How High Skilled Immigrants Affect Natives' Educational and Occupational Choices

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Abstract

How will the inflow of foreign computer scientists to U.S. labour market affect wages, employment, educational and occupational choices of native skilled workers? This paper structurally estimates a dynamic discrete choice model using data from U.S. Current Population Survey (CPS) and American Community Survey (ACS) over two decades (1994-2014). The structural estimation framework that I develop fully imposes the restrictions of optimization theory and permits an investigation of whether such a theoretically restricted model can succeed in quantitatively fitting the observed employment and wage data patterns. I generalize the static Roy model to a dynamic general equilibrium setting where natives make choices based on their comparative advantages. Using sufficiently flexible sector production functions, I find skilled immigrants and natives are imperfect substitutes. Substitution elasticities vary across occupations, 5.73 for computer science (CS) sector and 1.97 for other science technology engineering mathematics (STEM) sector. The covariance matrix of unobservable heterogeneity implies mild positive selection of natives in both sectors. In the counterfactual simulation, when restricting the number of foreign computer scientists to its pre-internet booming level, I find a smaller crowding-out effect than previous literature.

1 Introduction

Over the past two decades, substantial literature on the impact of immigrants in U.S. labor market has appeared, but the discussions mainly surround the mid to lower tail of the skill distribution. This is manly due to the fact that a large fraction of early immigrants consisted of low skilled (high school graduates or below) workers with limited English skills. Recently, discussions on high skilled immigrants are increasing, accompanying the increasing number of high skilled (college graduates or above) immigrants entering U.S. labour market; skilled immigrants play a quantitatively and qualitatively important role in U.S. economy. According to the Migration Policy Institute (MPI), U.S. experiences secular growth of skilled immigrants with an annual growth rate about 4.8% from 1990 to 2010. In 2013 28.8% of the 35.7 million foreign workers over the age of 25 in U.S. have a Bachelor's degree or higher.

Many of these high skilled immigrants are produced by the U.S. higher education system. Currently approximately 900 000 international students are enrolled in American universities and approximately 24.4% of doctoral degrees are awarded to foreign students. Many of these newly-minted foreign skilled workers remain in the U.S. after graduation [1]. This can be viewed as sizable supply shocks in the labour market. Meanwhile, nonresident aliens unevenly spread across occupations, concentrating in electronic engineering, computer sciences, industrial engineering, material sciences and economics. When we look at a more restricted labour market, the impact of high skilled foreigners would become even more pronounced.

Despite the large supply shocks and their important consequences, we have little knowledge of how natives will behave in response to such supply shocks. This paper aims to explore the labour market for native workers in science, technology, engineering and mathematics (STEM)[2] occupations when there is a huge immigrant influx. I use a structural model to answer the following three

[1] There are no firm data on stay rates except for doctoral completers, who have been documented at much higher rates than college graduates, with two-year stay rates of almost 70% in 1999, ranging from 75% in physical and computer sciences and engineering to 40-45% in economics and agricultural science.

[2] The U.S. Immigrantion and Customs Enforcement list disciplines including: Physics, Actuarial Sciences, Chemistry, Mathematics, Applied Mathematics, Statistics, Computer Science, Computational Science, Psychology, Biochemistry, Robotics, Computer Enginnering, Electrical Enginnering, Electronics, Mechanical Enginnering, Industrial Enginnering, Information Science, Civil Engineering, Aerospace Enginnering, Chemical Enginnering, Astrophysics, Astronomy, Optics, Nanotechnology, Nuclear Physics, Mathematical Biology, Operation Researh, Neurobiology, Biomechanics, Bioinformatics, Acoustical Enginnering, Geographic Information Systems, Atmospheric Sciences, Software Engineering, Econometrics, etc.

questions. First, how will labour market situations faced by natives change in respond to increasing number of foreign skilled workers? Second, how will native workers' educational and occupational choices be affected? Last, what is the welfare implication?

1.1 Literature Review

Many literature on immigration policy attempts to determine the extent to which the arrival of immigrants, both low skilled and high skilled, helps or harms their native counterparts. The early studies on impacts of low skilled immigrants relied on simple conceptual models and reduced form estimations. Various elasticities of substitution were at the core of discussion. Borjas (1987) explores the variation of the local immigration concentration at the level of the standard metropolitan statistical area (SMSA) and finds that the increased supply of immigration [3] has adversely affected while but slightly benefited black native-born men. Altonji and Card (1991) also explore the city-specific variations and find a modest degree of competition between less-skilled natives and immigrants that 1 percentage point increase in the fraction of immigrants in a SMSA reduces less-skilled native wages by roughly 1.2 percent. Card (2009) looks closely into the skill distribution of immigrant and native workers when evaluating the impact of immigrants. Low skilled immigrants will cause more adverse effects on natives if low skilled and middle skilled labour are closer substitutes. The spatial analysis in Card (2009) has two main results: first, high school dropouts and high school graduates are perfect substitutes and high school-equivalent and college-equivalent workers are imperfect substitutes with the elasticity of substitution on the order of 1.5-2.5; second, within broad education groups the elasticity of substitution between natives and immigrants is large but finite (on the order of 20). Early papers focus on locally defined labour markets. Unfortunately, these analyses ignore the crucial fact that firms and workers adjust to immigrant supply shocks by migration to other geographic locations, leading to estimation biases of underlying impacts (Borjas, Freeman and Katz 1997). Card (2001) explicitly estimates the native workers' migration responses and finds that natives are insensitive to immigration inflows in terms of intercity mobility. In this paper, I propose another mechanism describing how will US-born workers respond to increasing number of immigrants. Natives rather than move to different locations, they switch fields of study and occupations to where they have comparative advantages. I do find sufficient evidences to support this

[3] In 1980 U.S. census data, immigrants are majorly Hispanic men.

mechanism.

As pointed out by Borjas Freeman and Katz (1997), cross-city comparisons are far from a panacea. More recent studies consider labour markets to be specialized fields of study, expertise or skill groups. This new approach relaxes the geographic definition of labour markets and instead focuses on national markets for narrower skill and occupation groups. Borjas (2005) finds that an immigration-induced 10-percent increase in the supply of doctorates in a particular field at a particular time reduces the earnings of that cohort of doctoral recipients by 3 percent. Other examples with respect to skilled immigration include Borjas and Doran (2012) which studies the surge of Russian mathematicians into U.S. following the Soviet Union's collapse and Moser et al (2012) which analyzes the impact of Jewish expellees from Germany. Borjas and Doran (2012) find a crowding-out effect induced by the Soviet inflow, while Moser et al (2014) find positive externality and a crowding-in effect along with substantial long-run patent growth. Kerr (2013) gives one potential explanation to these controversial results that Borjas and Doran (2012) study within institutional settings with an almost vertical demand curve while Moser et al (2014) look at a longer time horizon allowing for growth potentials. In this paper I will define labour market in a similar fashion, studying national labour markets for computer scientists and other-STEM occupations.

All above papers are based on reduced form estimation; results vary a lot, which is partly due to the selection bias and the possible reverse causality. More recently, the improvement of computing power makes the more plausible structural estimation possible. In the structural estimation framework, natives' responses to immigrant supply shocks is explicitly modeled. This directly addresses the selection issue. To the best of my knowledge, Bound, Brage, Golden and Khanna (2014) (BBGK) is the only paper, besides this one, that utilizes a structurally integrated model when studying the impact of immigrants. BBGK analyze the employment and wage adjustments of computer scientists during 1994 to 2000 and their counterfactual simulation finds that had firms not been able to hire more foreign computer scientists in 2000 than in 1994, the wages of U.S. computer scientists would have been 2.8% to 3.8% higher, and there would have been 7% to 13.6% more Americans working in the CS sector. I believe that these numbers overestimate the actual crowding-out effect because BBGK assume a decreasing return to scale production function and treat skilled immigrants and natives as perfect substitutes. In this paper I will use the same analytical framework as BBGK(2014) but expand the analysis in two directions: 1) I generalize the production function so as to allow for the possibility that labour inputs can be gross complements as well as substitutes rather than directly impose the assumption that natives and immigrants are perfect substitutes. 2) I allow for heterogeneity in skills among natives and allow natives to choose sections according to their comparative advantages.

For methodological foundations, I follow the literature of dynamic discrete choice programming (DDP). Generally speaking, I generalize the famous occupational choice model proposed by Keane and Wolpin (1997) to general equilibrium settings. As mentioned by Keane and Wolpin (1997), the underlying unobservable heterogeneity is crucial to model individual occupational choices. I add classical Roy model flavor to this simple DDP model by assuming a continuous distribution of unobservable abilities. Estimation of this model relies on the combination of approximation and intropolation techniques (Keane and Wolpin 1994) and simulation method of moments (SMM) (MacFadden 1989).

1.2 General Approach and Contribution

First my paper contributes to immigration literature by proposing another plausible mechanism of how skilled natives react to challenges posed by increasing skilled immigrants. The crucial assumption is the existence of a national labour market for narrowly defined occupation groups. Accounting for this assumption, I employ a general equilibrium model. The unbalance distribution of skilled immigrants changes market conditions differently across occupations. Changing market conditions (wages) induces natives to re-optimize, switching fields of study and occupations. By explicitly modeling the decision making process of skilled natives, this paper directly addresses the selection and reverse causality concerns. My estimates show that natives are quite sensitive to wage fluctuations. To make the mechanism more reliable with sound optimization foundations, I introduce the classical Roy component into this simple framework. The unobserved skill endowments are important determinants of life-cycle earning outcomes.

Second, previously researchers estimate the elasticity of substitution between immigrants and natives in general skill groups. I take one step further to study this elasticity within detailed occupation groups and find that substitutability varies across occupations. Occupation task contents could be one possible explanation; immigrants are closer substitutes to natives in occupations demanding quantitative and analytical skills, while natives are less substitutable in occupations requiring interactive and communication skills[4].

This paper also contributes to the human capital accumulation literature in the following sense. Human capital is occupation specific in this paper as supported by the empirical results of Kambourov and Manovskii (2008) and is accumulated in a stochastic way that the probability of acquiring an additional unit of human capital is a decreasing function of experiences. My estimates indicate the accumulation stops around age 45-50 with minor differences across occupations which is consistent with the definition of the earning age profile flat spot in literature (Bowlus and Robinson 2010).

My model differs from BBGK (2014) fundamentally in the following ways. Natives are heterogeneous in terms of occupation specific skill endowments. BBGK(2014) exclude completely the human capital accumulation while occupation specific human capital evolves endogenously here. BBGK's (2014) model is in essence a partial equilibrium focusing only on the market for computer scientists and ignoring any wider impacts that foreign computer scientists might have on other sectors. Formulating a general equilibrium model, I study more comprehensive impacts of skilled immigrants. Last, I estimate the elasticity of substitution directly instead of assuming perfect substitution between natives and immigrants.

The paper is organized as follows. In section 2, I describe the context of the market for CS since 1994 in detail and I also describe the OPT and H1B visa program in U.S.. In section 3 I present the model to characterize the behavior of native workers faced with a surge in the supply of foreign workers. In section 4, I will first describe the data used in this model followed by the discussion of identification and how I estimate the model parameters. Section 5 presents the results, and section 6 presents two counterfactual simulations. I conclude with discussions of the results in section 7.

2 Background

2.1 Demand of Computer Scientists in 1994-2014

Over the past two decades, we witness striking variations in the U.S. dot-com industry. The growth rate of computers, communications equipment and software (IT) industry boomed in the late 1990s and 2000 before plummeting in 2001 which brought the growth rate to a screeching halt. It took almost

[4] Peri and Sparber (2011) find evidences that support this result.

one decade for the industry to recover from the previous crash and in 2013 the media started to talk about the Tech Boom 2.0 fueled by the social media revolution. In Figure 1, I plot the Nasdaq Composite Index in the past two decades to demonstrate the variations mentioned above. The internet boom would form a strong positive demand shock for computer scientists. In Figure 2, I plot the employment time series of CS and total STEM sector in relative terms computed using March CPS data. The detailed sample selection and data adjustment are discussed in appendix B. In brief I follow the method proposed in Lemieux (2006). Figure 2 demonstrates two main points. First, the percentage of STEM workers in U.S. skilled labour force[5] is relative stable, about 4%. This supports my assumption that there is no structural or systematic changes that make STEM occupations more favorable for skilled natives during the period of interest. Second, the percentage of computer scientists in STEM increased by nearly two-thirds over the same period. Most of the growth occurred prior to the burst and afterward the fraction stagnated. The second point implies that during the high tech boom, there was increased interests in computer science related occupations and switching occupations within STEM category is achievable. Combining the two pieces of information, we can conclude that selection within STEM occupations attributes mainly to the observed increase in CS employment. Figure 2 supports one of my fundamental assumptions that different STEM occupations are close substitutes to computer scientists and there is little selection across STEM and Non-STEM occupations.

2.2 The U.S. Immigration Policy and Its Impact on CS Labour Market

In this part I will briefly discuss two immigration policies that will support my exogenous supply of skilled immigrant assumption. The Optional Practical Training (OPT) program[6] especially favors the STEM occupations with total length of 29 months which is one and half year longer than ordinary OPT length. When OPT expires, if students fail to acquire a valid working visa, they have to either leave the country or enroll into another educational program. For the working visa, the Immigration Act of 1990 established the H1B visa

[5]The skilled labour force is defined as those who currently work or search for a job and with at least a college degree.

[6]OPT is a period during which undergraduate and graduate students with F-1 status who have completed or have been pursuing their degrees for more than nine months are permitted by the United States Citizenship and Immigration Services (USCIS) to work for at most one year on a student visa towards getting practical training to complete their fields of study.

program for temporary workers in 'specialty occupations'[7]. This regulation requires applicants to have at least a college degree in order to be eligible. One distinct feature of the H1B visa program is that the visa is attached to specific firms who sponsor foreign workers in the process of visa application. The sponsoring firm will file a petition to U.S. Citizenship and Immigration Services Bureau (USCIS). Once the application is approved, it allows foreign high skilled workers to stay a maximum of six years on a H1B temporary visa. An important result of this program is that workers are effectively tied to their sponsoring firms, which to some extent prevents immigrants from switching occupations. And every year, the USCIS places a cap on the number of H1B visa granted. During the early 1990s, the cap was rarely reached. By the mid 1990s, the allocation based on a first come first served principle and the quota was usually exhausted within a short period of time. And the USCIS now employs a lottery mechanism to randomly select qualified petitions. In Figure 3, I show the changes of the H1B visa cap and the probability of approval. The probability of winning the lottery is about 50-60%. The H1B visa requirement of staying with employers which prevents occupation switches and the cap of overall number of total visa issued imply that the supply of immigrants is inelastic.

Over the years, a noteworthy portion of H1B beneficiaries[8] have worked in STEM occupations, especially computer related occupations. In 2000, almost 91000 H1B workers were employed in computer-related occupations and they made up 47% of all H1B beneficiaries. See the occupation composition of H1B beneficiaries in Figure 4. In Figure 5, I plot the time series of immigrant[9] fraction in three different groups. The bottom flat line is the fraction of immigrants in total high-skilled labour force. The proportion of foreign workers is relatively stable, consisting approximately 10% of the high skilled labour force. The proportion of foreign workers in CS is persistently high than other-STEM sector. One of the reason I choose to study CS and other-STEM occupations is because they are the occupation groups that are most influenced .

[7]The specialty occupations are defined as requiring theoretical and practical application of a body of highly specialized knowledge in a field of human endeavor including, but not limited to, architecture, engineering, mathematics, physical sciences, social sciences, medicine and health, education, law, accounting, business specialties, theology and arts.

[8]Workers renewing their H1B visa as well as newly arrived workers

[9]In the data, I define immigrants as those who does not become U.S. citizens until the age of 18.

3 A model of Natives' Choices

The model describes the sequential decision problem of skilled natives beginning at age 22. Time is discrete, and the occupational decision is made on a yearly basis. Individual's preferences are defined over consumption and taste shock only. Here I study only the full time full year workers, the leisure choice is thus omitted. The timing of this model is described as follows.

Prior to age 22, natives draw ability endowments from a joint distribution $F(\epsilon_{cs}, \epsilon_{ncs})$. At each following period, individuals will receive i.i.d. taste shocks in CS sector[10]. Individuals then choose to work in one of two sectors sequentially. While working in a sector, agents stochastically accumulate occupation specific human capital. To sum up, native skilled workers make occupational choices conditional on their permanent comparative advantages in ability, a temporary taste shock and current occupation specific human capital. Since human capital is occupation specific, switching means losing human capital and consequently lowering income.

On the labour demand side, there are two representative firms using only labour as inputs. These two firms consider skilled natives and immigrants to be different inputs. I assume very flexible production functions allowing substitution even complementarity between natives and immigrants, also allowing either decreasing or constant return to scale. Through the model, labour is measured in efficiency unit; firms face an inelastic supply of immigrant labour and a upward sloping native labour supply. The equilibrium rental rates clear both labour markets.

In the basic model, I assume stable recursive equilibrium. The aggregate technology shocks will move markets from equilibrium to equilibrium. In the model extension part, I will relax the steady state assumption and solve for perfect foresight equilibrium instead.

3.1 Labour Supply Side

3.1.1 Immigrants

As mentioned before, because of the H1B sponsorship policy, skilled immigrants are effectively attached to employers, making it less likely for foreign workers to switch occupations. Meanwhile, from the historical data that the probability

[10] Even though it is called taste shock, it actually captures all other factors influencing utility function that I don't explicitly include in. And I also choose to normalize the shocks in other-STEM occupation to zero.

of successful application is proximately 0.5, we know that firms have always wanted to hire more immigrants than they actually can. It is reasonable to assume that the immigrant labour supply is inelastic and the actual quantity is determined exogenously by immigration policies.

In the CPS and ACS data, we observe the annual income for full-time full-year skilled workers regardless of their citizenship. The occupation specific rental rate of foreign labour is measured by the average annual income of new foreign entrants. In order to be able to do this, we need to assume the following income wage equation.

$$W_{it}^{s} = \Pi_{t}^{s} H_{it}^{s}$$

Individual i 's income working in occupation s in year t, W_{it}^{s}, depends on the current market rental rate Π_{t}^{s}, as well as individual i's current occupation specific human capital H_{it}^{s}. H_{it}^{s} is an exponential function of occupation experiences and ability. New entrants have no previous working experiences and the mean of ability is normalized to 0. H_{it}^{s} equals unity for new foreign entrants.

The human capital of immigrants is measured by the ratio of income and the estimated rental rate $\frac{W_{it}^{s}}{\hat{\Pi}_{t}^{s}}$.

3.1.2 Natives' Individual Labour Supply Decision

Natives choose the optimal career path to maximize the life-time expected utility. In each period, natives either work as computer scientists or in other-STEM occupations. Define the action space $d \in \{cs,ncs\}$.

Preferences

I assume that the market is complete. Individuals can fully insure against risks, so no precautionary saving is required nor is risk aversion utility.

In each period, natives observe an i.i.d taste shock which is repeatedly draw from a normal distribution.

$$\eta_t \sim \mathbb{N}\ (0,\ \sigma_{\eta}^{2})$$

The flow utility takes linear functional form depending on the current consumption and the realization of the taste shock[11].

$$
\begin{aligned}
u_{cs,t} &= C_{cs,t} + \eta_t && \text{(1a)} \\
u_{ncs,t} &= C_{ncs,t} && \text{(1b)}
\end{aligned}
$$

All the labour income will be used to finance the current consumption $C_{s,t} = W_{s,t}$.

Before a high skilled native enters the labour market, this agent observes his or her own ability endowments following a bivariate normal distribution.

$$
\epsilon = \begin{pmatrix} \epsilon_{cs} \\ \epsilon_{ncs} \end{pmatrix} \sim N(\mu, \; \Sigma)
$$

The initial ability endowments are occupation specific and are considered as permanent shocks providing individuals with persistent comparative advantages. Once entering the labour market, individuals start to accumulate human capital. I assume there are competitive labour markets. Thus wages are determined by the current equilibrium rental rates ($\Pi_{cs,t}$ and $\Pi_{ncs,t}$) and individuals' occupation specific human capital (H_{cs} and H_{ncs}).

$$
\begin{aligned}
W_{s,t} &= \Pi_{s,t} H_s && \text{(2)} \\
s &\in \{cs, ncs\}
\end{aligned}
$$

In human capital production functions, I incorporate the basic idea of Mincer earning equation[12].

$$
\begin{aligned}
H_{cs} &= \exp[\alpha_1 x_{cs} + \alpha_2 x_{ncs} + \alpha_3 (x_{cs} + x_{ncs})^2 + \epsilon_{cs}] && \text{(3a)} \\
H_{ncs} &= \exp[\alpha_4 x_{cs} + \alpha_5 x_{ncs} + \alpha_6 (x_{cs} + x_{ncs})^2 + \epsilon_{ncs}] && \text{(3b)}
\end{aligned}
$$

The occupation specific human capital depends on the experience in the current occupation, the experience in other occupations and the general working experiences.

[11] I estimate the model with flow utility $u = \log(c)$, and the alternative specification doesn't make substantial changes to the results

[12] There is no constant in H_{CS} because constant is not separately identifiable from the equilibrium rental rates. Or we can think any shift of human capital level in one occupation can be reflected as the increases in the rental rate.

The log wage equation takes a linear functional form.

$$
\begin{aligned}
w_{cs} &= \pi_{cs} + \alpha_1 x_{cs} + \alpha_2 x_{ncs} + \alpha_3 (x_{cs} + x_{ncs})^2 + \epsilon_{cs} && \text{(4a)} \\
w_{ncs} &= \pi_{ncs} + \alpha_4 x_{cs} + \alpha_5 x_{ncs} + \alpha_6 (x_{cs} + x_{ncs})^2 + \epsilon_{ncs} && \text{(4b)}
\end{aligned}
$$

The occupation specific human capital evolves endogeneously with age. The wage equation is formulated to capture the concave shape of wage profiles.

Evolution of State Space

The state space of this DDP problem is $\mathbb{S} = (a,\ x_{cs},\ x_{ncs},\ \epsilon,\ \eta)$. Ability endowments ϵs are permanent heterogeneity which don't change over the entire career path; the taste shock η is repeatedly draw from the same distribution; age a evolves in a deterministic way. Sector specific experience x_{cs} and x_{ncs} evolve in a Markovian manner.

If the native worker spends one period in sector s ($d_s = 1$), this individual randomly accumulates experiences according to the following rule.

$$
x'_s = \begin{cases} x_s + 1 & p = \exp(-\gamma_s x_s) \\ x_s & 1 - p \end{cases}
$$

When $d_s = 0$ then $x'_s = x_s$. γ_s is restricted to be positive. It implies that when working in an occupation longer, individuals are less likely to accumulate an additional unit of human capital. This law of motion also allows the model to better fit the wage profile than simply imposing a quadratic functional form in the earning equation.

Individual Choices

Given the state space $\mathbb{S} = (a,\ x_{cs},\ x_{ncs},\ \epsilon,\ \eta)$, agents choose between two mutually exclusive alternatives in the action space $d = (cs,\ ncs)$. The state space $\mathbb{S}$ contains current experiences in both sectors, ability endowments describing comparative advantages and the current realization of the taste shock. The relevant history of career choices and the past realization of shocks are summarized by current experiences. The two alternative value functions when $a < 65$ are

$$
\begin{aligned}
V_{cs}(a, x_{cs}, x_{ncs}, \epsilon, \eta) &= W_{cs} + \eta + \beta \mathbb{E} V(a+1, x'_{cs}, x'_{ncs}, \epsilon, \eta' | d_{cs} = 1, \mathbb{S}) && \text{(5a)} \\
V_{ncs}(a, x_{cs}, x_{ncs}, \epsilon, \eta) &= W_{ncs} + \beta \mathbb{E} V(a+1, x'_{cs}, x'_{ncs}, \epsilon, \eta' | d_{ncs} = 1, \mathbb{S}) && \text{(5b)}
\end{aligned}
$$

In each period native workers choose the greater of V_{cs} and V_{ncs}.

$$V(a,\ x_{cs},\ x_{ncs},\ \epsilon,\ \eta) = max\ \{V_{cs},\ V_{ncs}\}$$

This finite horizon DDP problem is solved by backward iteration. The decision problem stops after retirement age 65. To initiate this iteration, I specify the value functions for age 65.

$$V_{cs}(65,\ x_{cs},\ x_{ncs},\ \epsilon,\ \eta) = W_{cs} + \eta \tag{6}$$

$$V_{ncs}(65,\ x_{cs},\ x_{ncs},\ \epsilon,\ \eta) = W_{ncs} \tag{7}$$

Let me summarize the decision process at individual level: beginning at one's career, given the comparative advantages ϵ, individual draws a temporary taste shock η and compute the current realized utility levels as well as two alternative-specific value functions. Finally this individual chooses the occupation that delivers higher expected value.

3.1.3 Aggregate Labour Supply

Even though there are no leisure choices in this model, the individual labour supply in efficiency unit still differs among natives since at any given time levels of individual human capital (H_{cs} and H_{ncs}) are different . When one works in occupation s, he or she supplies H_s efficiency units of labour. Given the initial ability density function $f_\epsilon(\epsilon)$, I first aggregate the labour supply for age group a. The native aggregate labour supply for age group a can be expressed by the following integration,

$$N_a^s = \iint \mathbb{I}_s(a,\ x_{cs},\ x_{ncs},\ \eta,\ \epsilon) H_s(\ x_{cs},\ x_{ncs},\ \epsilon) \mathrm{d}F(x_{cs},\ x_{ncs},\ \epsilon|a) \mathrm{d}F(\eta)$$

For age group a, there is a joint distribution of the ability endowments and the sector experiences $f(x_{cs},\ x_{ncs},\ \epsilon|a)$ which depends on the entire history of rental rates and taste shocks. Jointly with the distribution of the current taste shock $f(\eta)$, $f(x_{cs},\ x_{ncs},\ \epsilon|a)$ governs the aggregate labour supply.

I normalize the measure of native high-skilled workers in STEM occupations to unity. The aggregate native labour supply in one sector is the weighted average of labour supply by age groups.

$$N^s = \sum_{a=22}^{a=65} w_a N_a^s$$

Where the weight is the cohort population size which I measure using the CPS data by $w_a = \frac{N_a}{\sum_i N_i}$.
Unlike the model in BBGK(2014) which completely omits individual production differentials, here, the aggregate labour supply (in efficiency unit) differs from the proportion of individuals in one sector. The model predicted proportion of native CS workers in age group a has the following expression,

$$P_a^{cs} = \iint \mathbb{I}_{cs}(a,\ x_{cs},\ x_{ncs},\ \eta,\ \epsilon)\mathrm{d}F(x_{cs},\ x_{ncs},\ \epsilon|a)\mathrm{d}F(\eta)$$

.

3.2 Labour Demand Side

The two production sectors are occupied by two representative firms respectively. For simplicity and data availability, I assume that labour is the only input in production. Each representative firm faces two types of labour, native labour N_s and foreign labour M_s. As already been mentioned in the background section, each year firms face vertical supplies of foreign workers whose quantity is determined by immigration policies[13]. In the production side, representative firms solve static profit maximization problems in every period. No dynamic structure is imposed on the demand side.
I assume flexible CES production functions in both sectors. The profit maximization problem of the representative firm in sector s is :

$$\max_{\{N_{s,t},M_{s,t}\}} Z_{s,t}((1-\delta_s)N_{s,t}^{\rho_s} + \delta_s M_{s,t}^{\rho_s})^{\psi_s/\rho_s} - \Pi_{s,t}N_{s,t} - \Pi_{s,t}^{\star}M_{s,t}.$$

The functional form is quite flexible. ψ_s is the parameter that governs the return to scale which will be estimated from the data. The elasticity of substitution between natives and immigrants is $\frac{1}{1-\rho_s}$. These two types of labour could be gross substitutes or complements. The FOCs with respect to native workers deliver the implicit demand functions.

$$\Pi_{s,t} = Z_{s,t}\psi_s(1-\delta_s)((1-\delta_s) + \delta_s(\frac{M_{s,t}}{N_{s,t}})^{\rho_s})^{\psi_s/\rho_s - 1}N_{s,t}^{\psi_s - 1}.$$

The parameters of interests are ψ_s , ρ_s and δ_s. They inform us the fundamentals of sector production technologies.

[13]Peri (2013) assumes that the city-level foreign STEM workers changes exogeneously. Kerr and Lincoln (2010) explores the same variation. In order to identify the model, they also have to assume the supply of foreign STEM workers is exogenous. Their arguments as well depend crucially on variations in the H1B visa program.

3.3 Equilibrium

In the basic model, I discuss the steady state equilibrium. A dynamic steady state general equilibrium can be characterized by the system of choice functions and value functions, the stochastic process of technological movement and equilibrium rental rates. To close the model, I hereby specify stochastic processes of technological evolution. Because we are interested in a relatively short period of time, I choose to specify the $Z_{s,t}$ as an AR(1) process with a constant.

$$\begin{aligned} Z_{s,t} &= \theta_s Z_{s,t-1} + \bar{Z}_s + \xi_{s,t} \\ \xi_{s,t} &\sim i.i.d \end{aligned}$$

For simplicity, I don't allow correlation between sector innovations. $\xi_{cs,t}$ and $\xi_{ncs,s}$ are independent shocks.

4 Data, Identification and Estimation Method

4.1 Data

Given the nature of the model, the ideal data would be longitudinal data with long time span containing detailed records about citizenship, education, occupation, fields of study, annual income, labour market participation and etc. Unfortunately there doesn't exist this kind of ideal data set. As a compromise, the March CPS is the most suitable data set available for the estimation procedure. The span of the data, from 1964 to 2014, is the longest among comparable surveys. Even though I only focus on the recent two decades,[14] a much longer time span is critical. This is because that in the model extension part, instead of studying the steady state equilibrium, I take special care of the cohort effect by building a perfect foresight model. The perfect foresight model requires the knowledge about the entire history of efficiency wages as well as some out-sample forecasting. Furthermore, the annual frequency of the March CPS data fits the timing of the DDP model. The sample is constructed following the work of Lemieux (2006) . The detailed description about how to define variables are presented in Appendix B.

[14] The reason it starts from 1994 is that the variable ' Year of Immigration ' only becomes available after 1994. And the survey methodology in terms of occupation changed dramatically from independent coding to depending coding.

CPS has a large monthly sample about 60000 U.S. households. However, only a very restricted subsample–the high skilled[15] full-time full-year[16] STEM and CS workers–is studied in this paper. Especially, when computing the income wage age-profile, CPS suffers from the small sample problem. The problem is severe at the beginning of the career path and when approaching the retirement age. In Table 1, I present the maximum and minimum sample size over 20 year for each occupation and age cell. We can see that for CS workers when approaching retirement age, barely no observations are left. This provides the motivation to incorporate ACS and the census data in the analysis. ACS has much larger sample size about 1% of total U.S. population every year. However ACS covers a shorter sample period compared with CPS starting only from 2001. In 2000, I will use the 5% census data. The principle here is to use ACS and census whenever they are available and use CPS otherwise.

4.2 Estimation by Simulated Method of Moment

The estimation method I use is the Simulated Method of Moment (SMM) due to the data structure. The data I have are repeated cross section survey data. It prevents me from using the nested full information maximum likelihood (FIML) method as in Keane and Wolpin (1997). Instead, the strategy here is to choose parameters that deliver simulated moments which best match various moments of the native's annual earning and the occupational choice distribution.

4.2.1 Choice of Moments

The data moments to be matched are presented as follows:

Age Profile of Occupational Choices
p_t^a =proportion of age a native STEM workers working in CS sector in year t.

Age Profile of Incomes
1. First moments: the mean annual income of occupation s, in age group a and year t, $\bar{W}^s_{a,t}$.
2. Second moments: the standard deviation of annual income of occupation s, in age group a and year t, $\bar{\sigma}^s_{a,t}$.

[15]Defined as has a Bachelor's degree or higher.
[16]those between 22-65 who participate in the labour force at least 40 weeks in the year, working at least 35 hours per week.

4.2.2 Estimation Procedure

The parameter space Θ in the model can be naturally separated into two subsets $[\Theta^s \mid \Theta^d]$. Θ^s contains parameters that determine the native labour supply decision, including preference parameters, parameters in the human capital accumulation process and ability heterogeneity parameters. Θ^d are parameters describing the sectoral production technologies, such as TFP evolution processes, share parameters, elasticities of substitution and return to scale parameters. The supply and the demand side can be reasonably treated as two separate parts. The key factors connect these two components are equilibrium prices and quantities. Here I propose a two-step estimation procedure that separates the supply side estimation from that of the demand side[17].

I assume that over the past 20 years, fundamentals of the labour markets remain unchanged. The ability distribution, preferences and the way occupation specific human capital gets accumulated remain unaltered. Variations in rental rates generate different occupation choices and wage distributions. In the labour supply side, rental rates across years are treated as free parameters along with the fundamentals mentioned before. The first stage select the best fundamental parameters and 20 year's rental rates that best match the sector choice age profiles and the wages age profiles. At the end of first stage, I get time series of rental rates $\Pi_{s,t}$ and sector labour supplies $H_{s,t}$ in efficiency unit as final outputs.

In the second stage, I will combine the first stage outputs $\hat{\Pi}_{s,t}$ and $\hat{H}_{s,t}$ with observed quantities $\Pi^{\star}_{s,t}$ and $H^{\star}_{s,t}$ for immigrants[18] to estimate the following equations by maximum likelihood.

$$
\begin{aligned}
z_{s,t} &= \log\left(\frac{\hat{\Pi}_{s,t}}{(1-\delta_s)\psi_s[(1-\delta_s)+\delta_s(\frac{\hat{M}}{N})_t]^{\psi_s/\rho_s - 1}\hat{N}^{\psi_s - 1}} \right) \qquad (8a) \\
&= \bar{z} + \eta_s z_{s,t} + \xi_{s,t}
\end{aligned}
$$

Where $\xi_{s,t}$ is white noisy with variance σ_s^2. Further more, I assume that there is no correlation between error terms across sectors.

[17] Kim and Manovskii (2014) apply the same principle. They also first estimate the wage equations treating prices for experience as free parameters and next use the estimated prices and predicted quantities from the first stage to estimate production functions.

[18] In 3.1.1 I discuss how to measure these quantities for immigrants.

4.3 Identification

It is impossible to prove the identification of all parameters rigorously over the whole parameter space. Here instead, I am going to provide some intuitive illustrations on how these parameters are possibly identified with data variations[19].
The within year mean income age profile helps to identify parameters that guides return to experiences in human capital production and accumulation processes. Between year shifts of income profile reveal information about changes in the rental prices, which will eventually help to identify the technology processes.
The unobservable heterogeneity is identified through occupation choices and income dispersion in multiple sectors. First, for individuals with identical experiences, the unobservable heterogeneity directly maps to income heterogeneity. Choices of new entrants who haven't started human capital accumulation directly relate to the endowment distribution. Thanks to the booms and busts of dot-com industry occurred during the period of interests, there are a lot of variations in rental prices. Price variations help to identify the unobservable heterogeneity.
As for the taste shock parameter, in the flat spot area of the income age-profile where accumulating an addition unit of human capital is barely possible, variations in occupation choices reflect the magnitude of the taste shock.
When exploring exogenous changes in immigration supply and variations of rental prices across years, I can identify the substitution elasticity and share parameters in the production function. The exogenous foreign labour supply act as an instrument variable.
So far, when I impose the steady state equilibrium to solve the model and match the simulated moments to empirical moments computed from cross sections, I completely ignore the cohort effect. In the steady state equilibrium, individuals face one fixed set of steady state rental prices for their entire career. Older cohorts differ from the younger people only in one dimension, the age. However, in empirical data, older cohorts entered the labour market faced with different rental prices and over the years have accumulated different occupation specific human capital. There exists this fundamental discrepancy between the basic

[19]The identification of this paper can be considered as a direct application of Heckman and Honore (1990) in dynamic Roy setting. In the discussion of non-parametric identification of static Roy model, Heckman and Honore prove that for general skill distributions, with sufficient price variation, the model can be identified from multimarket data. Moreover, cross-sectional variation in regressors can substitute for price variation. In this paper, with repeated cross section multimarket data, I observed sectoral choices and wages . Meanwhile, the period I study covering two booms and one bust in CS sector which contains sufficient price variations. Last, occupation specific experiences act as additional regressors.

model and the data I am using. To better match the available data, in the model extension part, I will solve a perfect foresight model that explicitly addresses the cohort effect problem.

5 Results

Rust (1994, 1996) shows that the discount factor in standard DDP models is generically not identified since it only acts as a shifter of the lifetime utility level[20]. In this paper, I fixed the discount factor to value 0.95 which is within the reasonable range in literature[21].

5.1 Estimation Results

In Table 2, I present the estimates of Θ^s.Except for the taste shock parameter, all other parameters are statistically significant at 1% level. The basic model generates parameter values that appear to be consistent with previous literature. For example, the first year of the CS experience augments CS human capital by about 10.4% with little attenuation in the rate of increase at higher years of experience. The first year of other-STEM experience increases other-STEM skill by 12.4%[22]. Both sectors value working experiences in other occupations but to a lesser extent. An additional year of CS (other-STEM) experience augments other-STEM (CS) skill by less than 4.2 % (4.7%).

If we plot the income age profile of two occupations in the same graph, we will notice that CS workers start with higher initial income but the income grows at a lower rate because the experience prices are lower both for its own experience or experience in other occupation. And it reaches a lower flat spot faster compared to other-STEM occupations. These two income age profiles cross around age 40. The random accumulation parameters can be viewed as the speed of decreasing probability of human capital accumulating; the decreasing speed is slightly larger in CS sector.

[20] Rust paper models the impatience of the decision makers by assuming that agents discount future streams of utility or profits exponentially over time. With exclusive condition and hyperbolic discounting, the discount factor is identifiable.

[21] In BBKG(2014), they fix the discount factor to 0.9. According to the World Bank historical data, the U.S. real interest rates vary between 1.5% to 7%. The implied discount factor lies between 0.93 and 0.98.

[22] The corresponding numbers in Keane and Wolpin (1997) is about 11.7%.

These two unobservable abilities are mildly negatively correlated with a correlation coefficient $\rho = -0.18$. By the usual interpretation of Roy model, both sectors are positively selected. Since other-STEM sector actually aggregates multiple occupations, it has a larger income variance .

The variance parameter of the taste shock is not significant. One explanation could be that data variations that help to identify the taste parameter are individuals' switching behaviors in the flat spot area. In the data, the switching behaviors are measured by the between year variations in the fraction of CS workers. This is in fact a measure of the net occupation switch. However, the gross occupation switch, which is the true variation generated by the taste shock, could be more prevalent. Using net rather than gross occupation switch data could result in underestimating the taste shock.

The estimates of the labour demand side are presented in Table 3. First, the implied elasticities of substitution vary across occupations. Immigrants and natives are closer substitutes with an elasticity value of 5.73 in CS sector. This value is close to the Borjas' (2008) estimate (6.6) using annual earning data. Natives are less substitutable in other-STEM occupations with the substitution elasticity equal to 1.97. These estimates are sensitive to measures of new entrants to the labour market. But the result that CS sector has a larger elasticity is very robust in regardless of the measure choices. Both sectors have decreasing return to scale with estimate values approximately 0.54.

5.2 Sample Fit

Figure 6 to 10, based on a simulation of 500 individuals, graphically depict the fit of the basic model in 2000 as a snapshot. These simulated data match the log income profile very well. It captures the curvature at the beginning and also the flat spot in the latter part of one's career. The random accumulation of human capital component in this model forbids the simulated data to fall when approaching retirement. This model outperforms the model with deterministic human capital accumulation and a quadratic earning equation. In terms of the second moment, data moments present this U shape which have already been documented many times in literature. However, there is no mechanism in this simple DDP model that generates this U-shape. As a result, the simulated data only matches the level rather than the curvature of the wage dispersion profiles. For the choice probability fit, the empirical moment is computed using solely the 2000 census data. It is a cohort profile of the occupational choice probability whereas the choice probability computed using simulated data is in essence a life cycle choice profile. In data, those people at age 65 in 2000 entered labour market in 1956, which is considered as the 'Stone Age' in the history of CS industry. They faced completely different market conditions when making their educational and earlier occupational choices. Consequently, they also accumulated specific human capital in other-STEM occupations. All these contribute to the lower fraction of CS workers among older cohorts. When I impose the steady state equilibrium, the age profile in the model is essentially a life cycle profile. Ignoring the cohort effect is the major reason that the simulated data only matches the choice in the beginning and divert from real data later.

5.3 Sensitivity Check

As I mentioned in the estimation procedure part, rental rates are treated as free parameters. The estimation procedure picks efficiency prices that best match wage and choice profiles over 20 years. I take the ratio of the two efficiency wages $\frac{\pi_{cs,t}}{\pi_{ncs,t}}$ and plot this series against time. I put the Nasdaq composite index aside in Figure 11. The model predicted relative efficiency price basically reproduces the Nasdaq patterns. The relative efficiency wage peaked around 2000 before the dot-com burst hit. Then it was gradually recovering until 2007 when the financial crisis occurred. Recently it has stayed on a uphill track for about 6 years. The pattern of relative efficiency wage mimics closely the Nasdaq composite index except that the recent growth for the efficiency wage is milder. The correlation coefficient between these two series is 0.81.
Taking the changes of the relative prices as given, which are the fundamentals that drive natives' choices about fields of study and occupations, how sensitive the natives are in response to these changes? In Figure 12 I plot the share of 22 year old native workers who choose to be a computer scientists from 2000-2013[23] and also the model predicted relative efficiency wage. It seems that there is no strong correlation. But if I lag the relative efficiency wage by 3 years (1997-2010), there appears to be a stronger correlation. Natives do respond to price variations when they decide their fields of study and latter on occupations. After their initial moves in choosing fields of study, natives remain alert to price variations as well. However, switching occupation becomes less

[23] The reason I start from 2000 is that there are too few high skilled CS workers at age 22 using CPS data. The share calculated from CPS is too noisy.

and less favorable in latter part of one's careers. The reason is that given the previous career choices, agents have already accumulated fair amount of occupation specific human capital that makes them less sensitive to price shocks. There are at least two points in Figure 14 we should pay attention to. First, there is a level effect that cohort groups who enter the market faced with high relative efficiency prices $\frac{\pi_{cs}}{\pi_{ncs}}$ remain to have higher proportion of CS workers in the subsequent decision periods. The 1978 cohort finished college in 2000 at the peak of internet boom with the highest relative efficiency price and this cohort stays unambiguously higher than the 1986 cohort who entered the labour market almost at the lowest point of the relative prices[24]. Second, I compute the correlation coefficients between the fraction of CS workers and the relative price by birth cohort. The number is higher for younger workers and is lower for older workers.

Correlation Coefficient

	1978 Cohort	1982 Cohort	1986 Cohort
Relative Efficient Price	0.41	0.60	0.89

6 Counterfactual Exercises

6.1 Fixed Foreign Worker Counterfactual

In the first counterfactual exercise, I adopt the same setting in BBKG (2014) to simulate counterfactual period from 1994 to 2014 as if the representative firms had restrictions on the number of foreign computer scientists that they can hire. The number of immigrant CS workers is fixed at its 1994 level, while the exogenous supply of foreign workers in other-STEM sector would follow its original path. The purpose of this exercise is to assess that to what extent the rapid growth in the recruitment of foreign computer scientists would influence the skilled native STEM workers.

Figure 15 graphically depicts the counterfactual exercise and its results. In the top right panel I present the resulting impact on the efficiency wage for CS

[24] This provides some limited evidences that support Khan's (2010) conclusion about long term labour market consequences of graduating from college in bad economy. Here at least we can say graduating at different phases of industry cycle will have lasting effect on occupational choices.

workers. In the counterfactual economy, the efficiency rental rate for CS workers would be higher. As illustrated in the bottom left panel, the native labour supply in CS sector would also be higher. One advantage of a general equilibrium model is that it enable me to study broader effects of foreign computer scientists, for instance, the impact on the labour market of other-STEM sector. In the second row of Table 5, I quantitatively evaluate these effects.[25] Had the immigrant CS workers been fixed at its pre-boom level, the efficiency rental rate for CS workers would have increased by 0.89% . The cap placed to the number of foreign CS workers would also benefit natives working in the other-STEM sector. The efficiency rental rate would have increased slightly by 0.35%. This spill-over effect should be primarily attributed to the selection behavior of native skilled workers. When experiencing less competition from immigrants, which in this model also implies that the equilibrium rental rate in CS sector would increase, skilled natives who once didn't have comparative advantages working as computer scientists now would find it beneficial to switch to the CS sector. This leads to increases of the native labour supply in CS sector, decreases of the native labour supply and consequently increases in the equilibrium rental rates in othe STEM sector. The counterfactual simulation confirms this channel. On average the native labour supply in CS sector would grow by 2.47% while the native labour supply in other-STEM sector would reduce by 2.34%. The asymmetricity in labour supply changes implies that those who switch are only marginally better working as other-STEM workers under the old prices.

Compared to BBGK's (2014) findings, my simulation results illustrate a very conservative crowding-out effect[26]. Three major modeling factors are responsible for delivering this limited crowding-out effect. First, native and foreign workers are imperfect substitutes as opposed to BBGK's (2014) model. This limits the immigration induced competition to some extent. As a result, my model only generates small efficiency wage responses in the CS sector and a even smaller effect on other-STEM sector because natives are less substitutable there. Second, natives are heterogeneous in terms of their production comparative advantages. Those who would switch in the counterfactual simulation are not as productive as always-takers in the CS sector. Measuring the labour supply in efficiency unit would further shrink the magnitude of the effect. Also, the occupation specific human capital added in the model would restrict the

[25] The number reported is the 20 year average of percentage changes between counterfactual data and the real data.

[26] In BBGK (2014), for the same counterfactual setting, they find CS workers wage would be 2.4% to 3.9% higher and CS domestic employment would be 4.6% higher in 2000.

occupation mobility further.

In the first row of Table 5, results of another counterfactual simulation are presented. In the second counterfactual exercise, both foreign computer scientists and other-STEM workers are restricted to their 1994 levels. Rental rates for both sectors would increase, but the incremental magnitudes would be smaller compared to the first counterfactual. The reason is the that the equilibrium rental rate in the other-STEM sector has the following expression which is an increasing function of immigration labour supply, given the estimates $\rho = 0.4914$ and $\psi = 0.5384$.

$$\Pi_{ncs} = A\psi(1-\alpha)[\alpha M_{ncs}^{\rho} + (1-\alpha)N_{ncs}^{\rho}]^{\frac{\psi}{\rho}-1}N^{\rho-1}$$

Since $\frac{\psi}{\rho} - 1 > 0$, the marginal product of skilled native in the other-STEM sector actually decreases when the foreign labour is restricted to a lower level. When experiencing wage drops in their current occupation and observing wage growth in other sector, more native other-STEM workers move towards CS sector. Because of the drop in natives' marginal product, the second counterfactual economy experiences large quantity changes (3.39% increase in CS and 2.55% decrease in other-STEM sector) which in turn weaken the positive market conditions brought by limiting the number of foreign CS workers that can be hired. The efficiency rental rates only increase by 0.78% and 0.31% respectively.

The different quantitative results from the previous counterfactual exercises demonstrated the importance of a general equilibrium model when assessing the impacts of skilled immigrants. The interaction among sectors will have influential effects on natives occupational and educational choices.

7 Conclusion

In this paper, I develop and estimate a dynamic structural model of natives' occupational decisions. The structural estimation framework that I have developed fully imposes the restrictions of the optimization theory and permits an investigation of whether such a theoretically restricted model can succeed in quantitatively fitting the observed employment and wage patterns. Moreover, the general equilibrium studied in the model enables me to understand impacts of high skilled immigrants in the U.S. labour market in a more comprehensive manner. Focusing on the recent two decades, I develop a model to answer the counterfactual question: what would have happened to the employment of U.S. high skilled residents, and to efficiency wages in both CS and other-STEM sector had the number of foreign workers been restricted to its level prior to the first technology boom? The simulation results suggest a very conservative crowding-out effect.

My simulation results differ from previous literature. This suggests that the unobservable heterogeneity in sector specific endowments and production differentials are important factors to be considered in the debate over the impacts of high-skilled immigration. When describing the heterogeneity by a bivariate normal distribution following the classic Roy specification, my model gets an estimate of correlation coefficient equal to -0.18. As a result, natives positively select into two sectors. Those who switch occupations are not severely hurt since now with the new market equilibrium prices they are better off by not working as computer scientists. For the economy as a whole, the total negative impact is mitigated through the selection of production heterogeneity.

Skilled immigrants and natives are, in general, imperfect substitutes. My estimates suggest that the elasticities of substitution vary across occupations. In the CS sector, these two types of labour are closer substitutes than that of the other-STEM sector with an elasticity equal approximately to 5.7. Representative firms distinguish the native labour from the immigrant labour. This will effectively restrict the magnitude of the possible negative impact induced by increasing number of skilled immigrants.

Had the foreign labour supply in CS sector been fixed at its 1994 level, the efficiency CS rental rate would have increased mildly by 0.89%, and the native labour supply would have been higher by 2.47%. Moreover, the efficiency rental rate in other-STEM sector would have increased as well, even though by lesser magnitude (0.35%). Meanwhile, we would observe a reduction in native labour supply in other-STEM sector predicted by natives' responses to price changes.

Human capital is modeled to be occupation specific in my model. This generates a declining age profile of the occupation switch probability. One implication is that younger native workers are more sensitive to price changes and thus more sensitive in terms of the occupation switch to immigrant inflows than older cohorts. I find empirical evidence to support this argument.

My paper should be viewed as the a step towards modeling the comprehensive impact of foreign STEM workers in the U.S. skilled labour market. In the model, I incorporate features that were ignored in the earlier model developed by BBGK (2014). Specifically, occupation specific human capital evolves endogenously in a stochastic fashion; natives are different among themselves in terms of sector specific endowments; natives and immigrants are allowed to be different from the production perspective. All of the above mentioned are obviously important in the context of understanding the impacts of skilled immigrants. This model can be further generalized to include natives' choices between STEM and non-STEM occupations.

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Appendix A

Figure 1: CS Industry

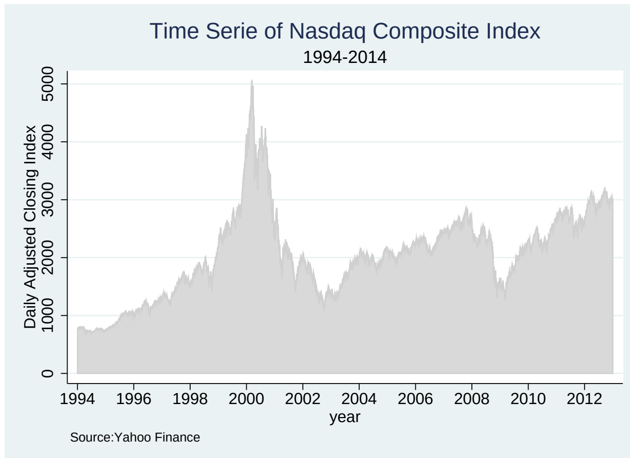


Figure 2: Employment of STEM and CS Workers

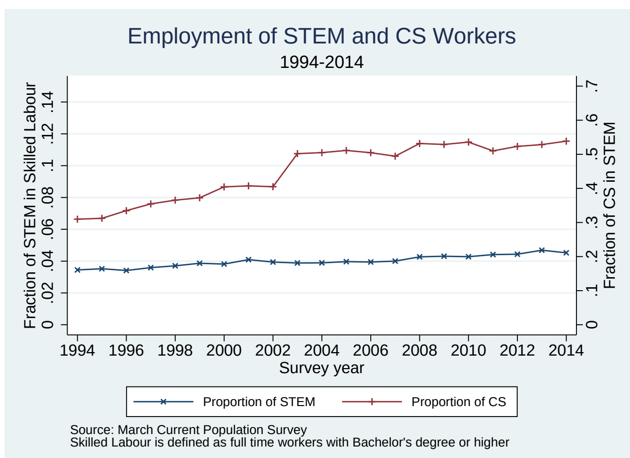


Figure 3: H-1B Petition Cap and Probability of Approval

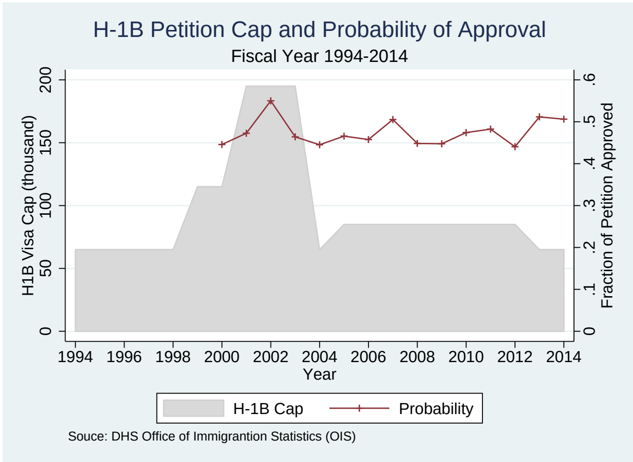


Figure 4: Occupations of H1B Worker Beneficiaries in 2010

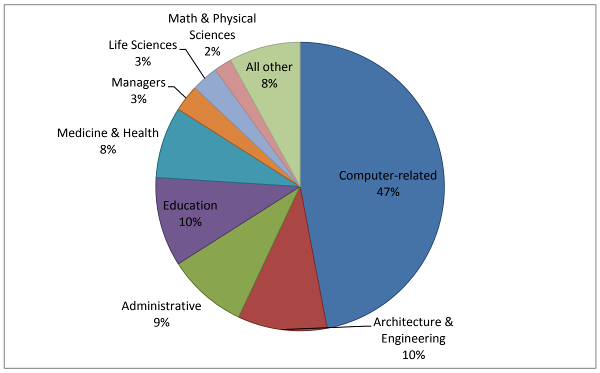


Figure 5: Fraction of Immigrants

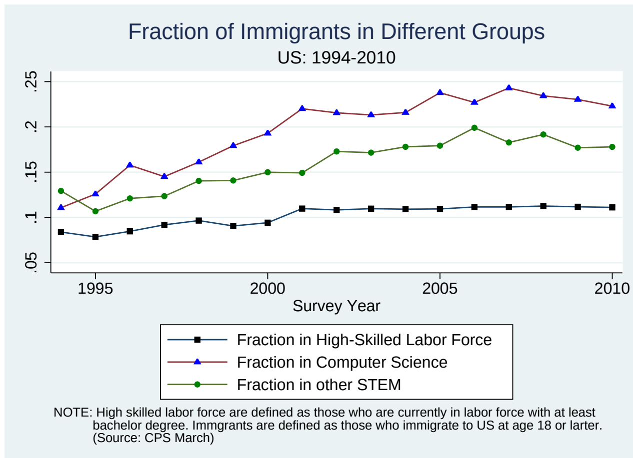


Figure 6: Log Income Age Profile Fit for CS

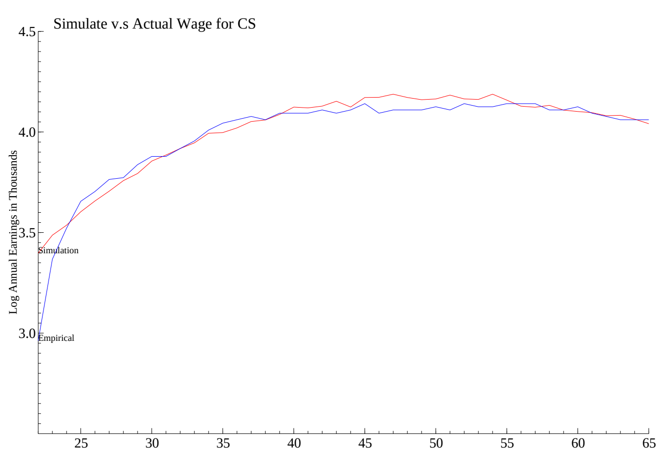


Figure 7: Log Income Age Profile Fit for Other-STEM

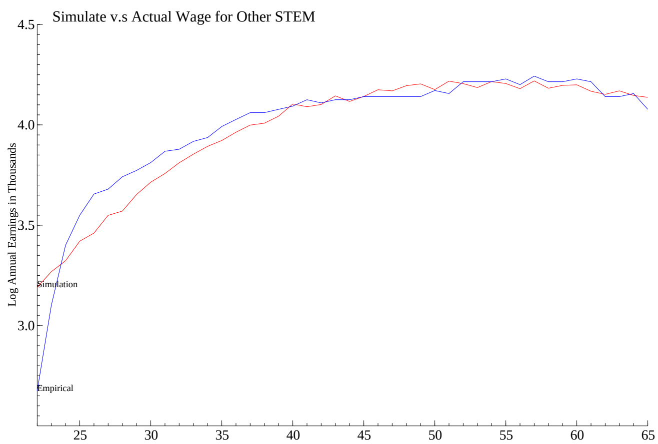


Figure 8: Second Moment Age Profile Fit for CS

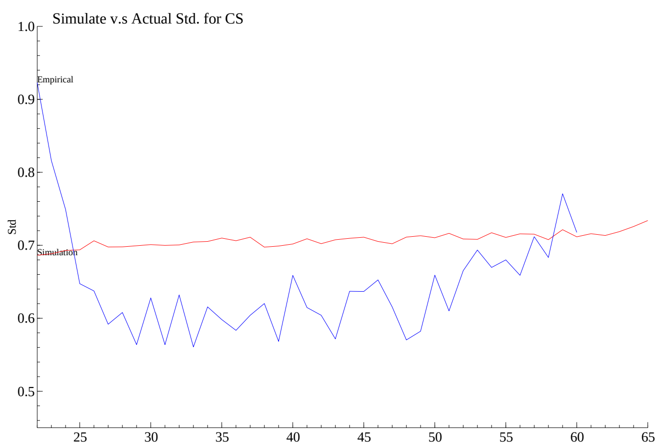


Figure 9: Second Moment Age Profile Fit for other-STEM

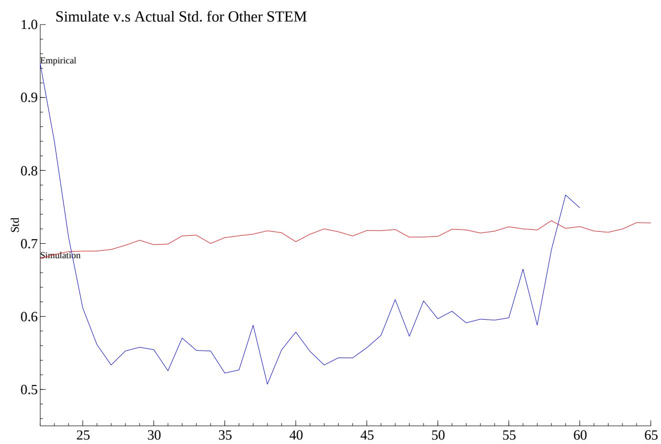


Figure 10: Choice Probability Age Profile Fit

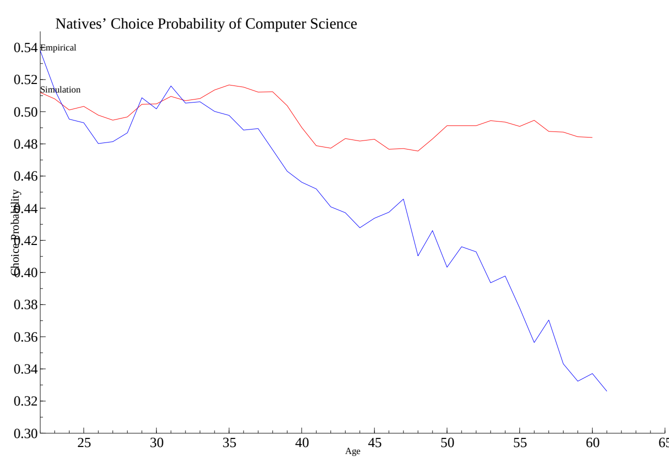
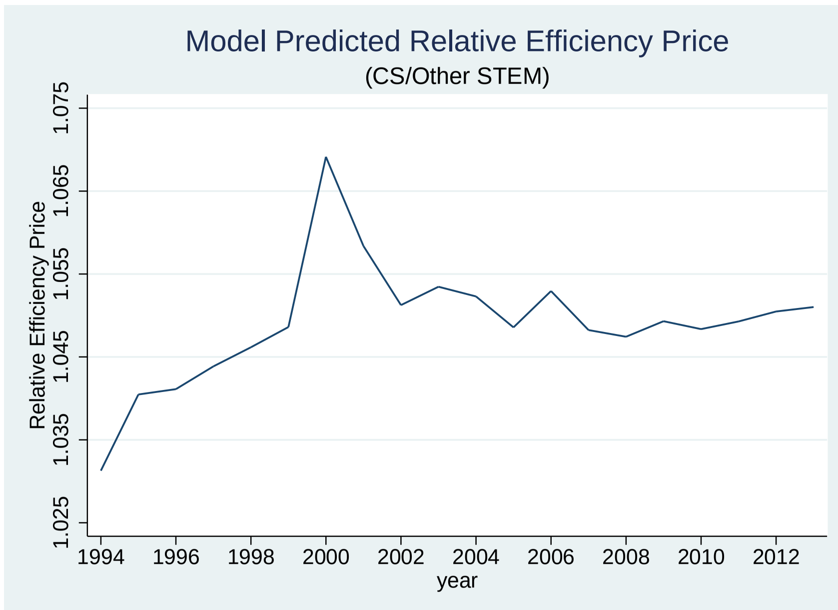


Figure 11: Model Predicted Prices v.s. Nasdaq Index

(a) Model Predicted Relative Prices



(b) Nasdaq Composite Index

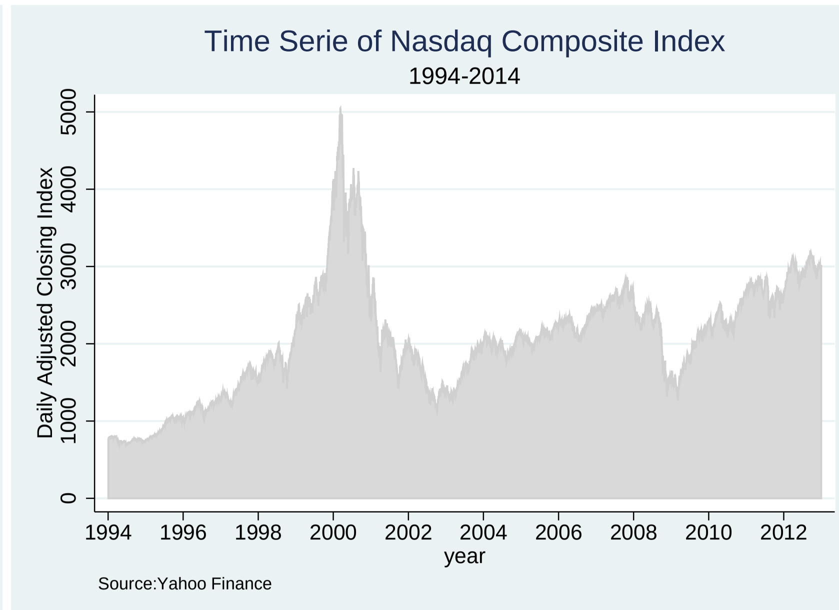


Figure 12: Response of New Entrants

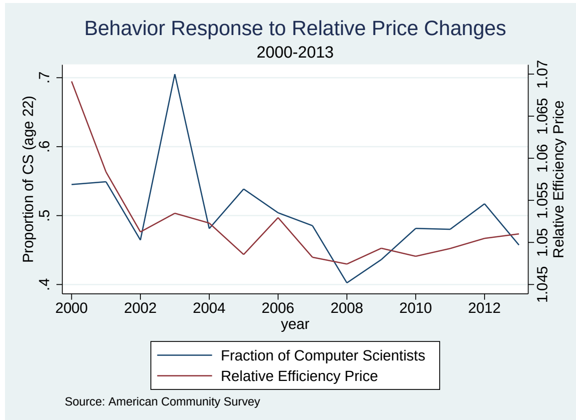


Figure 13: Lagged Response of New Entrants

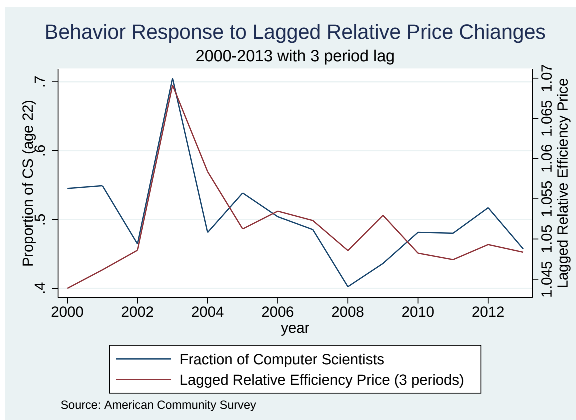


Figure 14: Cohort Response

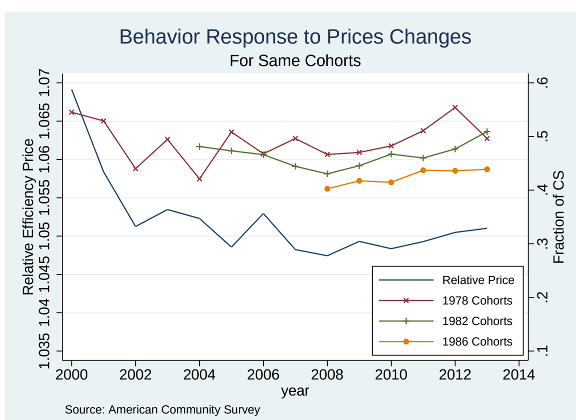


Figure 15: Fixed Foreign Computer Scientists at 1994 Level

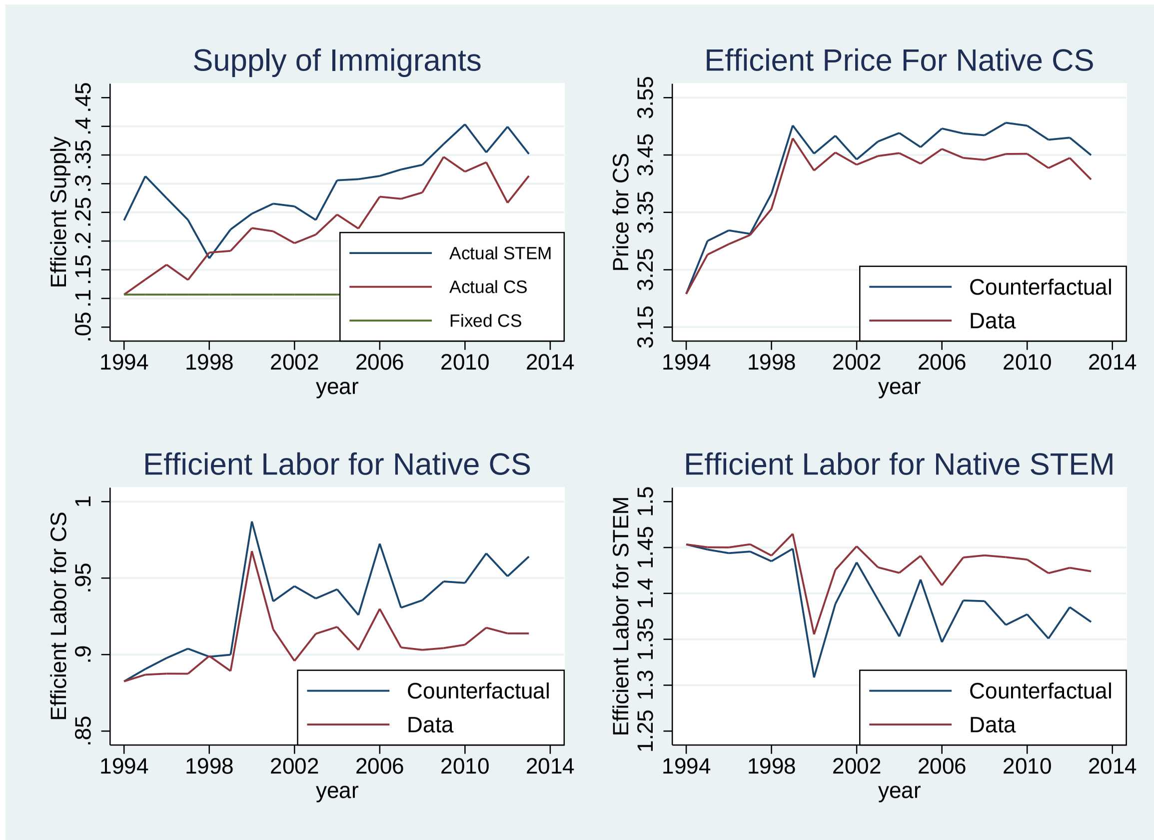


Table 1: Sample Size of Income Age Profile (1994-2013)

Age	Total STEM min	Total STEM max	CS min	CS max	Age	Total STEM min	Total STEM max	CS min	CS max
22	4	27	11	33	44	14	66	51	140
23	8	27	21	55	45	13	73	53	119
24	9	37	23	73	46	13	65	41	120
25	10	43	39	79	47	11	68	42	116
26	10	47	39	93	48	12	68	40	120
27	18	57	47	105	49	7	62	32	117
28	13	50	42	98	50	5	50	16	103
29	19	52	51	104	51	5	46	22	101
30	23	62	54	108	52	7	48	28	104
31	25	61	62	124	53	6	49	19	86
32	27	68	57	130	54	4	39	21	93
33	16	60	41	108	55	4	46	18	83
34	19	72	50	122	56	3	34	20	78
35	17	72	65	121	57	0	32	17	64
36	24	64	60	109	58	3	30	14	63
37	14	59	46	127	59	1	21	13	58
38	16	71	55	137	60	0	24	9	44
39	20	62	56	122	61	1	21	5	51
40	18	70	53	140	62	1	14	5	40
41	15	73	56	130	63	0	13	5	30
42	13	60	58	120	64	0	8	3	19
43	13	79	46	140	65	0	12	4	22

[1] For each age group, there are 20 samples for 1994-2013.

Table 2: Estimates of Human Capital Profile (Asymptotic Variance)

Coeff	Computer Science		Other-STEM	
	val.	std. err	val.	std. err
CS Exp.	0.1038	(0.0048)	0.0465	(0.0036)
other-STEM Exp.	0.0428	(0.0034)	0.1238	(0.0023)
Total Exp^2 /100	-0.1701	(0.0083)	-0.1749	(0.0064)
Random Accumulation	0.0459	(0.0035)	0.0424	(0.0033)
		Covariance Matrix		
unobs. Heterogeneity	0.0818	(0.0026)		
	-0.0159	(0.0013)	0.0918	(0.0041)
Taste Shock	0.08976	(0.0593)		

Table 3: Estimates of Industry Production Function

Coeff	Computer Science val.	other-STEM val.
Share	0.4944	0.4228
Rho	0.8255	0.4914
Return to Scale	0.5363	0.5384
	Implied Substitution Elasticity (Immigrants vs U.S. Workers)	
$\frac{1}{1-\rho}$	5.7322	1.9663
	Industry AR(1) TFP Process	
$\bar{Z}$	8.4101	7.1781
AR coef.	0.5725	0.7148
σ	0.0141	0.0144

Table 4: Production Parameters

Panel.A			
Return to Scale (ψ)		Computer Science	other-STEM
1.00	ρ	0.7782	0.5117
	share	0.5230	0.3395
0.875	ρ	0.6584	0.5046
	share	0.4803	0.4210
0.750	ρ	0.5638	0.4920
	share	0.4909	0.5463
0.625	ρ	0.4615	0.4780
	share	0.4926	0.7809

Panel.B			
Elasticity (ρ)		Computer Science	other-STEM
1.00	ψ	0.9981	0.4059
	share	0.4919	0.0038

Table 5: Fixed Immigrant Labour Supplies at Their 1994 Level

	$\Delta\pi_{cs}$	$\Delta\pi_{ncs}$	Δ_{CS}^{N}	Δ_{ncs}^{N}
M_{cs} Fixed & M_{ncs} Fixed	0.78%	0.31%	3.39%	−2.55%
M_{cs} Fixed & M_{ncs} Old Path	0.89%	0.35%	2.47%	−2.34%

Appendix B

Detailed Description of Data Cleaning

For the data cleaning, I first restrict the analysis applying only to the skilled labour force, defined as those who have a Bachelor's degree or higher and are currently in the labour force. The status 'in labour force' is defined as currently at work , having jobs not at work, in armed force, unemployed with experience and unemployed without experience. Because the hour choice is ommitted in the discrete choice model, I further restrict the sample to full-time full-year workers whose total hours worked (the product of usual hour worked per week and usual weeks worked) exceed 1500 per year to better match the model. For the income wage data, I first use CPI index suggested by IPUMS website to deflate the income in 1999 dollar, and top-coded values are multiplied by 1.4. The hourly wage rate is calculated following the standard approach, dividing income wage by total hour worked. Then the hourly wage rate is employed to deal with possible outliers. Individuals with hourly wage rate lower than 7 dollars[27] and higher than 200 dollars are discarded. I use the variable 'year of immigration' to differentiate immigrant and native workers. If a worker migrates to U.S. older than age 18, they are considered as foreign workers. To define two occupation groups, I use the IPUMS suggested occupation crosswalk (OCC1990) and define CS workers as computer system analysts, computer scientists and computer software developers.

The efficiency rental rates paid to skilled immigrants are measured by the average annual income of foreign new entrants to each sector. There are two major ways to define new entrants. First, in the model I assume skilled workers enter the labour market after graduating from college at 22. The average annual income of 22-year-old foreign computer scientists is treated as the measure of the sector rental rate. I try different measures by varying the age range, such as the range from 22 to 24 which is the normal range of college graduation. Another way to define the new entrants is to use another variable: reason not at work last year. For individuals aged 22 to 30, if their answer to the previous question is ' at school ' then they are classified as new entrants. The later measure suffers from the small sample problem because most of the answers are not available.

[27] The level of federal minimum wage

Appendix C

More Counterfactual Results

Explore the Demand Parameters

In this section, I will explore more counterfactual economies in which the labour demand parameters differ in various ways from the basic model estimates. I mainly do two sets of exercises. First, I use my estimates of the other-STEM sector, but make changes in the parameters of CS sectors. To be comparable to the BBGK (2014) results, the same sets of CS production parameters are employed. In BBGK (2014) immigrants and native workers are assumed to be perfect substitutes ($\rho = 1$), and skilled immigrants are assumed to be more productive than natives. The comparable share parameter takes a value of 0.52302. They explore different return to scale parameters ($\psi = 0.75,\ 0.50,\ 0.25$). The results from the counterfactual economy discussed above are presented in Panel A Table C.1 . Second, instead of allowing two sectors to have different production functions, in the next set of exercises whose results are shown in Panel B Table C.1, I force both sectors to use the same production technology. For all the counterfactual exercises above, I consider the same scenario that the recruitment of foreign computer scientists is set at its 1994 level.

When comparing results from Table C.1 to the results in Section 6, it is obvious that in both panels the magnitudes of the counterfactual immigrant inflow are more saline. The reason is fairly direct: skilled immigrants and natives are considered to be perfect substitutes in CS sector. Switching from imperfect to perfect substitution will amplify the potential impacts of high skilled immigrants in US labour markets.

When comparing the three results within each panel. The order of magnitude is consistent with findings in BBGK (2014). When imposing the perfect substitution and decreasing returns to scale functional form on the CS production function, demand elasticity for native workers equals to $\frac{1}{\psi-1}\frac{(1-\alpha)N+\alpha M}{(1-\alpha)N}$. With same size immigration shocks and other parameters holding constant, high elastic labour demand (high ψ values) generates small wage changes; smaller wage changes then cause small responses in native labour supply.

Another important message that can be learned from Table C.1 is by comparing the same column across panels. The only thing differs within each column is the production technology used in the other-STEM sector. Different counterfactual results across panels reiterate one of the points that I make at

Table C.1: Summary of Results from Counterfactual Simulation

Panel.A Same Production Function in Both CS and other-STEM sector (ρ=1)			
	ψ=0.75	ψ=0.50	ψ=0.25
$\Delta\pi_{cs}$	0.75%	1.25%	1.78%
$\Delta\pi_{ncs}$	0.16%	0.44%	0.82%
Δ_{cs}^{N}	2.64%	4.53%	5.14%
Δ_{ncs}^{N}	−2.63%	−3.53%	−4.32%

Panel.B $\rho_{cs} = 1$ While other-STEM sector Using Estimated Production Function			
	ψ_{cs}=0.75	ψ_{cs}=0.50	ψ_{cs}=0.25
$\Delta\pi_{cs}$	0.78%	1.32%	1.72%
$\Delta\pi_{ncs}$	0.27%	0.54%	0.70%
Δ_{cs}^{N}	2.05%	4.05%	5.41%
Δ_{ncs}^{N}	−1.85%	−3.58%	−4.60%

the end of section 6 that to be able to better assess the impact of high skilled immigrants in US economy a general equilibrium model is more appropriate. Production technologies in the other-STEM sectors will have impacts on the natives' occupational choices. The more elastic the native labour demand is in the other-STEM sector, the better buffer the economy can provide to native workers against demand shocks induced by foreign computer scientists. Whenever there are huge CS immigration inflows, native workers will react by switching occupations towards the other-STEM sector where the market price is relatively high; the more elastic the native labour demand is in the other-STEM sector, the smaller the efficiency wage reduction will be caused. The small efficiency wage reduction also implies that more native workers who now lose comparative advantages to work as computer scientists can find better "shelters". More natives responding by leaving CS sector neutralizes negative shocks to a greater

Table C.2: Summary of Elasticities of Counterfactual Simulation

	Panel.A Same Production Function in Both CS and other-STEM sector (ρ=1)					
	ψ=0.75		ψ=0.50		ψ=0.25	
	CS	NCS	CS	NCS	CS	NCS
Elasticity	-4.00	-4.00	-2.00	-2.00	-1.33	-1.33
	Panel.B $\rho_{cs} = 1$ While other-STEM sector Using Estimated Production Function					
Elasticity	-4.00	-2.12	-2.00	-2.12	-1.33	-2.12

extent by restricting wage fluctuations. The native labour demand elasticity in the other-STEM sector has the following expression[28].

$$\begin{aligned}
\eta_N^{STEM} &= \frac{1}{\frac{\mathrm{d}\Pi}{\mathrm{d}N}\frac{N}{\Pi}} \\
&= \begin{cases} \frac{1}{[(\rho-1)+\frac{(1-\alpha)(\psi-\rho)N^\rho}{\alpha M^\rho+(1-\alpha)N^\rho}]} & \rho \neq 1 \\ \\ \frac{1}{\psi-1}\frac{(1-\alpha)N+\alpha M}{(1-\alpha)N} & \rho = 1 \end{cases}
\end{aligned}$$

In Table C.2, the above expression is evaluated using quantities at 1994 level. In column 1, the native labour demand of the other-STEM sector is more elastic in the upper panel, which means in this counterfactual the other-STEM sector can better "absorb" the immigration induced shocks. The quantitative results confirm my conjecture. For the exact size of immigration shock, the upper panel economy is able to generate more occupational switching responses (2.64% native labour supply growth in CS sector); but the resulting wage fluctuations are attenuated (0.75% CS efficiency wage increase). The same argument also applies to the second column. However, in the third column, the native labour demand of the other-STEM sector in the upper panel becomes less elastic. As a result, the price system of the counterfactual economy is more fragile to immigration shocks, and fewer natives are able to re-optimize by switching

[28]The formula that uses inverse demand function to derive demand elasticity is valid when the inverse demand function is monotone. The local monotonicity is true at least for the point that I evaluate various elasticities.

occupations (only 2.05% native labour supply growth in CS sector). The interaction between CS and other-STEM sector is crucial when evaluating the impact of large inflows of foreign computer scientists over the past two decades.

BBGK (2014) finds that wages for computer scientists would have been 2.8-3.8% higher and that Americans employed as computer scientists would have been 7.0-13.6% higher in 2004. In both panels, even though I believe the CS production functions are comparable, the magnitudes of changes in efficiency wages and efficiency labour supply are smaller. The general equilibrium alone cannot account for these numbers. Human capital accumulation and unobservable heterogeneity are also important model specification components that deliver the limited consequences.

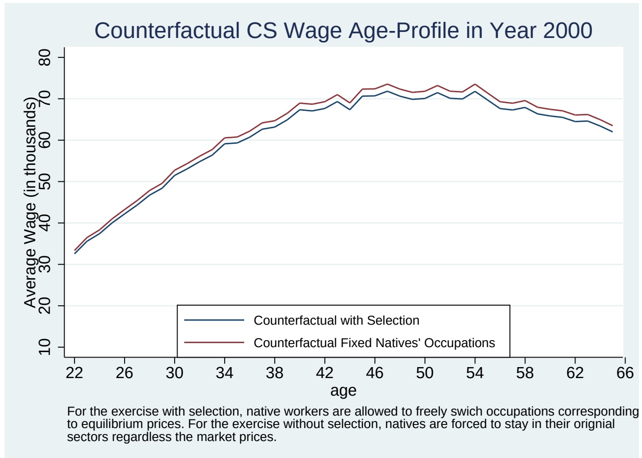
To summarize what I learn from these counterfactuals in which different labour demand parameters are explored, I draw the following three conclusions. First, to be able to more precisely assess the impact of skilled immigration inflows, more accurate sector production parameters are necessary. The crucial parameters of interests in the CES production function are the substitution elasticity and return to scale parameters. Second, the general equilibrium which studies the interaction between CS and other-STEM sector is more appropriate because the interaction will have non-negligible impact on natives' occupational choices. Last, as mentioned in Keane and Wolpin 1997, human capital accumulation and unobservable heterogeneity are important modeling components when studying the occupational choices of natives.

Power of Selection

As argued in the previous section, human capital accumulation and unobservable heterogeneity are important model aspects when studying the natives' occupational choices. In this part, I will show quantitatively how strong the economic power of selection will be and who are more vulnerable and passive among natives toward immigration shocks?

Here I ask a similar but slightly different question: What would the wage *distribution* be had the number of foreign computer scientists be restricted to their 1994 level. The variations come from the following two aspects. First, I focus on the wage distribution in one specific year (year 2000) not just the sectoral efficiency wages. Second, the selection channel will be shut down. Skilled natives are no longer allowed to freely switch occupations in responses to immigration induced demand shocks. The purpose of this exercise is to quantitatively

Figure C.1: Counterfactual CS Wage Age-Profile in Year 2000



evaluate the economic power of occupation selection mechanism. Meanwhile, I will explore the heterogeneity in selection effect across cohort groups. The results are graphically presented in Figure C.1 in which I plot the average wages of different age groups in thousands of dollars .

When placing a cap on the quantity of skilled foreign CS workers that can be hired, the efficiency wages in both sectors would be higher as indicated in the counterfactual results in Section 6. What would happen if free occupational mobility is strictly forbidden? The wage age profile of the counterfactual exercise with free mobility is depicted as the lower red line in Figure C.1. When occupational mobility is strictly restricted regardless of the current equilibrium market prices, native CS workers of all ages will be better off. The wage age profile without selection is depicted as the upper blue line. Moving the location of the profile when selection is shut down is because restricting occupational mobility means protecting native CS workers from competition imposed by their fellow workers in other sector.

As indicated by the gap of the two lines, not everyone is affected equally from the selection mechanism. The two profiles are almost parallel for middle-age and old workers but barely distinguishable for younger workers. This is because even when relaxing the restriction on occupational mobility, middle-age and old workers who already accumulate a significant amount of occupation specific human capital will tend to stick to their original occupations. For these workers, there exists purely the price effect which corresponds to the parallel shift in the latter portion of the age-profile. There is no composition effect. However, reoptimization is still favorable for the young workers. For the early part of the age profile, the composition effect induced by free occupational mobility will counteract the negative price effect thus closing the gap.

To evaluate the economic power of selection, I compute the differences in average annual incomes (in thousands of dollars) between counterfactuals with and without selection for all age groups. Occupational mobility on average will account for 794 dollar annual income loss for 22-year-old workers in CS sector and account for 1737 dollar loss for 50-year-old workers using my estimates from the basic model. I also repeat this calculation using different sets of labour demand parameters. The economic power of selection effect for all other parameters is not negligible.

Appendix D

Model Extension

Recover Sectoral Trends

In order to identify the trend of rental rates for both CS and Other-STEM , I implement the flat-spot method[29] used in literature (Bowlus and Robinson 2012). 4 time series are recovered using ACS and CPS. Let us denote x_t^o the efficiency rental rate of occupation o from CPS, and y_t^o the efficiency rental rate of occupation o from ACS, where $o \in \{cs,\ ncs\}$.
Let us assume both x_t^o and y_t^o are noisy measures of some fundamental process θ_t^o that governs the deterministic component in the evolution of efficiency rental rates.

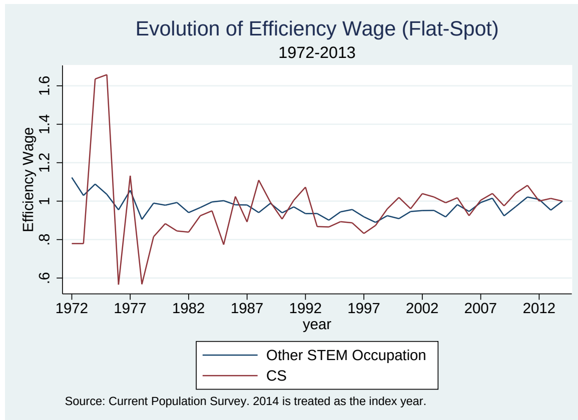
$$\begin{aligned} x_t^o &= \theta_t^o + \epsilon_t \\ y_t^o &= \theta_t^o + e_t \end{aligned}$$

where ϵ_t and e_t are auto correlated innovations with different variances (with different noise levels). x_t^o is considered to be a nosier measure because CPS has a relatively smaller sample size than ACS. I construct the efficiency wage series

[29]I make a small modification of the flat-spot method. Because the problem I face here is majorly due to small sample size, I try to expand the age span of flat spot area (age 45 to 59). The change of occupation specific efficiency wage in two adjacent years is computed as the ratio of age weighted median annul income.

using a very restricted sample. For example, I use the subsample of native full-

Figure D.1: Evolution of Sector Efficiency Wages

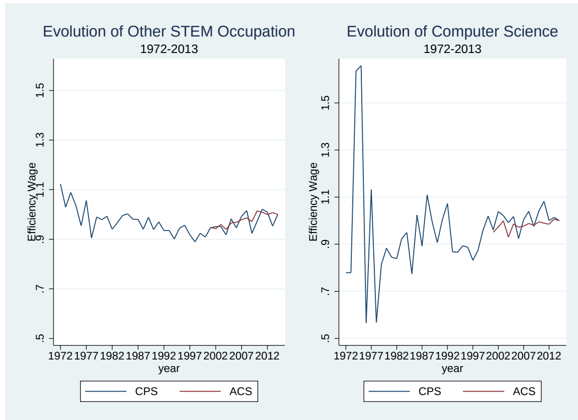


time full-year workers with at least a bachelor's degree or higher, aged between 45 and 60 who work as an Occupational o in a given year t. The CPS sample size is quiet small for CS especially in the early 1970s only about $10 - 20$, and this number gradually increases to 300 as the industry grows. In Figure D.1 I plot x_t^os recovered using CPS. We can observe that the rental rates for both occupations are more volatile in early periods. And CS series is more volatile in general compared to that of the other-STEM sector. The efficiency rental rate time series recovered from CPS is too noisy to get a clear picture of the evolutionary patterns.

Fortunately, I have a second, less noisy measure y_t^o of the same fundamental, but with a shorter time span as depicted in Figure D.2. The purpose of the current adjustment is to propose a statistically valid method to retrieve meaningful pattern from the noisier measure (x_t^o) by studying the behavior of x_t^o and y_t^o. The way I propose to correct the efficiency wage series derived using CPS sample is to impose a functional form on θ_t^o and also some error structures on ϵ_t and e_t. From now on I will focus my discussion on one occupation and thus the occupation notation o is suppressed.

$$
\begin{aligned}
\theta_t &= \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \alpha_3 t^3 \\
\epsilon_t &= \rho^{\epsilon} \epsilon_{t-1} + \mu_t \qquad \mu_t \sim iid\ (0,\ \sigma_\mu^2) \\
e_t &= \rho^{e} e_{t-1} + v_t \qquad v_t \sim iid\ (0,\ \sigma_v^2) \\
& \quad \sigma_\mu^2 > \sigma_v^2
\end{aligned}
$$

Figure D.2: Compare Efficiency Wage Serials (CSP vs ACS)



I fit ACS and CPS series to fourth polynomials of deterministic trend with AR(1) error terms respectively. If the assumptions above are reasonable, the fitted series from CPS and ACS would show improvements in their correlation coefficient compared to the unadjusted series.

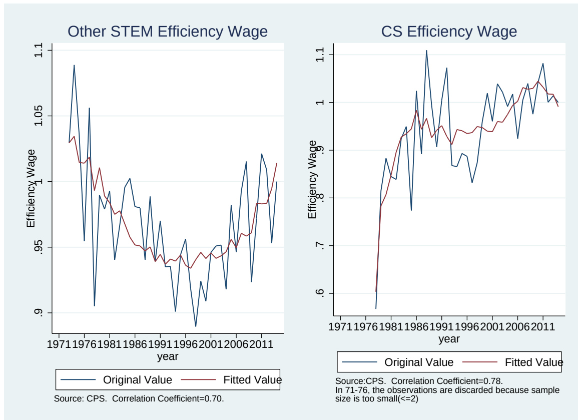
Table D.1: Correlation Coeficient Between Statistially Adjusted Series

	x_t^{cs}	y_t^{cs}	$\hat{x}_t^{cs}$	$\hat{y}_t^{cs}$		x_t^{ncs}	y_t^{ncs}	$\hat{x}_t^{ncs}$	$\hat{y}_t^{ncs}$
x_t^{cs}	1.00				x_t^{ncs}	1.00			
y_t^{cs}	0.324	1.00			y_t^{ncs}	0.624	1.00		
$\hat{x}_t^{cs}$	0.644	0.260	1.00		$\hat{x}_t^{ncs}$	0.576	0.902	1.00	
$\hat{y}_t^{cs}$	0.357	0.752	0.415	1.00	$\hat{y}_t^{ncs}$	0.458	0.945	0.885	1.00

As presented in Table D.1, both adjusted series show approximately 30% increases in the correlation coefficients. The correlation coefficients for CS and other-STEM increase from 0.324 to 0.415 and from 0.624 to 0.885 respectively. For both occupation groups, the ratio of the noise variance between two samples $\frac{\sigma_u^2}{\sigma_v^2}$ equals to10.

Next I apply the model to the full CPS sample (1972-2013). For CS sector, the first 5 years of observations are discarded for the concern of small sample size. The original and recovered series are depicted in Figure D.3. The simple moving average smoother works equally well. The reason I prefer imposing a functional form is that it makes easier to project the series both forward and backward out of the available sample periods.

Figure D.3: Statistical Adjusted Efficiency Wage Series



Perfect Foresight Model

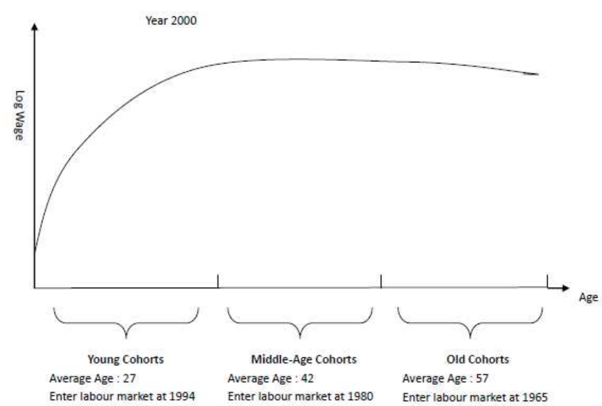
In the previous part, the evolution of the two efficiency wages is derived using the flat spot method. Both series are measured in relative terms and the efficiency wages in 2000 are normalized to unity. I assume now the native labour forces consists three cohort groups: young, middle-age and old workers[30]. The reason that I only consider three cohort groups is simply for the computation feasibility. For each group, the average birth year is computed which in the following analysis will be treated as a group characteristic. Taking old cohort group as an example, in 2000[31] old workers are on average 57 years old who entered the labour market in 1965. When native workers enter the labour market, they are assumed to be capable of correctly forecasting the industry evolution patterns. Perfect foresight skilled natives will take the industry evolution as additional information when making their lifetime occupational choices. These three cohort groups solve different dynamic choice problems since they experience the different phases of industrial development. Then in a particular year,

[30]Each group of workers have an age span of 14-15 years. For example, workers aged between 22 to 36 are considered to be young workers, while workers aged 37-51 and aged 52-65 are considered as middle-age and old workers respectively.

[31]The reason I choose year 2000 is that in the estimation procedure the simulated moments will match data moments generated using 2000 census data.

the combined income age profile of these three cohort groups as well as the choice cohort profiles for each of these groups are generated by simulation to match data moments computed using repeated cross section data. The following graph takes the year 2000 as an example to show graphically how to construct the combined income age profile using the simulated data from three DDP problems.

Figure D.4: Illustration of the Perfect Foresight Model



All other model specifications are identical to the basic model. For the estimation part, there are a few minor changes as mentioned before. Instead of matching the choice-age profile of choosing to be computer scientists conditional on being STEM workers each year, the choice cohort profiles are used in addition to the wage age profiles. Taking the year 2000 again as an example, for each cohort group described above, I can track the proportion of native CS workers out of total STEM workers over 1994-2013 period (very similar to the way to construct a synthetic panel using repeated cross-section data). To be more specific, for the defined young, middle-age and old cohort group in 2000, the choice probabilities ranging from age 22 to 41, from age 36 to 55 and from age 51 to 65 are computed respectively.

The following table presents the supply estimates from the perfect foresight model.

Table D.2 shows that the perfect foresight model estimates are very close to the basic model in terms of signs and magnitudes. However, there are certain

Table D.2: Estimates of Perfect Foresight VS Basic Model

Coeff	Computer Science		other-STEM	
	Foresight	Basic	Foresight	Basic
CS Exp.	0.0845	0.1038	0.0589	0.0465
other-STEM Exp.	0.0630	0.0428	0.1016	0.1238
Total Exp^2 /100	-0.1758	-0.1701	-0.1843	-0.1843
Random Accumulation	0.0523	0.0459	0.0640	0.0424
	Covariance Matrix			
unobs. Heterogeneity	0.0722	0.0818		
	-0.0166	-0.0159	0.1273	0.0918
Taste Shock	0.0423	0.08976		

changes worth noting. First, both sectors value less the experience in current occupation and more the experience in other occupation compared to the basic model. For example, the first year of CS experience augments CS human capital by about 8.5% while in the basic model the number is 10.4%. Also, the first year of other-STEM experience increases other-STEM skill by 10.1% as oppose to 12.4%. Both sectors value working experiences in other occupations more than the steady state model. An additional year of CS (other-STEM) experience augments other-STEM (CS) skill by less than 6.4 % (5.9%). There are little changes in the attenuation rate. One possible driven force behind this shift could be attributed specifically to adding the old cohort group. In old workers' early working years, almost nobody in CPS data was hired as a computer scientist . This situation lasted at least another one decade. As oppose to 1960s, later in the sample period (1994-2013) which I am interested in, even for the old cohort group, 25%-30% of native STEM workers are being hired as computer scientists. Experiences in other sector being valued more enables natives to switch occupations even at the latter phases of their career. Matching the wage distribution and choice of old cohort group forces the estimates to tilt towards experiences in other occupations. As mentioned before, one of another important changes is to use the choice-cohort profile in the estimation process rather than the choice-age profile. The sector trend (expectation) generated

Table D.3: Estimates of Demand Side (Perfect Foresight)

Coeff	Computer Science val.	other-STEM val.
Share	0.4956	0.4229
Rho	0.8542	0.4914
Return to Scale	0.5863	0.6085
	Implied Substitution Elasticity (Immigrants vs U.S. Workers)	
$\frac{1}{1-\rho}$	6.8587	1.9662

by the flat spot method would help to explain some of the variations in the choices-cohort profile over time in addition to the taste shock. Unlike the perfect foresight model, the taste shock in the steady state model is the single force that generates variations in the choice-age profile. Consequently, the taste shock variance estimate decreases from 0.08976 in the basic model to 0.0423 in the perfect foresight model.

For the labour demand side, the estimated coefficients are very similar to that of the basic model. The new estimates are presented in Table D.3 .

Similar to the basic model part, I compute the correlation coefficient between the estimated relative efficiency price and the Nasdaq composite index as a sensitivity check of the new model. The correlation coefficient is 0.73 and the number in the basic model is 0.81.

Figure D.4: Model Fitting (Choice Cohort Profile)

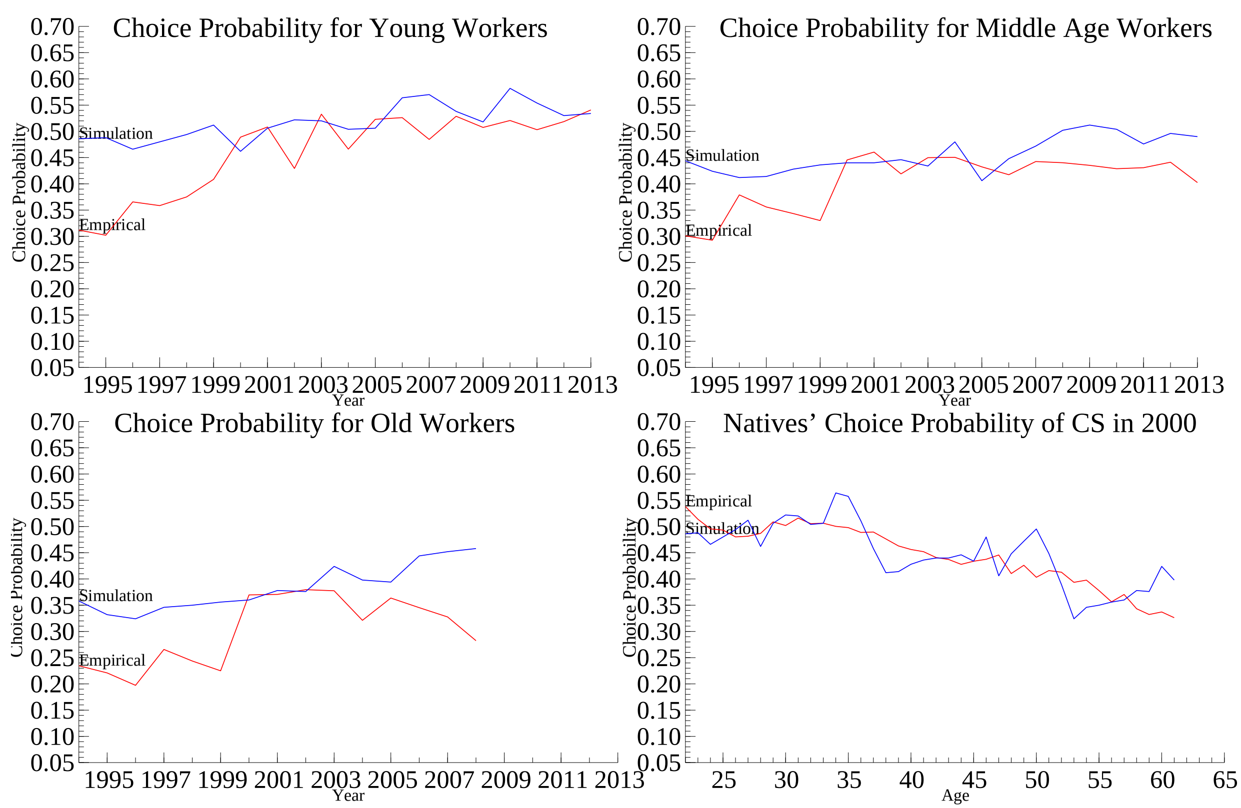
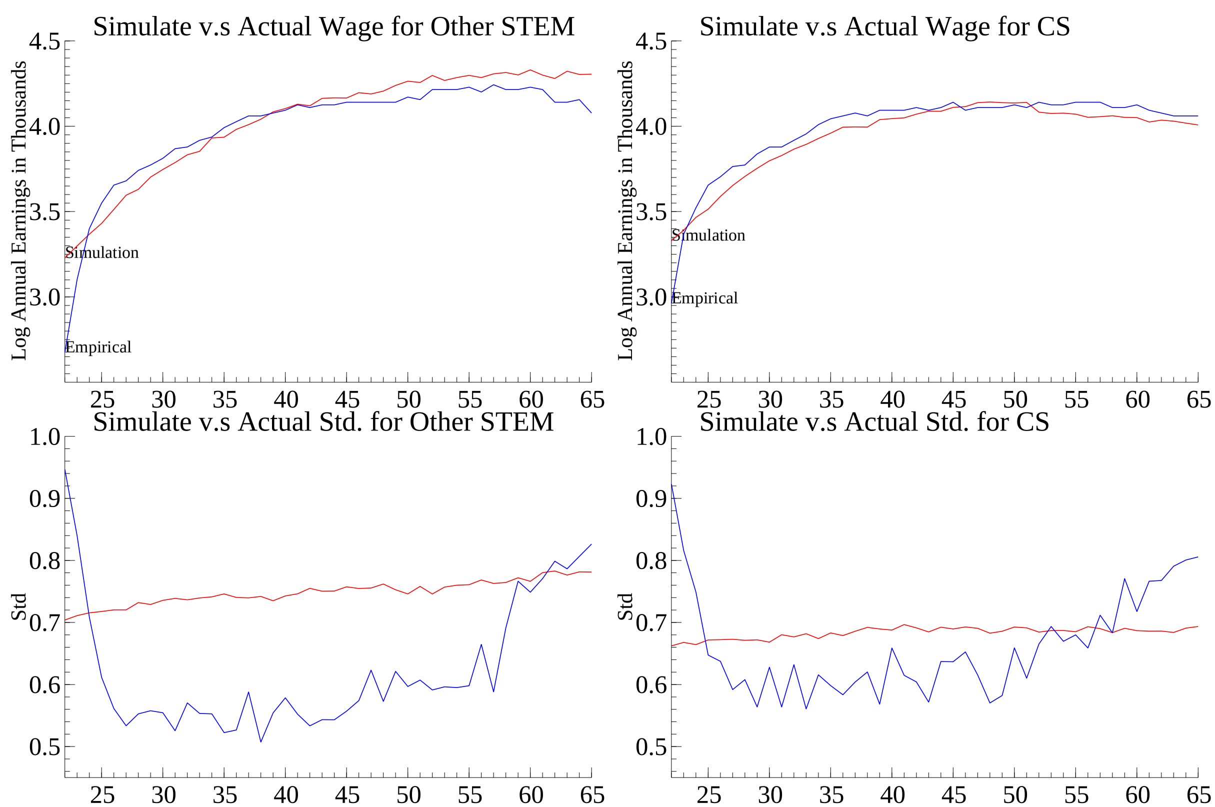


Figure D.5: Model Fitting (Wage Profile)



In Figure D.4 and D.5, I show graphically the performance of the perfect foresight model. In Figure D.4, the top two panels and the bottom left panel depict the data (red) and simulated (blue) choice-cohort profiles for each of the three cohort groups. These three are the moments that are being matched in the estimation process. First, we can notice that the level effect across cohort groups is obvious. The probability is the highest for the young workers which approximately equals to 0.5 and the lowest for the old workers about 0.3. The simulated choice-cohort profiles track the levels for all three groups relatively well. However, for the young cohort group(top left panel), the simulated data fail to generate the increasing pattern; and for the old cohort group (bottom left panel), it seems that the simulated data over predict the probability. The within sample fit of the choice cohort profile is acceptable. The bottom right panel is the one that shows clearly the improvements of the perfect foresight model performance. To make the performance of the perfect foresight model directly comparable to that of the basic model, I plot the choice-age profile in the bottom right panel. Unlike the basic model, the choice-age profile is not the data moment directly to be matched. Even not being matched deliberately, the simulated choice-age profile using three cohort groups outperforms the basic model. The simulated data track the empirical moment well through the entire profile. There is one drawback of using only three cohort groups. The simulated choice-age profile presents a pattern of a step function. The discontinuity will be removed if finer age span and more cohort groups are included in the perfect foresight model.

For other empirical moments, the model fit is presented as above in Figure D.5. Compared to the basic model, the income-wage age profile fit is compromised because in the modified version of the model the predetermined industry evolution patterns are imposed implicitly in the DDP problem acting as additional constraints.