of the H-1B program on the US and Indian economies, we conduct counterfactual exercises where we first reduce the migration cap by 50% every year since 1995.[18] With a lower cap, some workers who may have been granted visas to the US are now forced to work in India. We look at the changes in going from the counterfactual scenario with limited

[18] In our model, we only allow for migration of Indian workers to the US. Hence, we calibrate the cap with the number of Indians that came to the US under the H-1B program every period.

Table 5: Comparing model and reduced-form elasticity to migration

Log(Workers in India)	Empirical Brain-Gain Elasticity					
	All		Young		Old	
	H-1B Policy Cap Instrument					
Log(IN Migrant's US Earnings)	0.565***	0.894**	0.779***	1.360***	0.108	-0.734
	(0.149)	(0.377)	(0.158)	(0.483)	(0.269)	(0.789)
KP F-stat	24.35	6.435	24.26	6.309	20.74	4.379
	Migrant Demand Instrument (Non-Indians)					
Log(IN Migrant's US Earnings)	0.534***	0.640***	0.638***	0.780***	0.360*	0.166
	(0.107)	(0.159)	(0.107)	(0.169)	(0.197)	(0.303)
KP F-stat	51.28	30.03	50.67	29.33	37.76	20.61
Observations	1,937	1,937	1,937	1,937	1,582	1,582
State-by-Occ FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Broad Occ-by-Year FE	No	Yes	No	Yes	No	Yes

	Model-implied Elasticity		
	All	Young	Old
Log(IN Migrant's US Earnings)	0.592***	0.614***	0.021***
	(0.011)	(0.013)	(0.004)

Notes: $***p < 0.01, **p < 0.05, *p < 0.1$. All coefficients can be read as the change in labor supply in India for occupation o of a 1% increase in the earnings of new migrants in occupation o. In the model, by assumption, we only allow CS to migrate. The first two columns look at the effect on all workers, columns 3 and 4 look at those with ages below 40 years of age, columns 5 and 6 look at those above 40 years of age. The top panel uses the instrument of the cumulative H-1B cap as the shifter. The middle panel shows the results using the non-Indian migrant employment by occupation in the US. The bottom panel calculates the change in the stock of CS in India in response to a 1% change of the migrant wage bill in the US after an exogenous change in the H-1B cap.

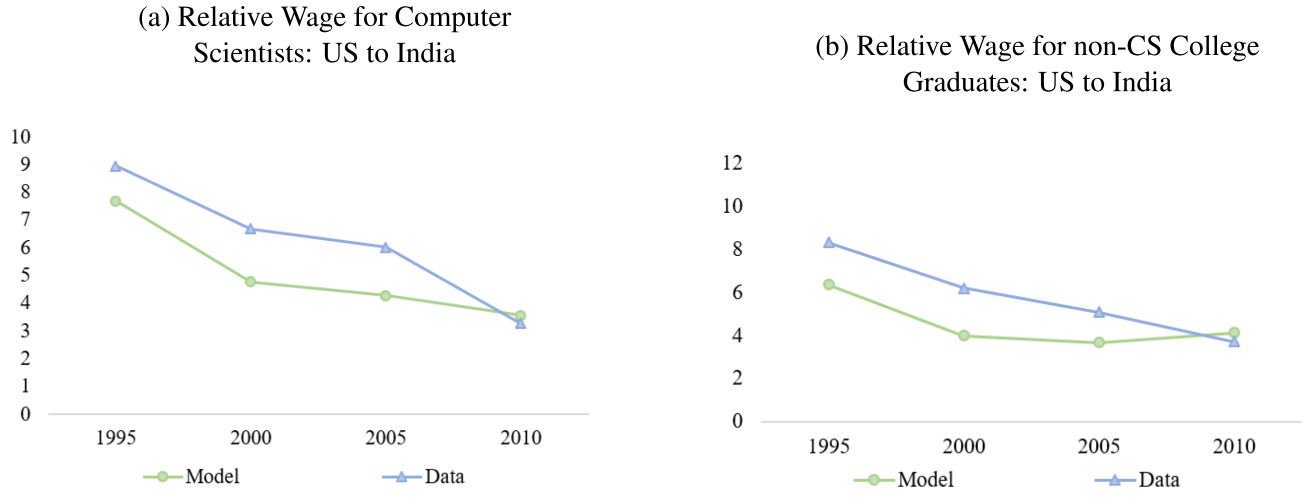
migration (50% of the cap) to the real scenario where migration is as observed in the data. Hence, we refer to the impacts as a result of 'increased migration,' or simply migration under the H-1B program.

Our attempt is to empirically resolve theoretical ambiguities. Some of these ambiguities include whether the effects of brain drain outweigh brain gain, whether wage gains due to innovation overcome wage depression due to an influx of workers, and whether immigration allows the US IT sector to grow or instead facilitates the shift in production to India.

6.1 Baseline results

Figure 8 and Column 1 of Table 6 describe our baseline results. As we show in Figure 8a, when going from the counterfactual to the real scenario, the total number of CS migrants in the US (mechanically)

Figure 7: Model fit on relative wages across countries



Notes: Figures plot the simulated model output and the actual data for the endogenous variables of interest. We plot the relative wages for CS (left panel) and non-CS (right panel) college graduates between the US and India. For data sources please refer to Data Appendix A

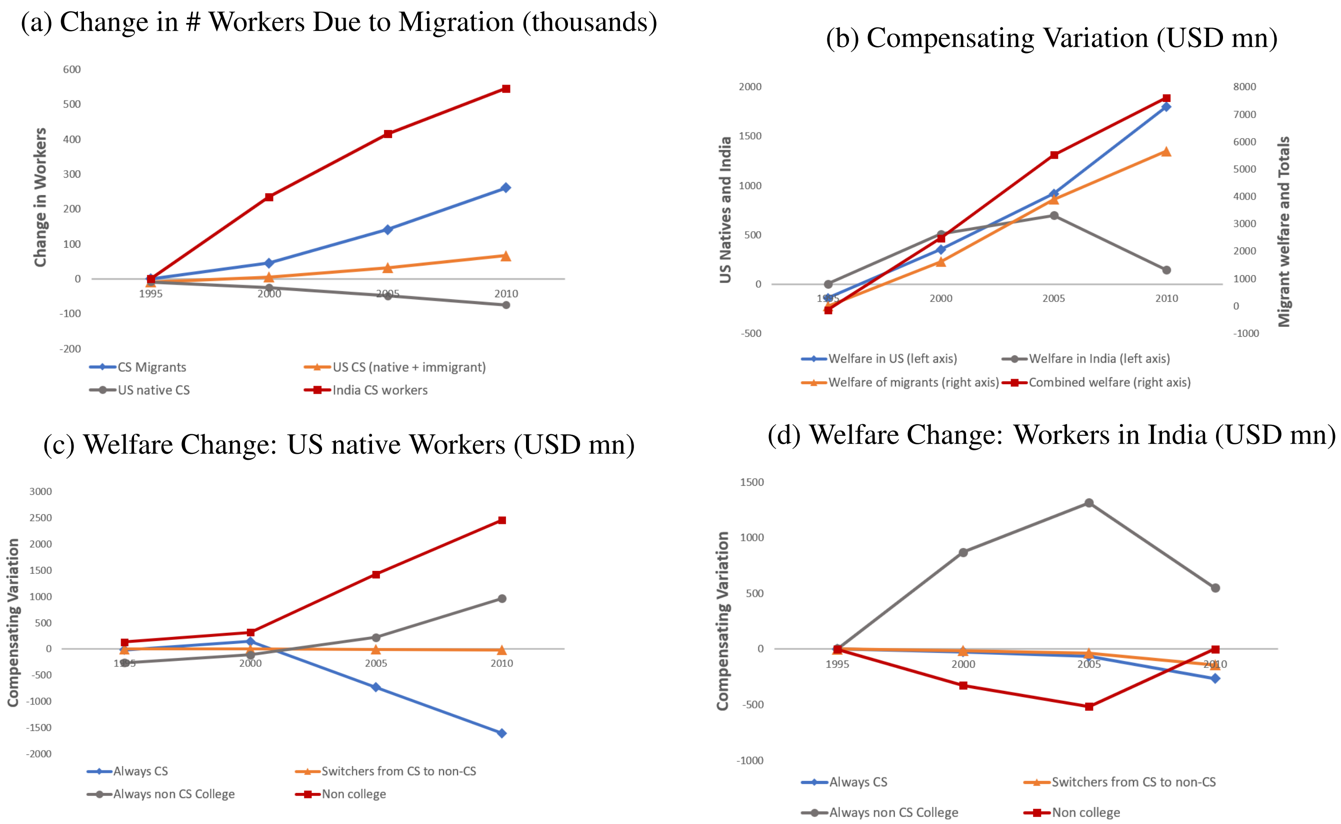
increases by more than 45,000 by 2000 and by over 260,000 in 2010. The increase in migration of CS drives down CS wages in the US, leading more than 75,000 US-born CS to switch to non-CS occupations by 2010. In India, college graduates respond to the migration incentives by switching to CS occupations. While some migrate many others stay in India, increasing the number of CS in India by more than 513,000 workers by 2010.

Both the US and India increase the total number of CS, an occupation complementary to non-CS college graduates and high-school graduates. In addition, CS workers have a spillover effect that benefits all workers, making total net welfare gains positive for both countries, as shown in Figure 8b. Welfare for US natives increases by $1.8 billion by 2010, while Indian natives who stay in India gain $159 million when migration to the US increases. In Appendix Table D1, we summarize the distributional gains and losses per migrant for each group of workers. In 2010, there is a net welfare gain to US workers of $13,031 per migrant, and of $1,119 per migrant to workers in India. If we also include gains to migrants themselves, overall net welfare increases by $55,038 per migrant.

The larger gains per migrant for the US are partly driven by the assumption that more skilled CS have higher probabilities of migrating. Hence, the US captures a larger share of the spillover through the migrants, while the new CS in India, who switch due to expanded migration, are lower-skilled on average. The hump-shaped pattern for India's compensating variation shown in Figure 8b can be explained by changes in magnitudes of two opposing effects. In the earlier periods, Indians motivated by migration start selecting into CS and working in India, increasing productivity domestically. As time goes by, getting a lottery slot gets harder given the large numbers of local CS, which makes migration play less of a role in welfare.

Even though natives from both countries benefit from migration, there are distributional gains

Figure 8: Effect of immigration on occupational choice and welfare



Graphs show the consequences of increase migration. The top left panel shows 'CS Migrants' as the difference in migration between the real and the counterfactual (restricted lower cap) scenario. The occupational choices in the top left panel are responses to this increased migration. The remaining panels show the compensating variation for agents due to a restriction in migration. Compensating variation is defined as the amount of USD that must be provided to agents in a world with restricted migration to provide them with the same welfare as in a world with H-1B migration.

and losses, seen in Figures 8c-8d and Appendix Table D1. Since the total number of CS in both countries increases, those already working in CS lose from migration (despite gains from innovation) as their wages decline with increased competition. The effect on non-CS college graduates differs by country. In the US, as the number of migrants increases, some college graduates working in CS switch to non-CS occupations. This creates two counteracting effects: on the one hand, the non-CS college graduate wage reduces due to increased competition. On the other hand, they gain due to complementarity with the new migrants. Their overall effect on welfare of non-CS college graduates is positive. In India, some college graduates switch into CS, leaving non-CS with fewer workers and increasing their wages and welfare. Non-college graduates in the US benefit from migration as prices are lower, and they are complements in production. In India, non-college graduates face two counteracting effects: They gain from the additional productivity from local CS but lose since the total number of graduates decreases in India (due to emigration). Overall, they lose in the earlier periods and slightly gain in the last period when the stock of CS in India is sufficiently high.

Accounting for the occupational response of US and Indian college graduates to changes in migration policy in the US is important to quantifying the gains and losses from migration. To see this, in Table 6 we compare the results between our baseline model (column 1), and alternative models that shut down the supply response in the US and India. Column 2 shows the results for a model where in-

Table 6: Effect of Migration in 2010: Baseline vs No Occupational Choice

		No occupational choice	
	Baseline	**In both countries**	**In India only**
Wages			
US CS workers	-0.64%	-2.40%	-0.54%
India CS workers	-12.27%	1.31%	1.47%
Occupational Choice			
US CS (native plus immigrant)	2.88%	6.72%	3.16%
US CS workers	-3.89%	-	-3.60%
India CS workers	42.23%	-	-
IT production			
US IT output	1.06%	3.84%	2.21%
India IT output	25.02%	-10.41%	-10.17%
Welfare			
Welfare of US natives	0.043%	0.061%	0.045%
Welfare in India	0.066%	-0.055%	-0.053%

Notes: Percent difference in main outcomes when we go from a scenario with restricted migration (counterfactual) to a scenario with full migration (real). In the counterfactual, the H-1B cap is reduced by 50% in every period, starting in 1995. 'No occupational choice in both countries' is a model where occupational choice is prohibited. 'No occupational choice in India only' is a model where occupational choice is only prevented in India.

dividuals in both countries cannot switch occupations, thus ignoring endogenous occupational choice in each country. Finally, column 3 shows the results for an alternative model where workers in the US are allowed to switch occupations but workers in India are not (and thereby, cannot respond to the increased prospect of migrating to higher wages abroad).

In our baseline model, 3.89% of US graduates in CS switch to other occupations when migration is increased, driven by a -0.64% reduction in the CS wage. In India, the total supply of CS increases (despite emigration) when migration is allowed. This increases the size of the Indian IT sector by 25.02%. The US IT sector increases by only 1.06% as natives switch away from CS, and there is increased competition from India for the world market. Welfare is higher by 0.043% for US natives, and by 0.066% for those working in India. The combined increase in welfare, including the welfare of migrants, is higher by 0.15% (Appendix Table D2).

In an analysis that did not allow for endogenous occupation choice in India (column 3), India would only experience brain drain as their CS leave the country, *lowering* IT output by 10.17%. As a consequence, the increase in total CS in the US would increase US IT output by 2.21%, a larger effect than in the baseline model, as the US captures the market that was satisfied by India. A model that ignores the supply response only in India has significant consequences for welfare. The total welfare of US natives due to immigration is 3.7% higher than in the baseline, while in India, welfare *decreases* by 0.05% as there cannot be brain gain when supply is fixed. When restricting occupational choice in both countries (column 2), total welfare in the US is 40% higher than in the baseline, as US CS cannot change occupations, and the US captures all the spillover created by CS innovation.

The results in Table 6 highlight the importance of the main mechanism introduced in this paper: taking into account supply responses in sending countries would predict an opposite effect for the sending countries like India, and mute the welfare effects of migration for the US.

7 Mechanisms and Alternative Specifications

Our model is comprehensive enough to capture the main channels through which migration affects both India and the US. We run several extensions to our model in order to tease out the mechanisms underlying our base specification, recalibrating the entire model to match the moments whenever applicable. First, in Section 7.1, we separate out the mechanisms underlying brain drain and brain gain. We additionally evaluate how our quantitative results change when we do not include the possibility of return migration. In Section 7.2, we explore the role played by endogenous technology by varying the technology elasticity, which is important to determine the welfare gains or losses for India. Finally, Section 7.3 discusses alternative modeling specifications, such as incorporating an endogenous college decision where workers choose to either go to college or join the labor market as high-school graduates. We also discuss alternative policies that include different migration caps, starting immigration restrictions in later periods, and changes in trade policy.

7.1 Brain Drain, Brain Gain and Brain Circulation

The baseline results in Section 6.1 include a combination of brain drain and brain gain for India. On the one hand, some CS leave for the US, driving brain drain. On the other, some graduates choose CS with the prospects of migrating but end up staying, generating a spillover effect and brain gain. To disentangle such effects, we compare the baseline with two alternative scenarios. First, we shut down India's occupational response to migration opportunities. While workers are still allowed to migrate, they do not take into account the possibility of migrating when choosing occupations, such that India experiences pure brain drain. As shown in Table 7 column 2, if Indians do not respond to migration incentives, the CS workforce in India decreases by 10.44% since some CS migrate and not many join the workforce. Net welfare gains from migration are larger in the US, but welfare falls in India, as India only experiences brain drain, and no brain gain, when migration is increased.

As a second exercise in Table 7 column 3, we remove the possibility of brain drain by shutting down migration but still allowing workers in India to choose occupations in response to the prospect of migrating (i.e., allowing brain gain). The CS workforce in India grows rapidly, and IT output expands by 26.08%. Such increases make the US IT sector shrink by 0.61%. When there is no brain drain, total welfare in India increases by 0.076% while decreasing in the US by 0.001%. In Appendix Table D3, we show how the brain drain and brain gain channels affect each of the different types of workers in the US and India.

Last, we examine the importance of return migration. In our modification, Indian CS migrants no longer have the choice to return to India and stay in the US until the end of their careers. As shown in Table 7 column 4, the US experiences larger welfare gains when there is no return migration. This is driven by two channels. First, the stock of migrants in the US increases more as they no longer

Table 7: Brain Drain vs Brain Gain: Main Outcomes

	Baseline	No occupational choice in India	No migration but reallocation	No return migration
Occupational Choice				
US CS (native plus immigrant)	2.88%	3.16%	-0.18%	2.59%
US CS native	-3.89%	-3.60%	-0.18%	-4.64%
India CS	42.23%	-10.44%	45.62%	19.33%
IT production				
US IT output	1.06%	2.21%	-0.61%	1.65%
India IT output	25.02%	-10.17%	26.08%	12.46%
Total Welfare				
US natives	0.043%	0.045%	-0.001%	0.053%
Welfare in India	0.066%	-0.053%	0.076%	0.037%

Notes: Percent difference in main outcomes when we go from a scenario with restricted migration (counterfactual) to a scenario with full migration (real). In the counterfactual, the H-1B cap is reduced by 50% in every period, starting in 1995. The 'no occupational choice in India' scenario shuts down occupational choice and inhibits 'brain gain' in response to migration opportunities but allows for emigration ('brain drain'). 'No migration but reallocation' restricts migration (no 'brain drain') but allows for responses to migration opportunities ('brain gain'). 'No return migration' shuts down the possibility of returning back to India.

return to India. The additional CS have higher ability units due to selective migration and create a larger innovation spillover benefiting all US workers. Second, India does not have the additional productivity effect provided by return migrants, which stymies the shift in IT production from the US to India. India experiences lower welfare increases than in the baseline, as now they have only one type of (never-emigrated) CS in the country.

7.2 Endogenous Technology and Innovation

The endogenous technology elasticity that we estimate in Section C.4 using an instrumental variables strategy has a value of 0.226, and is consistent with other values in the literature (Kerr and Lincoln, 2010; Khanna and Lee, 2018; Peri et al., 2015). However, the literature on immigration has found different results on the impact of immigrants on innovation. Bernstein et al. (2023) show that immigrants have a positive impact on innovation. Similarly, Kerr and Lincoln (2010), Hunt and Gauthier-Loiselle (2010) and Peri et al. (2015) find a positive effect of H-1B-like immigrants on patenting. Doran et al. (2022), on the other hand, finds the effect on patenting to be close to zero. To investigate how our conclusions change based on this parameter, we show in Table 8, our main results as we vary the parameter value all the way down to 0 (no endogenous technology). We also try a specification where technological spillovers are positive in the US and smaller in India, in order to capture the fact that the US may do more R&D than India.

Migration affects US welfare in similar magnitudes as we vary this parameter. Yet, India is adversely affected when there are no innovation spillovers from CS workers (columns 2 and 3). In such a scenario, many Indian graduates switched to CS with the prospect of migrating, but were unable to migrate due to the cap. There is, therefore, a suboptimal oversupply of CS workers, but no gains from innovation, lowering welfare. For the same reason, when spillovers are lower (columns 4 and 5) than the baseline scenario, there is still a negative welfare impact for India, as CS contribute less to innovation. Also, due to selective migration, India loses high-ability CS while marginal CS

Table 8: Varying the Elasticity of Endogenous Technological Spillovers

	Baseline	No spillovers	US spillover=0.23, India spillover=0	Spillover = 0.1 in both countries	US spillover=0.23, India spillover=0.1
IT production					
US IT output	1.06%	0.90%	1.33%	0.97%	1.21%
India IT output	25.02%	14.88%	14.81%	19.08%	19.04%
Welfare					
Welfare of US natives	0.043%	0.033%	0.044%	0.037%	0.044%
Welfare in India	0.066%	-0.064%	-0.064%	-0.010%	-0.011%
Total (with migrants)	0.147%	0.102%	0.110%	0.121%	0.125%

Notes: Percent difference on main outcomes when we go from a scenario with restricted migration (counterfactual) to a scenario with full migration (real). In the counterfactual, the H-1B cap is reduced by 50% in every period, starting in 1995. In the baseline specification, the spillover elasticity is 0.226. In the scenario where there are no spillovers, the elasticity is 0 for both countries. In the scenario where the US has baseline spillovers, and India has no spillovers, the US elasticity is 0.226. We further include a robustness exercise where the spillover elasticity is 0.1 in both countries, and one where the spillover is 0.226 for the US and 0.1 for India.

joining and staying are, on average, of lower ability.

The technology spillover in India is key for our result that India experiences a brain gain. As noted by Stark (2004), when productivity depends on the average level of human capital in the economy, individual workers tend to under-invest in skills. The possibility of migrating to the US, motivates Indians to acquire CS skills and create a larger spillover that increases IT production and welfare in India. From the innovation literature (Byrne et al., 2013; Jorgenson et al., 2017), we expect a positive spillover generated by the IT sector. Columns 4 and 5 suggest that a high level of spillover is needed for India to experience positive welfare gains from migration.

7.3 Alternative Model Specifications

So far, we consider the pool of college graduates to be the same between real and counterfactual scenarios. This is to keep the model tractable and focus on the decision between computer science and other college-occupations, which we think is the key trade-off agents are facing. In Appendix D.1, we relax that assumption by allowing high-school graduates to choose whether to join the labor force without going to college, or go to college and join the labor force in the next period. We find that when increasing immigration, India reduces their high-school graduates by 0.07% since workers are motivated by immigration prospects to get into college. The US, on the other hand, increases their high-school graduates by 0.01% since some natives decide not to go to college given the lower wages for college graduates when high-skilled immigration is larger. In terms of welfare, our results are quantitatively similar to the baseline model, with slightly larger gains for the US and lower gains for India under the endogenous college specification.

In Appendix D, we evaluate alternative migration and trade policies. First, in Section D.2, we compute welfare changes for different cap changes. The changes in welfare are roughly proportional to the magnitude of the cap change. Second, we look at how welfare changes depend on what period the immigration restrictions start, and whether or not the Indian IT sector is already developed.

Finally, we explore how policies restricting trade in IT goods can affect the US and India. In Appendix Table D5, we show that when we go from a policy of restricted IT trade (where IT trade costs to export from India to the US are double), the US marginally loses in terms of welfare. More IT offshoring from India, means that the Indian IT sector grows while the US IT sector shrinks, pushing US native CS to switch to other occupations. Next, we consider going from an alternative policy of both restricted migration as in our baseline counterfactual and restricted IT trade to the observed equilibrium (real scenario). We find that more migration coupled with more trade amplifies the welfare gains experienced by India. The gains of migration for the US, on the contrary, are somewhat muted as the US IT sector grows by less and generates lower levels of innovation.

8 Discussion

India experienced a dramatic expansion in IT employment and a structural transformation in production over the 1990s and 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 the US tech boom, enabled the IT boom in India. 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 productivity in India and shifted the production of IT goods away from the US.

We explicitly test the explanatory power of certain conditions under which US policy stimulated growth in Indian IT. We do this by specifically focusing on four features over 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, the wage differential between the US and India was large, especially for IT workers. Third, US immigration policy, as embodied by the H-1B program, strongly favored skilled migrants. Finally, H-1B visas only last three to six years, obligating many to return to India with accumulated human capital and technical knowhow. Together, these features helped spread the boom across the world from the US to India.

The average worker in each country is better off because of migration. Yet, there are significant distributional consequences, where workers who are close substitutes are adversely affected while others benefit. These distributional effects have been at the forefront of political and academic discussion (Borjas, 1999; Peri and Sparber, 2011). 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 0.15%. This net gain is consistent with a literature reviewed in Clemens (2011).[19] The welfare gains are approximately \$7.8

[19]Specifically, see Iregui (2005); Klein and Ventura (2007); Moses and Letnes (2004); van der Mensbrugghe and

billion in total, a large fraction of which accrues to the migrants. US natives were better off by $1.8 billion in 2010 because of the H-1B program.

The gains are mostly driven by the development of the Indian IT sector. In a world with North-South trade, developing countries may 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, boosting IT exports and raising average incomes. The prospect of migrating to the US was a considerable driver of this phenomenon and led to a 'brain gain' that outweighed the negative impacts of 'brain drain' (Dinkleman and Mariotti, 2016; Stark, 2004; Stark et al., 1997).

One striking result is that as production shifts (or is outsourced) to India, the US IT market share actually falls. A driving feature of this is that increases in the Indian CS workforce increase the relative productivity of Indian IT. Such dynamics are discussed in a rich literature on trade. In Krugman (1979) and Vernon (1966), richer countries initially have a monopoly over new products given their technological superiority and rate of innovation. Developing economies catch up with technological diffusion and, over time, export these very products to the developed world. As the rate of technological diffusion increases, living standards may actually fall in richer countries. With quality differentiation in products, technical progress in the South brings a decline in the North's wages, harming workers as production moves abroad (Acemoglu et al., 2015; Flam and Helpman, 1987). Therefore, as Samuelson (2004) notes, technical progress in the South erodes the US comparative advantage and lowers US incomes.

The labor literature also emphasizes these channels. For instance, Johnson and Stafford (1993) show how the effect of foreign competition from abroad lowers aggregate incomes in the US. In fact, Freeman (2006a) argues that the growth in high-tech labor abroad adversely affects US industry and workers, and immigration can help maintain the US's lead by attracting overseas talent. However, this literature does not account for 'brain gain' or return migration, which we show have important consequences. Davis and Weinstein (2002) show how in a Ricardian framework, such as ours, a country that experiences immigration due to technological superiority loses from such migration through a deterioration in the terms of trade (for us, the US's terms of trade deteriorate as immigration lowers the IT price). Mobility tends to equalize wages across countries and, therefore, hurt workers in the country with superior technology.

In this way, our results combine and confirm canonical predictions in the literature. Even though migration increases the welfare of the average US and Indian worker, these averages hide significant distributional changes in each country. Academic discourse that ignores endogenous skill acquisition (in response to migration opportunities) in sending countries, trade, innovation, dynamic labor supply decisions, and price changes will miss important aspects of this discussion.

Roland-Holst (2009); Walmsley and Winters (2005).

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Appendix

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A Details of the Data Used

A.1 Data for Descriptive Figures

Figures 1a, and 1b use data from the March CPS, obtained from the IPUMS. 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.

Figure 2a uses data from the ACS from the US and the NSS from India, which is described in detail in Section A.5. For the US, we calculate the number of workers with college degrees who migrated to the US after the age of 18. We use the Census of 1990, and the ACS for 2000, 2006, 2008, 2010, and 2012. For the NSS, we use the samples of 1994, 2000, 2006, 2008, 2010, and 2012. We present the ratio for the IT sector and for all other economic sectors. The IT sector is defined as NIC04 code 72 for India and Census ind1990 code 732 for the US.

Figure 2b uses data on the H-1B cap and enrollment by stream in India. The H-1B cap series is calculated by the authors from USCIS reports. The enrollment data is from India's Ministry of Human Resources and Development, which records the number of degrees and universities by type of degree (for example, engineering degrees). We take a three-year moving average of enrollment (the data report total enrollment rather than first-time enrollment). We plot the year-on-year growth in Engineering enrollment.

Figure 3a uses data from Revelio Labs, that provided us with all LinkedIn data. We define computer science (CS) occupations to be those with SOC code 15. Binned scatter of state-level changes in the share of high-skill (on LinkedIn) employment that is in CS. Red dots show the growth between 1970 and 1990. Green dots show the growth between 1990 and 2020. Finally, for the exports data for Figure 3b, we use the OECD Trade in Value Added statistics, 2022 edition.

A.2 Data for Empirical Results on College Major Choice

We use two main sources of education data, which we describe below. The outcomes in Figures 4a and 4b are computed using information on state-level enrollment in engineering for the period 1992 to 2010. We obtain such data from the Ministry of Human Resources Development. For the subsequent analysis presented in Table 1, we use examination reports published by the University Grants Commission (UGC) in India, which keeps records of the number of students who take the annual examinations for every degree and university in India after the completion of each academic year. The annual examination reports for the years 2006-2010 can be downloaded directly from the UGC website. We supplement these reports with digitized reports from years 2000 to 2005, which were obtained from ministries in India. We clean the data in multiple ways. First, we harmonize the names of the universities to make them consistent across years. Second, we collapse the variety of degrees available into ten categories: "Commerce", "Architecture", "Medicine", "Education", "Law", "B.Sc/M.Sc", "Business", "Engineering/Tech", "B.A / M.A", and "Other". We then use the "Total Appeared" for examinations, and "Total Passed" by university, degree, and year.

A.3 Labor Market Histories from Revelio Labs

We use information on the universe of LinkedIn profiles obtained from Revelio Labs, a corporate data provider that collects online curriculum vitae data for over 100 million users, and predominantly includes publicly available data from LinkedIn. The dataset includes: 1) reported education history, including university names, field of study, and degree type; 2) Full employment history, including firm name, start and end date, job title, and position changes; and 3) User-level data, including current location, first and last name, imputed gender and imputed race among others. While the data is incredibly rich, it does not include precise identifiers on whether individuals are migrants or not. Because of that, we infer an individual is a migrant when we observe them obtaining some university degree in one country, and then working or reporting their current location in another country. Hence, if we observe a user with a degree from an Indian university but reporting that they are currently in the US, we label them as an Indian migrant in the US.

To compute migration exposure, we focus on the profiles of Indian migrants who are currently working in the US. While the users on LinkedIn are a selected sample of the universe of college graduates in the US, we show that its coverage is significant when compared to the population counts in the ACS. As shown in Table A1, LinkedIn users account for 54.3% of Indian migrants, and 62% of non-Indian migrants. The sample has particularly good coverage of those with engineering, computer science, business, and economics degrees, where the coverage is above 60%. For other fields, such as law and medicine, the coverage is lower given that many in those professions do not use LinkedIn for business networking and job search. As expected, young workers are more likely to appear in the dataset than older workers. Finally, the total share of migrants is somewhat lower than what we predict in the ACS, likely because we cannot identify migrants who did all of their studies in the US.

Table A1: College graduates in the ACS vs LinkedIn

	ACS	LinkedIn	Coverage		ACS	LinkedIn
Number of college workers				**Shares**		
Indian immigrants	1,223,542	664,553	54.3%	Female	52.2%	49.3%
Non-Indian immigrants	48,822,653	30,273,428	62.0%	Migrants	10.7%	7.3%
				Graduate degree	35.9%	31.6%
Numbers by Major				Age 22-30	23.2%	43.4%
Engineering and CS	6,726,992	4,077,538	60.6%	Age 31-40	29.7%	29.4%
Business and Economics	13,028,962	8,519,981	65.4%	Age 41-50	25.8%	16.5%
Other	14,689,959	3,168,242	21.6%	Age 51-60	21.2%	10.7%

Notes: We compare the total counts between our data from LinkedIn profiles and the ACS in 2019. An Indian immigrant is defined as someone whose reported current location is the United States but at least one university degree is from an institution located in India. For the ACS, we define an immigrant as someone who migrated after the age of 22 and has a college degree.

Finally, the occupation-state level analysis in Section 3.2 uses the job histories of workers in India to calculate the outcomes of our main specification. We map reported job titles to 6-digit occupation SOC codes to classify workers into occupations. We use the profiles of Indians in the US to compute migration exposure by occupation, similar to the one used in Section 3.1.

A.4 Data for Calibration

The time-varying parameters described in Section 5.2 and the targeted moments in Section5.3 are computed for 4 years: 1995, 2000, 2005, and 2010. For moments in India, we use the NSS for years 1994, 2000, 2005, and 2010. For the US, since the ACS does not have information for 1995, we use the IPUMS CPS for 1995, 2000, 2005, and 2010. This harmonized dataset is highly compatible with the ACS, and we can use the same classification of occupations and industries. For information on imports, exports, and RoW consumption of IT from the US and India, we use the OECD Trade in Value Added statistics, 2016 Edition. The dataset uses World input-output tables for the period 1995 to 2011. 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 industries. We use trade data for 1995, 2000, 2005, and 2010.

A.5 Data for Validation Exercise

Indian microdata comes from the National Sample Survey (NSS). We use the Employment / Unemployment surveys from rounds 50 through 66, which cover 1987 through 2012 with gaps in between. NSS is a nationally representative survey and the largest household survey in the country, asks questions on weekly activities for up to five different occupations per person, and weekly earnings for each individual. Computer scientists are defined as "213 Computing Professionals" and "312 Computing Associate Professionals" based on the National Classification of Occupations (NCO) of 2004. We use the earnings data for the primary occupation only. NCO 2004 codes follow the same structure as ISCO-88 3-digit occupations, which makes it useful to construct crosswalks with US and UK data between occupations. The IT sector is restricted to be "Computer and Related Activities', code 72 in the National Industrial Classification of 2004 (NIC).

For the regressions presented in Section 5.4, we focus on the NSS samples of 1994, 2000, 2005, 2010, and 2012. In certain robustness specifications, we use 1987 to calculate baseline shares. These rounds are often split over two years. For instance, the 2005 round was based on data collected between the end of 2005 and the first half of 2006. The NCO broadly groups occupation by skill. We keep 'college-graduate occupations,' which include all NCO 2004 codes from 211 to 422. This includes professionals, technicians, associate professionals, trade and craftsmen, and clerical support workers. As the H-1B focuses on high-skilled occupations, we exclude from the analysis shop service and sales, agricultural, plant and machine operators, elementary occupations, and armed forces from the analysis. We construct crosswalks to get all waves of the NSS in consistent NCO 2004 codes and NIC 2004 codes. We end up with 52 occupations, 31 Indian states and 5 periods for the analysis. However, not every occupation-state has observations for every year.

The US microdata used in Section 5.4 comes from the American Community Survey (ACS). We use the Census for 1990, 2000 and all ACS samples between 2005 to 2012. We use the 1990 Census Bureau occupational classification scheme, which provides consistent occupation codes for our period of study. As we are looking at a very specific group of workers (Indian college graduates in the US by occupation who migrated in the past 5 years), we pool years 2005-2006, 2009-2010, and 2011-2012, with the requisite weights to match the NSS years. We use a crosswalk to map the ACS occupational classification to ISCO-88 3-digit codes, which allows us to connect the 52 occupations in India with occupation codes in the US.

B Alternative Specifications and Robustness

Table B1: Lead Effect of the H-1B cap on Enrollment in Majors

	Log(Enrolled)				Log(Passed Exams)			
Migration Exposure X Log(H-1B Cap)	0.191***	0.104**			0.209***	0.142***		
	(0.0541)	(0.0416)			(0.0509)	(0.0320)		
Migration Exposure X Log(Non-Indian H-1Bs)			0.152***	0.0835**			0.164***	0.112***
			(0.0433)	(0.0332)			(0.0404)	(0.0256)
Observations	7,060	6,372	7,060	6,372	7,060	6,372	7,060	6,372
R-squared	0.926	0.958	0.926	0.958	0.896	0.938	0.896	0.938
School-by-Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field-by-Year FE	Yes	No	Yes	No	Yes	No	Yes	No
State-by-Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Field-State-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
School-Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Lead of enrollment is the number of students eligible to appear for an examination in school s, located in state r, studying in field f, and year $t+2$. Passed exams is the number of students passing the examinations in school s, located in state r, studying in field f, and year $t+2$. Migration exposure is defined as the number of pre-2000 graduates from school s and field f working in the US, divided by the total pre-2000 enrollment at school s and field f. The H-1B cap is the annual policy-determined cap. Non-Indians is the number of H-1Bs granted (including renewals) to workers from all other countries in the world, excluding India. Data for the migration exposure are from the universe of LinkedIn users that studied in India, and work in the US. Data on examinations are from annual Indian Government reports. Data details are in Appendix A.2. Standard errors clustered at the school level. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table B2: Occupational Response in India to the H-1B Cap with US Wage Bill Exposure

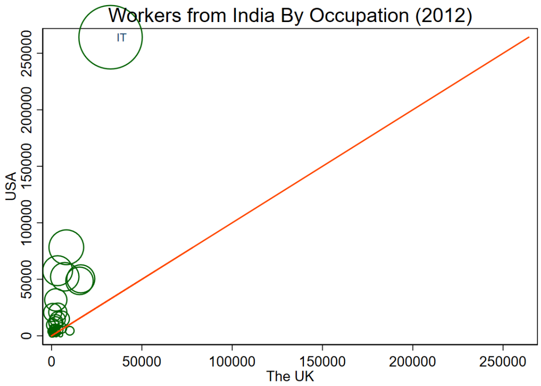
	Log(Employment)					
	All	Young	Old	All	Young	Old
US Wage Exposure X Log(H-1B Cap)	0.00592**	0.0133**	0.00363			
	(0.00283)	(0.00545)	(0.00223)			
US Wage Exposure X Log(Non-Indian H-1Bs)				0.0435***	0.0932***	0.00329*
				(0.00836)	(0.0143)	(0.00187)
Observations	283,133	89,533	45,287	234,369	77,682	35,930
R-squared	0.987	0.977	0.982	0.990	0.981	0.985
State-by-Occ FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occ-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Employment is the number of persons employed by state-occupation-year in India. We use the LinkedIn data to create retrospective work histories for all individuals, and job spells. Migration exposure is defined as the total wage bill of workers from an Indian state-and-occupation who migrated to the US before 1990. We normalize this variable into standard deviation units. The H-1B cap is the annual policy-determined cap. Non-Indians is the number of H-1Bs granted (including renewals) to workers from all other countries in the world, excluding India. Data for the migration exposure are from the universe of LinkedIn users that either ever worked or studied in India, and then worked in the US. Data details are in Appendix A.2. Standard errors clustered at the state level. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

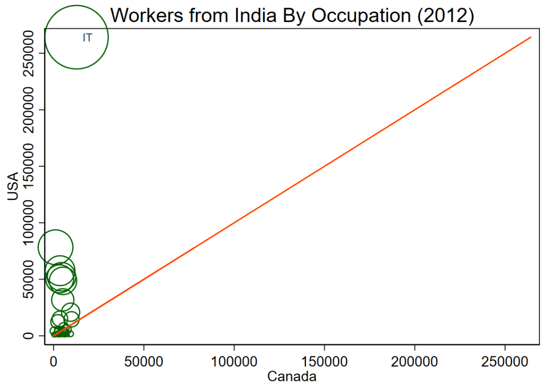
B.1 Correlated Demand Shocks

If the instrument did not rely on the H-1B policy changes, we may be concerned that the demand for Indian IT workers comes from correlated productivity shocks (say, in IT) in other countries. To test this, we obtain microdata for the top three destinations for Indian migrants. The scale of migration to the US, however, is a lot larger to other destinations – in 2012 the stock of college-educated Indian migrants in the US was 4 times that of the UK and 4.8 times that of Canada. There were 3.5 times more Indians in the US than in the UK in 2000.

Figure B1: Demand from the UK and Canada relative to the US

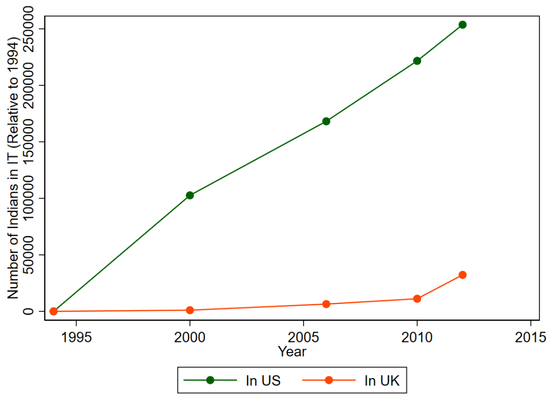


(a) Indians in the US and UK (2012)



(b) Indians in the US and Canada (2011-12)

(c) Indians in the US and UK (2000)



(d) Indians in the US and UK (1994-2012)

Notes: Sample of college educated. All figures with US data use the American Community Survey, Figures B1a, B1c and B1d use the UK Labor Force Survey, and Figure B1b is based on 2011 National Household Survey. Each bubble represents an occupation weighted by the size of the number of migrants from India in the US. Figure B1d plots the change in the number of workers over time relative to 1994. For instance, the last observation is the number of workers in 2012 minus the number of workers in 1994.

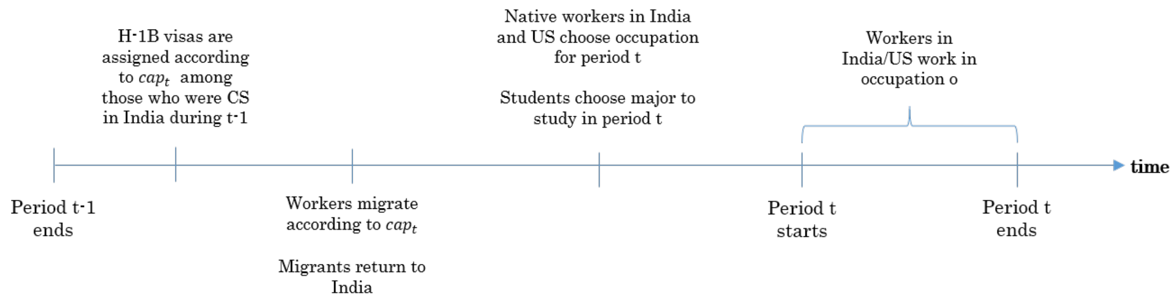
The specific demand for IT workers from India is swamped by the US. The US is larger, gets more migrants, and had a unique IT boom. Figure B1 describes the demand for Indian workers by occupations in the top destinations. In Figures B1a and B1b, we see that even in 2012, when other countries had time to develop their IT sectors, the US (on the vertical axes) swamps overall demand when compared to the UK or Canada (on the horizontal axes). In 2000, when only the US IT sector was developed, the scale of the difference in the demand for IT from the US was many magnitudes larger than the UK (Figure B1c). Indeed, the largest occupation for college graduate Indian migrants in the UK was that of physicians, and not IT workers. Furthermore, despite starting with a much larger scale at baseline, the US's growth in IT workers from India was also a lot larger (Figure B1d). So, the US was somewhat unique in its substantial demand for IT workers from India. The role played by the demand for Indian tech workers from other countries was relatively small.

C Model Timeline, Equilibrium, and Parameter Estimation

C.1 Model Timeline

Figure C1 summarizes the timing of the decisions each period, for college graduates in the model.

Figure C1: Decision timeline for college graduates in the model.



C.2 Equilibrium

Equilibrium in each period can be defined as a set of prices and wages ($P_{t,c,k}$, $P_{t,y,k}$, $w^{\ell}_{t,k}$, $w^{g}_{t,k}$, $w^{cs}_{t,k}$), quantities of output and labor ($C_{t,y,k}$, $Y_{t,k}$, $L_{t,k}$, $G_{t,k}$, $CS_{t,k}$), and the level of technology ($T^{s}_{t,k}$) such that: (1) consumers in the US, India, and the rest of the world, maximize utility by choosing $Y_{t,k}$ taking prices as given, (2) college graduates in the US and India choose their field of major and occupations, taking wages as given, and forming expectations, (3) firms in both the IT and the final goods sector maximize profits taking wages and prices as given, (4) trade between the three regions is balanced, and (5) output and labor markets clear.

Given the Frechet distribution assumption, we can aggregate across varieties and write the probability of country k buying goods of sector s from country b as in equation C1:

$$\pi^{s}_{t,k,b} = \frac{T^{s}_{t,b}(d^{s}_{t,k,b}\xi^{s}_{t,b})^{-\theta}}{\sum_{b} T^{s}_{t,b}(d^{s}_{t,k,b}\xi^{s}_{t,b})^{-\theta}}, \tag{C1}$$

where $\xi^{s}_{t,b}$ is the unit cost of production in country b, $d^{s}_{t,k,b}$ the iceberg trade cost of trading goods from b to k and $T_{t,b}$ is country b technology level. The price index in country k, sector s is a combination of production costs and technologies of different suppliers weighted by trade costs between each supplier and country k:

$$P^{s}_{t,k} = \bar{\gamma}\left(\sum_{k'} T^{s}_{t,k'}(d^{s}_{t,k,k'}\xi^{s}_{t,k'})^{-\theta}\right)^{-\frac{1}{\theta}}, \tag{C2}$$

where $\bar{\gamma} = \left(\Gamma\left(\frac{1-\iota}{\theta}+1\right)\right)^{\frac{1}{1-\iota}}$, and Γ is the Gamma function. As we assume trade balance, total income from sector Y in country k has to equal the sales to each of the markets. Similarly, for the IT sector, we have that total income earned has to equal the total sales of intermediate IT goods sold to each country.

Labor markets clear as long as total demand for each occupation in country k equals the total supply of labor for that occupation. Non-college workers' supply is fixed at $\bar{L}_k$ in both countries. Native college graduates in both countries face the decision of whether to work as CS or in non-CS college occupations. This decision has an inter-temporal dimension that requires us to define the dynamic equilibrium in the labor market for college graduates. Using the properties of the Type I Extreme Value, we derive for each worker with ability draw $\phi_{i,o}$, the probability that if working in occupation $o_{t-1} = o$ in period $t-1$ they would choose occupation o' in period t as in equation C3:

$$\pi^{o,o'}_{i,t,k,a} = \frac{exp(\frac{1}{\sigma_{\eta,k}}\bar{V}^{o,o'}_{i,t,k,a})}{exp(\frac{1}{\sigma_{\eta,k}}\bar{V}^{o,o'}_{i,t,k,a}) + exp(\frac{1}{\sigma_{\eta,k}}\bar{V}^{o,o}_{i,t,k,a})}\ , \tag{C3}$$

where $\bar{V}^{o,o'}_{i,t,k,a} = w^{o'}_{t,k} \times \phi_{o,i} + \chi_k(a) \times \mathbb{1}(o \neq o') + \zeta_k \times \mathbb{1}(o' = g) + \rho\mathbb{E}_t[V^{o'}_{i,t+1,a+1,k}]$. As in Bound et al. (2015), this equilibrium is characterized by the system of equations (3-7 and C1-C3) and a labor demand shifter Ω_t through which we characterize the expectations of workers with respect to future career prospects. A unique equilibrium is pinned down in each period by an aggregate labor demand curve in each country for native computer scientists relative to other college graduates. The labor demand shifter Ω_t represents the change over time in the production function parameters in both countries ($\delta_{k,t}$, $\alpha_{t,k,y}$, $T^s_{k,t}$, $d^s_{k,b,t}$, $\gamma_{k,t}$, and cap_t) that shift the relative labor demand curve of CS relative to other college occupations. Intuitively, the change in the production function parameters reflects the skill-biased technological change toward CS and IT that can be interpreted as innovation shocks (as seen by the IT boom) to the labor market that push workers to switch to CS occupations. Individuals have perfect foresight on the evolution of these demand shocks and make decisions based on that, as well as their preference shocks and migration probabilities.

The equilibrium in the labor market is a mapping from the exogenous demand shifter, Ω_{t-1} and state variables: $s = \{\mathbf{CS^a_{t-1,k}}, \mathbf{G^a_{t-1,k}}\}$ for all ages a to the values of $CS_{t,k}$, $G_{t,k}$, $w^{cs}_{t,k}$, $w^g_{t,k}$, and $\mathbf{V_t}$, the vector of career prospects at different occupations for different ages, that satisfies the system of equations 3-7, C1-C3 as well as each period's relative demand curve.

A note on uniqueness: While solving for equilibrium with multiple different initial values, our algorithm converges to the same unique solution. Issues of multiple equilibria arise, for instance, in models of economic geography, where agglomeration forces in a city attract workers to that city away from other cities (Allen et al., 2020). In such instances, authors suggest they study a counterfactual equilibrium that lies near the observable steady state real world (Ahlfeldt et al., 2015). Yet, in our context, even if β (the spillover parameter) were high, it increases demand for both CS *and* non-CS graduates as the spillover raises the productivity of *all* workers. So our analogous occupation-choice (instead of city-choice) is unlikely to generate multiple equilibria. In addition, since the total supply of workers is fixed, and the number of migrants is capped (by policy), this imposes a limit on how much companies can produce, as wages will start increasing until unit costs are sufficiently high that it will be optimal to not increase production.

Estimation of Other Model Parameters

C.3 Estimating τ

For the elasticity between college and non-college graduates, we replicate Card and Lemieux (2001) using the India NSS data and estimate an elasticity of complementarity of 0.55 (see Table C1). This corresponds to $\tau = 1.8$, and is statistically indistinguishable from 1.7, which is the value used in the calibration for both countries.

Table C1: Estimating τ: Doing Card and Lemieux (2001) in India

	Log(Col Wage / HS wage)
Log(Col L / HS L)	-0.553***
	(0.140)
Log(Col L / HS L) – Log(Col by age / HS by age)	0.322**
	(0.137)
Observations	60
R-squared	0.857
Fixed effects	Cohort, Year
Elas of Sub ($\hat{\tau}$)	1.8
Prob $> \chi^2$	0.000

We estimate τ in India using the National Sample Survey. We follow Card and Lemieux (2001) and divide the working-age population into 10 equally spaced age groups, and by whether or not they are college graduates. 'Col' represents having a college degree, whereas 'HS' is only a high school graduate. L is the number of workers in a college-age bin. The elasticity of substitution is the inverse of the estimated coefficient on $Log(Col\ L/HS\ L)$. This elasticity is precisely measured as indicated by the χ^2 test. It is statistically different from 0 but not 1.7.

C.4 Endogenous Technology: Patenting Response to CS

In Section 4.2.4, equation 16, we mentioned that the level of technology of the IT sector depended on the number of CS working in IT. Parameter β is the elasticity of the technology level with respect to the number of CS working for the IT sector in country k, time t. One advantage of the procedure we use, is that we can estimate the $T^s_{t,k}$ in equilibrium, so our estimate will already capture the baseline level of technology plus any endogenous component that affects the overall level of technology.

To estimate the elasticity of technology with respect to the number of CS workers, we use a shift-share instrumental variables strategy that interacts the industry-specific dependence on immigrant CS workers in a pre-period with the total number of immigrant CS in the US each year. Our instrument leverages variation in US immigration policy (like changes to the H-1B cap), sending country shocks, and the fact that immigrants are more likely to be CS.

Our aim is to estimate the parameter β that is shown in equation 16. We first combine our data on the number of CS workers by industry with data on patenting from the US Patent and Trademark Office (PTO) to proxy for the technology level. We use firm-level measures of patents granted from US PTO, match the firms to Compustat data, and then use the Compustat industry identifiers to compute industry-level measures of patenting. However, a simple OLS regression of patenting on the number of CS workers would be biased, as when industries increase investments in R&D they may concurrently increase hiring of CS workers.

To isolate variation in the size of the CS workforce by industry that is not driven by confounding factors, we use the fact that immigrants are concentrated in CS occupations, and the H-1B cap fluctuations affect the size of immigrant flows. In the vein of a modified shift-share instrument, we use the baseline dependence of an industry on immigrant computer scientists interacted with the differential growth in immigrant CS across industries, as an instrument for the CS workforce by industry.[20] Equation C4 captures the first stage of our strategy:

$$CS_{j,t} = \delta_j + \delta_t + \gamma\left(\frac{Imm\,CS_{j,0}}{Emp_{j,0}}\right) Imm\,CS_t + \varepsilon_{j,t}\ , \tag{C4}$$

where $CS_{j,t}$ is the number of computer scientists in industry j and year t, and $\left(\frac{Imm\,CS_{j,0}}{Emp_{j,0}}\right)$ is the baseline (in 1994) share of the workforce in industry j that is an immigrant computer scientist. $Imm\,CS_t$ is the number of immigrant CS workers in the US over time. The interaction between these two terms is the excluded instrument, conditional on industry δ_j and year δ_t fixed effects. Importantly, our instrument leverages variation in US immigration policies (say, changes to the H-1B cap), and the fact that immigrants are more likely to be CS. In our second stage, we study patenting activity:[21]

$$Log(Patents)_{j,t} = \delta_j + \delta_t + \beta_{tech}\widehat{CS_{j,t}} + \varepsilon_{j,t}\ , \tag{C5}$$

The results of this exercise are shown in Table C2. Our first stage is strong, and our 2SLS analysis produces an elasticity that lies between 0.226 and 0.24. We conduct a variety of robustness checks, where we vary the controls in the regression, look at only the flow of new patent filings, and exclude the truncated patent data.[22] Importantly, our estimated elasticity is very close to similar findings in the literature. Peri et al. (2015) estimate that a 1% increase in total US STEM workforce would increase average TFP by 0.27%, whereas Kerr and Lincoln (2010) find patenting elasticities that lie between 0.1 and 0.4. In 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. In recent work, Khanna and Lee (2018) find an elasticity of 0.2 when using measures of innovation derived from the Schumpeterian growth literature. In Section 7.2, we discuss how our results change for different values of β, including the case where there is no spillover in India.

C.5 Calibrating Time-Varying Parameters Parameters

The Cobb-Douglas parameters γ_k represent the share of income from the final goods sector spent on varieties of the IT sector. We determine the parameters for $k = \{us, in\}$ from the share of IT output to total output in each country, using data from the OECD, and get values: 0.7%-1.6% for the US and 0.2%-1.5% for India. By solving for these parameters every year, we capture changes in demand for IT varieties as an input into the final good production, which is increasing for both countries throughout the period. We do the same exercise to determine the IT share in the rest of the world (RoW).

The share parameter of non-graduates in the production function, $\alpha_{t,k}$, is determined in both India and the US such that it matches the observed share of expenditures from the final goods sector in non-graduates. Specifically, from the US March CPS and the Indian NSS data, we calculate the share of expenditures on non-graduates $\vartheta_{t,k}$ and the number of graduates and non-graduates in the final goods industry $\bar{L}_{t,k}$, $\bar{H}_{t,k}$, and using equation C6 we estimate $\alpha_{t,k}$:

$$\vartheta_{t,k} = \frac{\alpha_{t,k}(\bar{L}_{t,k})^{\frac{\tau-1}{\tau}}}{\alpha_{t,k}(\bar{L}_{t,k})^{\frac{\tau-1}{\tau}} + (1-\alpha_{t,k})(\bar{H}_{t,k})^{\frac{\tau-1}{\tau}}} \tag{C6}$$

Importantly, $\alpha_{t,k}$ decreases over time in both countries, capturing how skill-biased technological change shifts production to college-graduate occupations over time.

[20] The Card (2001) method derives an instrument for immigrants by region. Instead, here we create an instrument for CS workers by industry. Instead of exploiting regional migrant-networks, our underlying variation is driven by changes to H-1B caps and the fact that immigrants are likely to be CS.

[21] We use NBER patent data project, which matches patent assignees to the North American Compustat database between 1976-2006. This also includes utility patents. We then match these data to the Compustat database, which includes industry (NAICS) codes. We create a crosswalk between NAICS and the 1990 Census codes available on IPUMS, using the 2000 Census, which helps us measure the number of patents filed by industry in each year till 2006. We exclude 2006 as we believe the data are artificially censored in the last year, as evidenced by the small number of patents.

[22] As there is a lag between patents filed and granted, we exclude the last year as a robustness check.

Table C2: Migration, Computer Scientists and Patenting by Industry

	CS workers	Log(Patents)	Log(Patents)	Log(Patents)	Log(Patents)	Log(New Patents)
Shift Share	1.258***					
	(0.309)					
CS workers		5.45e-06**	5.79e-06**	3.99e-06**	5.53e-06**	5.90e-06*
		(2.59e-06)	(2.56e-06)	(1.89e-06)	(2.27e-06)	(3.10e-06)
Observations	275	275	275	250	250	250
R-squared	0.877	0.967	0.967	0.971	0.968	0.329
Number of Industries	25	25	25	25	25	25
Additional Controls	No. of Firms	No. of Firms	None	No. of Firms	None	No. of Firms
F stat		16.67	16.31	12.54	11.11	12.54
Elasticity		0.226	0.240	0.162	0.225	0.240
SE		(0.107)	(0.126)	(0.076)	(0.092)	(0.126)

Notes: Two-staged least squares regressions of Log(Patents) on the number of computer science workers by industry. Years 1994 to 2005. Controls include year and industry fixed effects, size of total industry workforce, and, when mentioned, the number of firms. Sample restricted to (the 25 top) industries that have at least a total of 50 patents over the entire period. In Columns 4-5, we exclude 2005 for robustness (as the data records all patents granted by 2006, there may be truncation based on patents applied for in 2005 but not granted by the end of 2006.) The last specification has the natural log of new patents (i.e., $patents_{t,i} - patents_{t+1,i}$) as the dependent variable. Standard errors clustered by industry.

The distributional parameter between CS and non-CS college graduates $\delta_{t,k}$ is calibrated so that it matches the within-country relative wages between CS and non-CS college graduates observed in the data. Empirically, $\delta_{t,k}$ 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 $\Delta_{t,k}$ captures the extra intensity of CS in IT. We calibrate $\Delta_{t,k}$ to be proportional to $\delta_{t,k}$ every period such that it matches the within-country relative share of CS between the IT and non-IT sector in 1995.

To estimate the productivity levels ($T^s_{t,k}$) and bilateral trade costs ($d^s_{t,k,b}$) for each country-sector pair, we use trade data such that we match the observed trade flows every year. We follow standard estimation procedures in the trade literature – specifically, 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 C1 and take the ratio between the probability of country k buying from country b and the probability of country k buying from itself, which yields the gravity equation C7:

$$\frac{\pi^s_{t,k,b}}{\pi^s_{t,k,k}} = \frac{EX^s_{t,k,b}}{EX^s_{t,k,k}} = \frac{T^s_{t,b}(d^s_{t,k,b}\xi^s_{t,b})^{-\theta}}{T^s_{t,k}(d^s_{t,k,k}\xi^s_{t,k})^{-\theta}}, \tag{C7}$$

where $EX_{t,k,b}$ is the value of expenditures that country k has on products from country b in sector s at time t. 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 C7 to estimate trade costs and a term that combines the technology level and the unit cost of production $T^s_{t,k}(\xi^s_{t,k})^{-\theta}$.

First, we parametrize the trade costs as in equation C8. Following Levchenko and Zhang (2016), we define the 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 $\nu_{t,k,b}$.

$$log(d^s_{t,k,b}) = dist_{k,b} + border_{k,b} + CU_{t,k,b} + RTA_{t,k,b} + exp^s_{t,k} + \nu^s_{t,k,b} \tag{C8}$$

To estimate trade costs and technology, we take logs of equation C7 and get equation C9, 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 $T^s_{t,k}(\xi^s_{t,k})^{-\theta}$.

$$\log\left(\frac{EX^s_{t,k,b}}{EX^s_{t,b,b}}\right) = \underbrace{\log\left((T^s_{t,k}(\xi^s_{t,k})^{-\theta}\right) - \theta exp_{t,k}}_{\text{Exporter fixed effect}} - \underbrace{\log\left((T^s_{t,b}(\xi^s_{t,b})\right)^{-\theta}}_{\text{Importer fixed effect}} \tag{C9}$$
$$-\theta(dist_{k,b} + border_{k,b} + CU_{t,k,b} + RTA_{t,k,b} + \nu_{t,k,b})$$

The distance variable $dist_{k,b}$ is a group of six 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, max), and 0 otherwise. 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.

We estimate equation C9 separately by sectors Y and C. Distance, currency union, and regional trade agreement data comes from the CEPII gravity database, and data on industry-specific trade flows, and GDP come from the OECD. We run the regression separately for 1995, 2000, 2005, and 2010. From the estimates of equation C9, 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 normalize 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 derive estimate $\hat{\Xi}^s_{t,k,us} = \left(\frac{T^s_{t,k}\xi^s_{t,k}}{T^s_{t,us}\xi^s_{t,us}}\right)^{-\theta}$.

When computing our GE model, we feed the estimated expressions for $\hat{\Xi}^s_{t,k,b}$ together with our preferred value of θ and total labor quantities for each occupation. This allows the model to endogenously calculate 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 US. We assume the technology level for the US is 1 for both sectors. For RoW, we get estimates for 57 countries. For each country in the RoW, we calculate the country weights based on the country-sector GDP. We then use these weights to compute a weighted average of trade costs and $\hat{\Xi}^s_{t,k}$.

For relative technology in the non-IT sector between India and the US, we choose $\left(\frac{T^y_{t,in}}{T^y_{t,us}}\right)$ such that we match relative wages of non-graduates between India and the US. Finally, we determine the number of college and non-college workers in each country using the US March CPS and the Indian NSS data. The total number of Indian CS who migrate to the US is calculated using administrative H-1B data, March CPS, and the American Community Survey, which provides information on birthplace and occupation. We calculate the observed migration cap every period and match the net change in the number of Indian CS in the US.

C.6 Identifying Dynamic Labor Supply Parameters

The Simulated Method of Moments (SMM) approach implies that all parameters are jointly estimated to match a series of targeted moments. For each parameter to be identified separately, we need each targeted moment to respond differently to changes in each parameter. In Section 5.3, we provide intuition on what moments in the data help us identify each labor supply parameter. In this section, we provide further evidence that confirms our intuition and explicitly relates each parameter to specific targeted moments.

We follow Lagakos et al. (2023) and calculate the elasticity of each targeted moment to a 1% change in each parameter. Once we estimate the supply side parameters, we exogenously increase each parameter estimate by 1% and compute the targeted moments predicted by the model. We then compute the change in the targeted moment with respect to the 1% increase in each of the parameters as shown in Table C3. As an example, in the first column, a 1% increase in the mean taste for non-CS in the US ζ_{us} causes a 2.69% decrease in the CS share in 1995, a 4.05% decrease in the CS share in 2010, and a 2.25% decrease in the transition rate across occupations in the US.

While it is true that changes in some parameters seem to have an effect on many moments, different parameters tend to affect disproportionately specific moments, in a manner consistent with our intuition. For example, ζ_{us} and $\sigma_{\eta,us}$ tend to affect moments in the US and India since they determine the occupation choices

Table C3: Elasticity of targeted moments with respect to parameters (%)

	ζ_{us}	$\sigma_{\eta,us}$	$\bar{F}_{us}$	$\chi_{0,us}$	$\chi_{1,us}$	$\sigma_{\phi,cs,us}$	$\sigma_{\phi,oth,us}$	ζ_{in}	$\sigma_{\eta,in}$	$\bar{F}_{in}$	$\chi_{0,in}$	$\chi_{1,in}$	$\sigma_{\phi,cs,in}$	$\sigma_{\phi,oth,in}$	$\bar{\Lambda}$
Share CS 1995 - US	-2.69	1.25	0.00	-0.59	-0.26	-1.16	1.49	-0.04	0.00	0.00	0.01	0.00	-0.13	0.01	0.00
Share CS 2010 - US	-4.05	1.53	0.02	-0.65	-0.41	-1.35	2.22	-0.12	0.00	0.00	0.02	0.00	-0.41	0.03	0.00
Ratio CS share [25-30]/[31-60] - US	0.05	0.63	0.03	-0.22	0.05	-0.14	-0.09	-0.01	0.00	0.00	0.00	0.00	-0.05	0.00	0.00
Transition rate - US	-2.25	2.79	0.02	-1.52	-0.70	-1.27	1.13	-0.05	0.00	0.00	0.01	0.00	-0.15	0.01	0.00
Share CS 1995 - India	-0.26	0.19	0.00	-0.07	-0.05	-1.01	0.52	-1.43	0.18	0.06	-1.63	0.00	1.35	0.12	0.08
Share CS 2010 - India	-0.05	0.05	0.00	-0.02	-0.01	-0.25	0.20	-1.60	-0.02	-0.03	0.06	0.00	-0.13	0.24	0.09
Ratio CS share [25-30]/[31-60] - India	0.05	-0.04	0.00	0.02	0.01	0.12	-0.05	0.34	0.01	0.01	-0.10	0.00	0.12	-0.05	-0.06
Transition rate - India	0.12	-0.07	0.00	0.03	0.02	0.17	-0.21	6.62	2.46	-0.23	-20.78	0.00	1.58	-0.54	-0.20
Ratio CS share [45-60]/[31-60] - US	0.24	0.05	-0.01	-0.05	-0.10	0.09	-0.20	0.02	0.00	0.00	0.00	0.00	0.07	0.00	0.00
Ratio CS share [45-60]/[31-60] - India	0.26	-0.21	0.00	0.07	0.04	0.69	-0.45	1.15	0.00	0.03	0.28	0.00	-0.04	-0.23	0.10
Dispersion CS wages - US	0.25	0.12	0.00	0.09	0.08	0.88	-0.32	0.01	0.00	0.00	0.00	0.00	0.03	0.00	0.00
Dispersion Other wages - US	0.02	-0.01	0.00	0.00	0.00	0.01	1.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Dispersion CS wages - IN	0.17	-0.15	0.00	0.05	0.03	0.78	-0.39	0.42	-0.09	-0.04	1.90	0.00	0.98	-0.16	0.01
Dispersion Other wages - IN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.10	0.00
Return rate to India	0.58	-0.42	0.00	0.14	0.08	1.11	-0.68	-0.16	0.01	0.00	0.04	0.00	-0.45	0.03	0.48

Notes: We calculate percent changes in each targeted moment when each supply-side parameter changes by 1%. ζ_{us} and ζ_{in} are the mean taste parameters for non-CS occupations, $\sigma_{\eta,us}$ and $\sigma_{\eta,in}$ are the taste dispersion parameters, $\chi_{0,us}$ and $\chi_{0,in}$ are the baseline occupation switching costs, , $\chi_{1,us}$ and $\chi_{1,in}$ are the age-specific occupation switching costs, $\bar{F}_{us}$ and $\bar{F}_{in}$ are the CS education fixed costs, $\sigma_{\phi,o,k}$ are the ability dispersion parameters by country and occupation and $\bar{\Lambda}$ is the mean taste to return to India.

for US workers over time. However, the CS shares in the US are the moments that predominantly respond to changes in those parameters. Changes in the occupation costs $\chi_{0,us}$ and $\chi_{0,in}$ lower the transition rates in each country respectively. The ability dispersion parameters ($\sigma_{\phi,o,k}$) increase the dispersion of wages in their respective occupation-country pair. Finally, an increase in the mean taste for home ($\bar{\Lambda}$) increases the return rate predicted by the model.

C.7 Details and Robustness for Model Validation Exercise

Our validation exercise focuses on estimating equation 18, as reproduced below:

$$Log(\text{Emp in IN})_{rot} = \beta Log(\text{IN Migrant Earnings in US})_{rot} + \delta_{ro} + \delta_{o't} + \delta_{rt} + \gamma X_{ort} + \varepsilon_{rot}$$

where $Log(\text{Emp in IN})_{rot}$ is the log employment in region r, occupation o and time t, calculated using data from the NSS. We control for region-occupation fixed effects, region-time fixed effects, and broad-occupation-time fixed effects. Broad occupations o' are one-digit occupation fixed effects. We include two demand-level controls, which are in the X_{ort} term. For the first control, we consider 1-digit industries. We calculate the share of employment of each industry in the total employment of a given occupation-region pair in 1994 and interact it with the national level growth of industry employment as shown in equation C10:

$$\text{Local}_{ort} = Ln\left(\sum_{ind} \frac{N^{ind}_{or,1994}}{\sum_{ind} N_{or,1994}} \times \text{Total employment in } ind \text{ and } t\right) \tag{C10}$$

We define "Total employment in *ind* and *t*" as the total number of college graduates in a given industry in t excluding own occupation-region employment in t. The term Local_{ort} also controls for aggregate demand for occupations across all regions. If the overall demand for occupation o_1 from firms based in India increases, Local_{o_1rt} will increase across all regions. In this way, we also control for any demand shocks from firms in India that are correlated with demand from other countries.

For the second control, we use industry-level trade flows between the US and India. We construct a demand control that leverages the US imports from India across industries as in equation C11:

$$\text{US Trade Control}_{ort} = Ln\left(\sum_{ind} \frac{N^{ind}_{or,1994}}{N_{or,1994}} \times \text{Total US imports from India}_{ind,t}\right) \tag{C11}$$

To construct the demand control, we use data from the World Input-Output Database (WIOD) to compute the total value of US imports from India over time for 35 industry categories that cover all economic activity. Similar to the local demand control from equation C10, we re-weight each industry trade shock with the share of Indian workers in each occupation-region pair at the baseline period 1994. The goal of this measure is to capture other demand channels through which occupation-region pairs in India respond to demand shocks in the US.

In addition to these controls and the rich fixed effects in the regression, we need an instrument to deal with endogeneity concerns. The main instrument is summarized by equation 19. A key limitation of US data from the ACS is that it does not include information on which Indian state the migrants come from. To deal with this issue, we use LinkedIn data by region and field of study, to compute the exposure share needed for the instrument, as described in equation C12.

$$\text{Instrument}_{ort} = \underbrace{\frac{(\text{N Indians in US})_{o,1990}}{(\text{N Indians in US})_{1990}}}_{\text{Occupation share}} \times \underbrace{\frac{(\text{LinkedIn profiles})_{r,o^*,1990}}{(\text{LinkedIn profiles})_{o^*,1990}}}_{\text{Region share}} \times \underbrace{(\text{Demand from US})_{ot}}_{\text{time shifter}} \tag{C12}$$

The initial share consists of two shares interacted. The first one, "Occupation share," uses ACS data and re-weights the shifter by the occupations Indian migrants in the US have in 1990. The second share, "Region share", predicts for each occupation, the share of workers that come from region r. To compute this, we calculate using the LinkedIn data, the number of profiles of those that graduated in India before 1990 and are currently working in the US. Since we are mapping regions to wherever the region where the Indian migrants obtained their bachelor degrees, we compute the region shares by broader occupation groups o^* using the reported field of study, where we group the 52 high-skill occupations into three categories: 1) Engineering/CS/Information Technology, 2) Accounting/Business/Finance/Economics/Marketing and 3) All other majors.

To compute the endogenous variable, we also need to use LinkedIn to predict how many of those who migrated in the past 5 years, to work in occupation o in the US, were coming from region r. To do that, we first compute from the ACS the number of Indians in US, working in occupation o who migrated in the past 5 years ($t-5$ to t): Indians in US_{ot}.

Then, we use the LinkedIn data to compute the share of individuals in occupation o^* who come from region r. Since we want to calculate the values for those who migrated in the past 5 years, we compute the region shares using those who graduated from Indian universities five years before that: from $t-10$ to $t-5$. The regional share used for reweighting is as:

$$\text{Region Share}_{o^*rt} = \frac{(\text{N LinkedIn profiles who graduated } t-10 \text{ to } t-5)_{o^*rt}}{(\text{N LinkedIn profiles who graduated } t-10 \text{ to } t-5)_{o^*t}} \tag{C13}$$

We conduct three types of robustness checks to the validation exercise in Section 5.4. First, in Table C4, we test for baseline correlations between our migration exposure (at occupation-by-region level) measure, and various other characteristics. We find balance in 1994 characteristics from the nationally representative NSS data. Next, in Table C5, we show how the independent variable of interest, is not correlated with baseline education and labor market characteristics. Finally, in Figure C2, we check the sensitivity of our elasticity estimates to dropping one state at a time (left panel), and one occupation at a time (right panel).

Table C4: Baseline Correlations with Migration Exposure

	Migrant Share in 1990			
P(Male) in 1994	-0.0336	-0.0328	-0.0531	-0.0562
	(0.0659)	(0.0659)	(0.104)	(0.104)
Age in 1994	0.00434	0.00412	0.00667	0.00619
	(0.00331)	(0.00334)	(0.00556)	(0.00560)
Highest Grade: Primary Schooling in 1994	0.000289	0.0181	0.0187	0.0789
	(0.0943)	(0.101)	(0.181)	(0.201)
Highest Grade: Middle Schooling in 1994	0.0762	0.0811	0.111	0.135
	(0.0735)	(0.0742)	(0.122)	(0.127)
Highest Grade: High School in 1994	-0.0530	-0.0575	-0.0538	-0.0446
	(0.100)	(0.101)	(0.161)	(0.161)
Unemployed and Looking for Work 1994	0.277	0.328	6.776	8.209
	(7.383)	(7.385)	(49.27)	(49.32)
Self Employed 1994	-0.0138	-0.00947	-0.0338	-0.0168
	(0.0583)	(0.0590)	(0.108)	(0.111)
Family Worker 1994	0.120	0.140	0.241	0.330
	(0.199)	(0.203)	(0.394)	(0.415)
Domestic Worker 1994	-0.0467	-0.0795	0.000871	-0.0635
	(1.942)	(1.944)	(2.595)	(2.598)
College Graduates 1994		0.0253		0.0624
		(0.0505)		(0.0905)
Observations	1,963	1,963	1,145	1,145
Sample	All	All	Skilled	Skilled
State FE	Yes	Yes	Yes	Yes
Joint F-stat	0.437	0.418	0.373	0.383
p-value of joint test	0.916	0.939	0.948	0.954

Notes: We test for correlation in our 1990 Migration Exposure measure (outcome) with respect to 1994 characteristics using the nationally representative NSS data.

Table C5: Baseline Tests Between Outcomes and Independent Variable

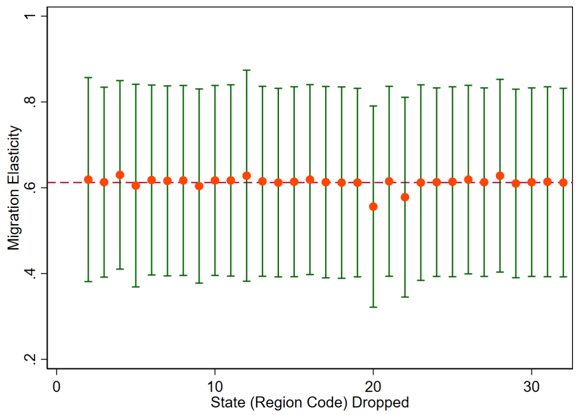
	Education Level at Baseline		
	Primary	Secondary	College
Log(Indian Migrant Earnings in US)	0.00225	-0.0232	-0.00934
	(0.00723)	(0.0436)	(0.0213)
Observations	1,758	1,758	1,758
First stage F stat	93.12	93.12	93.12

	Labor Characteristics		
	Self Employed	Family Enterprise	Domestic Work
Log(Indian Migrant Earnings in US)	0.0189	0.000159	-0.00807
	(0.0149)	(0.00328)	(0.00503)
Observations	5,096	5,096	5,096
First stage F stat	79.12	79.12	79.12

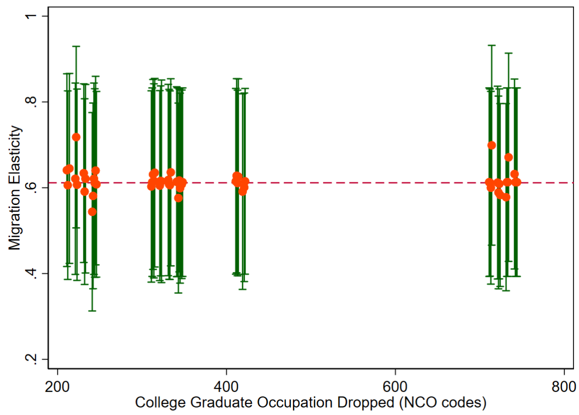
Notes: $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. Correlations with education (top panel) and other labor market outcomes (bottom panel). All regressions include occupation-region and region-time fixed effects. SE clustered at the occupation-region level. Data for India, from the National Sample Surveys, and data for the US from the US Census, and the American Community Survey. The H-1B cap changes are as recorded by the Department of Homeland Security. Details of the data construction can be found in Appendix A.5.

Figure C2: Robustness to Dropping a State or Occupation

(a) Dropping One State at a Time



(b) Dropping One Occupation at a Time



Note: We show robustness of our primary specification dropping one occupation at a time (left panel), and one region at a time (right panel). All regressions include occupation-region and region-time fixed effects. SE clustered at the occupation-region level. The main explanatory variable is the log of the number of Indian college graduates who migrated to the US in the past 5 years to work in occupation o. The sample is restricted to occupations that are high-skill intensive. We only include occupation-region pairs where workers are found in at least one year. Data for India, from the National Sample Surveys, and data for the US from the US Census, and the American Community Survey. The H-1B cap changes are as recorded by the Department of Homeland Security.

D Additional Tables for Model Counterfactuals

Table D1: Compensating Variation in 2010 By Worker

	Total Welfare (USD mn)		**Welfare per Migrant (USD)**	
	US	**India**	**US**	**India**
Always CS	-1647	-257.8	-11565	-1811
Switchers from CS to non-CS	-19.18	-127.30	-134.7	-894.1
Always non CS	996.4	566.4	6998.0	3978
Non college	2525	-21.979	17733	-154.36
Total Welfare non-migrants	1855.4	159.3	13031	1119
Welfare of Migrants	5822		40888	
Total	7837		55038	

Notes: Compensating Variation in USD (total and per migrant) defined as the amount in USD that must be provided to agents in a world with restricted migration to provide them with the same welfare as in a world with H-1B migration. In the counterfactual, the H-1B cap is reduced by 50% in every period, starting in 1995.

Table D2: Effect of Migration Over Time

	1995	**2000**	**2005**	**2010**
Wages				
US native CS	-0.1%	0.3%	-0.3%	-0.6%
US immigrant CS	-0.1%	-1.2%	-7.8%	-11.0%
US non CS college grad	-0.03%	-0.03%	-0.04%	-0.03%
US non college grad	0.01%	0.02%	0.07%	0.13%
India CS	16.09%	-13.9%	-12.0%	-12.3%
India non CS college grad	6.03%	6.2%	5.3%	2.1%
India non college grad	1.93%	0.7%	0.8%	0.9%
Occupational Choice				
US CS (native plus immigrant)	-1.0%	0.3%	1.6%	2.9%
US CS native	-1.0%	-1.7%	-2.9%	-3.9%
India CS	25.2%	58.0%	46.7%	42.2%
US non CS college grad	0.03%	0.1%	0.1%	0.2%
India non CS college grad	-0.02%	-0.5%	-0.9%	-1.3%
IT production				
US IT output	-1.4%	0.8%	0.8%	1.1%
India IT output	29.0%	19.7%	17.6%	25.0%
World IT output	9.1%	12.6%	13.6%	7.8%
US IT price	0.3%	-0.3%	-1.4%	-2.4%
India IT price	-3.06%	-2.3%	-2.1%	-9.4%
Welfare				
Welfare of US natives	0.00%	0.01%	0.02%	0.04%
Welfare of migrants	-0.2%	33.9%	38.8%	32.0%
Welfare in India	0.52%	1.03%	0.74%	0.07%
Combined welfare	0.06%	0.21%	0.25%	0.15%

Notes: Percent difference on main outcomes in going from a scenario with restricted migration (counterfactual) to full migration (real). In the counterfactual, the H-1B cap is reduced by 50% in every period, starting in 1995.

Table D3: Brain Drain vs Brain Gain: Welfare

	Baseline	No occupational choice in India	No migration but reallocation	No return migration
US Welfare				
Always CS	-1.14%	-1.00%	-0.09%	-1.20%
Always non CS	0.05%	0.05%	0.00%	0.05%
Non college	0.13%	0.12%	0.00%	0.15%
India welfare				
Always CS	-7.3%	1.31%	-7.5%	-2.82%
Always non CS	0.68%	-0.18%	0.65%	0.39%
Non college	-0.01%	-0.03%	0.02%	-0.04%
Total Welfare				
US natives	0.043%	0.045%	-0.0012%	0.053%
Welfare in India	0.07%	-0.05%	0.08%	0.04%
Combined (with migrants)	0.15%	0.12%	0.02%	0.17%

Notes: Percent difference on main outcomes when we go from a scenario with restricted migration (counterfactual) to a scenario with full migration (real). In the counterfactual, the H-1B cap is reduced by 50% in every period, starting in 1995. The 'no occupational choice in India' scenario restricts occupational choice and inhibits 'brain gain' in response to migration opportunities but allows for emigration ('brain gain'). 'No migration but reallocation' restricts migration (no 'brain drain') but allows for responses to migration opportunities ('brain gain'). 'No return migration' assumes individuals cannot return to India after they migrate.

D.1 Endogenous College - Details

In our baseline specification, the decision to go to college is made outside of the model and treated as exogenous. To relax that assumption, we allow individuals to choose at the age of 20, whether they want to join the labor market immediately and work as non-college graduates for the rest of their careers, or go to college, choose either CS or another college major, and join the labor market next period as in the baseline model. We present the college decision in equation D1:

$$\max\{\rho \mathbb{E}_t V_{t+1}^{coll} + \bar{F}_{coll} + \sigma_c \eta_{i,t}^{coll}, w_{ncoll,t} + \rho \mathbb{E}_t V_{t+1}^{ncoll} + \sigma_c \eta_{i,t}^{ncoll}\} \tag{D1}$$

$\eta_{i,t}^{coll}$ and $\eta_{i,t}^{ncoll}$ are *iid* preference draws from a Type I Extreme Value distribution for college and non-college respectively. This specification introduces two additional parameters for each country. $\bar{F}_{coll}$ is a fixed cost of going to college that is necessary to capture the large share of workers not going to college despite the higher wages. σ_c is the preference parameter that controls how sensitive individuals are to the preference shocks. If the value of not going to college is larger, individuals join the labor force immediately and work as non-college graduates until the end of their careers, earning wage $w_{ncoll,t}$. If they choose to go to college, they follow equation 3, and choose their college major. Then they follow the baseline model and join the labor force next period either as CS or other college graduate occupation. If they choose to go to college their value functions and decisions are identical to the baseline model.

To estimate the additional four parameters in the SMM routine, we add 4 targeted moments to identify them. We use the shares of college graduates among all workers for each country in 1995 and 2010. A high $\bar{F}_{coll}$ implies the shares for both years will be lower on average. A low σ_c implies workers are not as sensitive to preferences and respond more to changes in the wage. The change in the shares between 1995 and 2010 conditional on wages help identify this parameter.

Table D4: Endogenous college enrollment

	Baseline	Endogenous college
IT production		
US IT output	1.06%	1.29%
India IT output	25.02%	37.27%
Occupational choice		
US CS native	-3.89%	-5.31%
India CS	42.23%	60.56%
US college non-CS	0.19%	0.19%
IN college non-CS	-1.26%	-0.91%
US high-school	-	0.01%
IN high-school	-	-0.07%
Welfare		
US natives	0.04%	0.059%
Welfare in India	0.07%	0.06%
Combined (with migrants)	0.15%	0.23%

Notes: Percent difference on main outcomes when we go from a scenario with restricted migration (counterfactual) to a scenario with full migration (real). In the counterfactual, the H-1B cap is reduced by 50% in every period, starting in 1995. In the 'Endogenous college' model, individuals choose whether to go to college before joining the labor market.

D.2 Alternative migration and trade policies

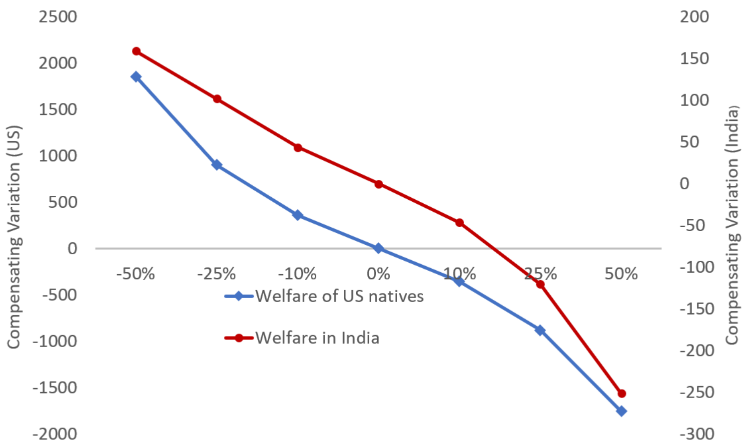
Our main counterfactual reduces the cap for Indian CS by 50% every year since 1995. We explore how our results would change when trying alternative counterfactuals, such as varying the size of the cap, and beginning the migration restriction in later years. Figure D1 shows how overall welfare for US and Indian natives (excluding migrants) would change for alternative changes in the migration cap. On the horizontal axis we plot the reduction in the cap (i.e. -25% is a world where immigration is restricted to 75% of the current cap). On the vertical axis we plot the welfare change of going from a scenario with an alternative cap (counterfactual) to a scenario with the observed cap (real). In general, the results are monotonic – more migration leads to higher welfare for US natives and Indian non-migrants. Yet, there are some interesting non-linearities when studying the welfare of US natives.[23]

In our baseline results we start our counterfactual experiment from 1995 onward. However, from a policy point of view, an important question may be what are the impacts of migration if we started the migration restriction in later years, once the Indian IT sector was already developed. As shown in Figure D2, a cap that starts later has similar effects on India since workers make expectations on future cap increases that are consistent with reality and start getting into CS before the cap comes into effect. For the US, if the cap restrictions start in later periods, workers initially gain as US workers start switching back to CS while the number of migrants is not yet restricted, generating additional spillover effects.

Finally, we look into how migration and trade policies interact. As we discussed before, a consequence of India expanding its IT sector due to more immigration, is that production can relocate from the US to India. This relocation can have ambiguous consequences for American workers. On one hand, if India becomes a more efficient producer of IT goods, consumers in the US can buy such goods from India at lower prices. On the other hand, India expanding its IT sector means that it will generate more of the knowledge spillover

[23] Here, we assume that as we raise the cap, the cap will still bind (i.e., supply from abroad is infinitely elastic).

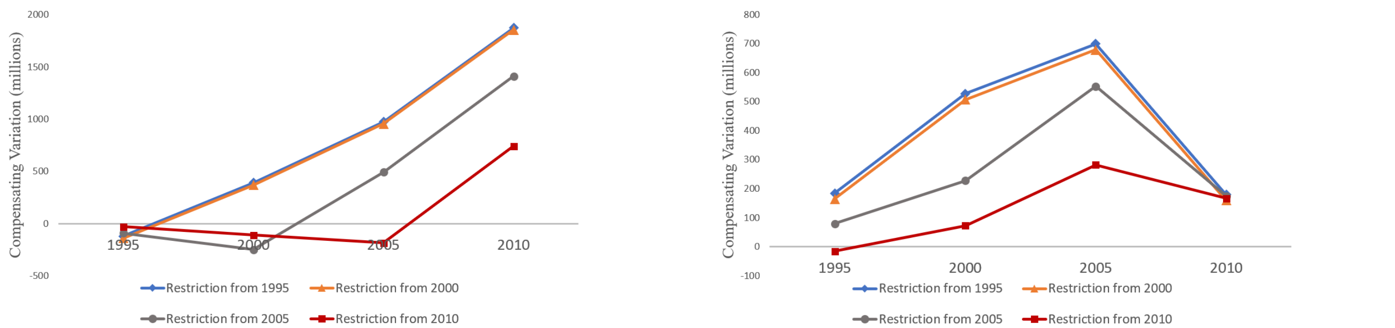
Figure D1: Welfare Loss by Different Cap Sizes (USD mn)



Notes: Percent difference on main outcomes when we go from a scenario with an alternative cap (counterfactual) to a scenario with the observed cap (real). We solve the model for different counterfactual scenarios to elicit the welfare loss for each intensity of migration restriction. For counterfactuals, we vary the cap from a 50% reduction in the current H-1B cap to a 50% increase. Compensating variation is defined as the amount of USD that must be provided to agents in a world with restricted migration to provide them with the same welfare as in a world with H-1B migration.

Figure D2: Expectations and Starting Restrictions in Different Periods

(a) Welfare Change: US natives (USDmn) (b) Welfare Change: India non-migrants (USDmn)



Notes: Graphs show the compensating variation of restricting H-1B migration by 50%, where we vary the first period of when the cap is lowered. All agents correctly expect the cap to be lowered in the corresponding future period. Compensating variation is defined as the amount of USD that must be provided to agents in a world with restricted migration to provide them with the same welfare as in a world with H-1B migration.

relative to the US. If US CS workers switch to other occupations, the US might end up generating lower levels of innovation and losing in terms of welfare.

In Table D5, we look into what happens when we change trade policy. In column 2, we compare the real scenario with a counterfactual where the IT trade costs to export from India to the US are doubled. Under more IT trade, the IT sector in India expands while the US IT sector shrinks. US CS workers become more likely to switch to other occupations, and the US marginally loses in terms of welfare. India, on the other hand, benefits from more trade with the US as IT production relocates to India, generating valuable innovation spillovers. In column 3, we show the results of the real scenario compared to a scenario with lower migration (50% lower H-1B cap since 1995) and lower IT trade (double trade costs to export IT from India to the US). When trade policy is coupled with migration policy, going to a scenario with more migration and more trade amplifies the positive effects experienced by India. The impact of increased migration for the US are muted, they have fewer computer scientists than in the baseline since their IT sector is smaller and more US CS workers move to other occupations. All in all, while expanding migration is a net positive for the US, expanding trade in IT has slightly negative consequences.

Table D5: The interaction between trade and migration policies

	More migration (baseline)	More IT trade	More migration and IT trade
Occupational Choice			
US CS (native plus immigrant)	2.88%	-0.22%	2.76%
US CS native	-3.89%	-0.25%	-4.01%
India CS	42.23%	0.23%	42.59%
IT production			
US IT output	1.06%	-1.06%	0.48%
India IT output	25.02%	1.48%	26.59%
Total Welfare			
US natives	0.043%	-0.001%	0.043%
Welfare in India	0.066%	0.007%	0.072%

Notes: Column 1 shows the percent difference on main outcomes when we go from a scenario with restricted migration (counterfactual) to a scenario with full migration (real). Column 2 shows the percent difference when going from a scenario with restricted trade in IT (double IT trade costs) to a scenario with observed trade (real). Column 3 looks at the change in both migration and trade. In the migration counterfactual, the H-1B cap is reduced by 50% in every period, starting in 1995. In the trade counterfactual, trade costs in IT for Indian exports to the US are doubled in every period since 1995.

E Why India?

While not the direct objective of our analysis, we find it both worthwhile and interesting to document why this spread of the tech boom was limited to certain countries like India in the period of our study. The other countries (Israel, Ireland, and Germany) that became important IT exporters, did not have trajectories that were linked to migration to the US.[24] For instance, a lot of Ireland's IT exports were simply US-based firms located there, initially for tax purposes (Athreye, 2005).

What, then, was special about India's relationship with the US in driving such a spread of the tech boom? Our paper quantitatively confirms qualitative work, discussed below, on the role played by the migration of technology workers from India to the US. Such qualitative work by other researchers was largely conducted during the IT boom, and allows us to unpack how India alone could take such great advantage of the H-1B program. Indeed, by the end of our period, 86% of computer science H-1Bs were awarded to Indians.

The qualitative literature relies on historiography, and on interviews and small-sample detailed surveys of industry leaders in Silicon Valley and India. While we unpack this rich evidence below, that complements our quantitative analysis, a few salient features of the drivers can be summarized:

First, India had made major investments in top Engineering schools in the 1950s that grew to have world-wide reputation. In later years, enrollment was driven by the prospect of migrating abroad as the domestic market was small. For instance, consistent with our hypothesis, Bhatnagar (2006) notes that "*growth (in training and degrees) was also driven by larger salaries in the IT industry abroad.*"

[24] Authors' calculations using the OECD Trade in Value Added (TiVA) statistics suggest that IT (code C72ITS) export growth was largest in these countries.

Related to strong training, was the fact that the urban population was widely comfortable (and trained) in the English language (Azam et al., 2013), giving India an advantage over other Asian giants, like China, in being a source of migrant workers. As such, most multinationals recruited directly from these Engineering colleges (Desai, 2003).

Second, India sent a lot of these top engineers during the earlier hardware boom of the 1970s and 1980s. This diaspora helped establish strong connections and a reputation for well-trained workers (Arora et al., 2001; Saxenian, 1999). Bhatnagar (2006) 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*" in the expanding IT sector. Consistent with our shift-share approach, when migration caps were raised, it is then in these occupations with strong connections that saw large emigration, as these tech workers "*migrate to better paid jobs in other countries*" (Kumar, 2006).

Finally, (as we model) wages were lower in source countries like India (relative to countries like Germany, Israel, or Ireland), and as such, there was a ready supply of trained, English-speaking workers willing to work at competitive wages (Heeks, 1995; Subramanian, 1992). Related to this, there was a large population to draw from, and so firms thought it meaningful to invest in the fixed costs of setting up recruitment systems from India.

While we also discuss other reasons mentioned by qualitative literature, we find those to be more likely to be read as anecdotes. For instance, Kumar (2001) notes another 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 software development life-cycle by half.

E.1 A Brief History of Indian IT

The Indian software industry was inextricably tied to the US. It was born in the 1970s when Tata Consultancy Services (TCS) opened shop and started sending Indian engineers abroad to the US to do software programming, referred to as 'bodyshopping.' Some companies were helped at the start by Indian Government policies that permitted duty-free imports of computer systems if importers would promise to export software and services (usually to the US) worth twice the value of imports within a specified time period. In 1978, however, IBM had to exit the market in violation of Foreign Exchange regulations, serving a blow to firms that required their hardware.[25] There was little seen of the US hardware boom in India as the industry was not mature and did not acquire the technical knowhow of firms like IBM, which had virtually a monopoly in mainframe computers (Bhatnagar, 2006).[26]

As the personal computer became more popular in the US, the demand for software programming services grew rapidly, especially for low-cost workers from India.[27] However, the lack of a domestic market and of the advanced technological capability required to write software meant that 90% of software revenues came from US on-site work (NASSCOM, 2003). These counted towards exports, and exports grew from about $50 million in the late 1980s to about $200 million by 1993, at a rate of about 30% a year.

In the early 1990s, with the start of the H-1B program, there was a spurt in the entry of multinational firms and demand for software services that were outsourced from the US. Yet, on-site work dominated because otherwise, software had to be transported on tapes, which faced heavy import duties. Kumar (2001) notes another significant advantage for the Indian industry in this period – 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. In 1992, satellite links were set up in Software Technology Parks (STP) to facilitate the smooth workflow process.

The Y2K threat was not to the detriment of the Indian industry (Desai, 2003). In fact, "*Y2K projects were an important source of revenue for Indian firms*" (Arora et al., 2001), and this helped build a reputation with their US counterparts. One commentator notes that the industry "*grew on the strength of Y2K and never looked*

[25] They were back as a joint venture with Tata Information Systems at the start of the H-1B program in 1992.

[26] At this time personal computers were absent from the Indian market altogether.

[27] In 1989, an Indian computer professional earned about $5486, whereas Microsoft was offering $40,000 plus relocation benefits and a green card for software engineers (Subramanian, 1992).

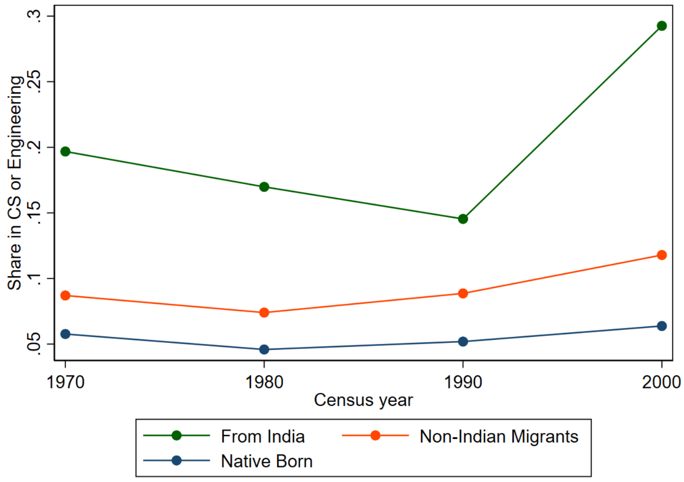


Figure E1: Share of US-based Workers in CS or Engineering (US Census 1970-2000)

back" (Dataquest, 2003).

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

Even at the end of our period, though, in 2011, 90% of the population was still not connected (World Development Indicators). As such, most of the growth was driven by exports to the US (Figure 3b).

E.2 The Indian IT Firm and its Relationship with the US

Unlike most Indian industries that focus on the large domestic market, the Indian IT firm was significantly export-oriented, catering to a consumer base abroad that has the purchasing power for its products (Figure 3b). 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 were directly exported from India. Bhatnagar (2006) 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, after the IT boom had spread to India.

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, but also the lowest revenue per employee. However, this low productivity could be a reflection of the types of services they provided – maintenance of data/legacy systems and other low-value services (Athreye, 2005).

As corroborated by Figure E1, India always sent a disproportionate fraction of Engineers to the US, even during the earlier hardware boom (in the 1970s and 1980s). Yet, since immigration was less widespread, the numbers were lower, even as the share of engineers as a fraction of the migrants was large. These engineers helped build connections and spread the reputation of Indian engineering graduates.

As such, a large part of the success of Indian firms is attributed to high-skilled Indian immigrant networks in the US. Bhatnagar (2006) 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.

We should note that our shift-share strategy implicitly leverages these networks and connections. As

Indians established connections in certain engineering-related occupations, the subsequent growth (under more migration as policy caps are raised) would be in these occupations as well (Figure E1).

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.

Saxenian (1999) shows that in 1998, persons with Indian names headed 774 high-technology Silicon Valley firms, overlooking sales of about $3.6 billion, which is roughly the same amount as the entire Indian IT sales bill in 1998. By the turn of the century, Indians headed 972 Silicon Valley firms, accounting for nearly 26,000 jobs. Bhatnagar (2006) claims that 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.

The US has historically been the largest exporter of software products, and continued 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 rapidly shifted to using India as a place for software development (Arora et al., 2001). By 1997, the US accounted for about 58% of all export revenues, whereas all the European countries combined accounted for only 21%. By the mid-2000s, however, India overtakes the US as the major exporter of IT products (Figure 3b).

Indian firms could use the H-1B program as a method to set up a base in the US with a ready supply of workers from India. Even as late as 2013, Indian firms were the largest sponsors of H-1B visas to the US. Even non-Indian firms are big employers of H-1Bs, some of which have Indians as their largest employment base. Table E1 shows that 10 out of the top 11 H-1B firms have Indians as their main 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).

Table E1: Number of H-1Bs by Firm (Approved)

Rank	Company	Headquarters	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 (2012-13). Rank is based on the 2013 number of visas approved. The last two columns indicate the number of H-1B visas that were approved for each year. To measure the employment base, we use the number of workers in each location by firm. For instance, the largest H-1B benefactor at the end of our period: Infosys received 5,600 H-1B visa approvals in 2012. In 2012, the company has 156 thousand employees worldwide, out of which 141 thousand are in India, making India its main employment base (see https://www.infosys.com/investors/reports-filings/quarterly-results/2012-2013/Q3/Documents/fact-sheet.pdf).

These workers come in search of higher wages, as working in the US provides substantial productivity premiums (Clemens, 2013). However, there is a cap on H-1B visas, and the visas are only for 3-6 years and, a large number of potential engineers must seek work elsewhere. Workers who are unable to obtain an H-1B visa because of the cap, or return to India after their visa expires are a ready supply of labor for firms in India.

This leads to a large skilled workforce in India, and enables the Indian IT sector to expand, tapping into this growing educated workforce. The growth in Indian firms are therefore strongly linked to larger exports to the US, and in the ready supply of labor.

E.3 Indian Students and College Choice

The boom in the US also affected the education sector in India. Consistent with the hypothesis posited in our analysis, Bhatnagar (2006) notes that "*Since engineers were willing to work as programmers in a domestic environment with few job opportunities, 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 2b).

In later years, as demand for such degrees expanded, India was somewhat uniquely placed in rapidly expanding the supply of Engineering colleges to meet rising demand, as we describe in other work (Jagnani and Khanna, 2020).

While the abundant stock of programmers had induced recruiters to come to India in the early 1990s, this was sustained till the end of the decade by a steady increase in freshly trained programmers (Desai, 2003). In 2002, these software engineers were young, with a median age of 26.5 years, and 58% of them had less than three years of experience (NASSCOM, 2003). In India, most programmers and the chief executives in IT companies are predominantly trained as engineers (Desai, 2003). Science graduates and those with master's degrees in computer applications make up the rest. A NASSCOM-Hewitt survey found that 88% of firms (primarily multinationals) visited engineering colleges to recruit, and 47% recruited *only* there.

Many of these recruiters themselves had been trained at these very universities, and others knew of colleagues from such reputable schools like the Indian Institutes of Technology (IITs), that were established in the 1950s. Arguably, such a strong engineering school sector gave Indian workers an edge over other countries (Desai, 2003).

A survey by Arora and Athreye (2002) found that 80% of all software professionals employed had engineering degrees, and show that over time, a number of engineering colleges have increased their emphasis on IT and even IT management. This, however, has meant that the number of PhDs in engineering disciplines has actually fallen from about 675 in 1987 to 375 in 1995. The industry was, therefore, attracting some of the brightest young graduates, with little academic bent and with only industrial ambitions. The salaries were among the highest across industries, growing at a steady rate, and some firms even offered stock options. Despite this, the attrition was quite high, as they "*migrate to better-paid jobs in other countries*" (Kumar, 2006).

The bulk of Indian workers get their degrees at Indian universities. India has historically been better at technical education like engineering and medicine (Arora et al., 2001). Furthermore, it has a linguistic advantage over East Asian countries, due to a vast majority of Indians being fluent in English. 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 (NASSCOM, 2012). This growth in engineering schools drives the growth in undergraduate enrollment in technical institutions (Figure 2b).

A large number of foreign students also come to the US for higher education, plausibly also exploring this as a pathway to the US labor market. Many students stay on to obtain work visas (Bound et al., 2014). 20,000 H-1B visas are granted to students who obtained their master's (or higher) degrees from US institutions, and this may incentivize students to obtain their degrees in US universities so that they may avail of the higher wages that come with an H-1B visa (Rosenzweig, 2006).