High Skilled Immigration and the Market for Skilled Labor: The Role of Occupational Choice

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Abstract

In recent years, immigration rates have increased dramatically among the most highly skilled workers. How does this inflow affect labor market outcomes among highly skilled native-born workers? I estimate a general equilibrium model in which individuals choose their occupations and invest into occupation specific human capital. I estimate the demand functions for native and immigrant workers and find that skilled immigrants and natives are imperfect substitutes in some occupations and complements in others. Counterfactual exercises indicate that even large inflows of foreign skilled workers have limited impacts on domestic workers. In particular, skill rental rates for native science and engineering workers would have been approximately 2% higher if firms were not able to hire more foreigners than they did in 1994. On the other hand, had U.S. workers being constrained to remain in their original occupations, the adverse impacts of foreign labor competition would be more severe. The restriction of occupational mobility would be particular costly for young workers whose cost is estimated to equal approximately $40000. When natives’ occupational choices respond to immigration, the negative effects are diffused. The extent to which this occupational mobility helps to absorb the immigration shock depends not only on the substitution elasticity in the directly affected occupations, but also on the demand elasticity of native labor in the destination occupations where natives move to.
1 Introduction

Contrary to popular perception, many of the immigrants to the US in the last decades were highly skilled. Between 1990 and 2010, the number of skilled immigrants residing in the US rose by about 4.8% annually\(^1\). Today 16% of the US workers with a bachelor’s education are immigrants. The inflow of immigrants has furthermore been unevenly spread. 25% of computer scientists and electronics engineers are immigrants, but only 6% of those working in the legal professions are. Basic economic arguments (Borjas (1999)) suggest that such an unbalanced and sizeable flow of migrants might have substantial detrimental effects on natives with similar skills working in the same professions. Given the empirical distribution of skilled migrants across occupations, we expect any labor market effects to be largest among US workers in science, technology, engineering, and mathematics (STEM)\(^2\) occupations. However, with a few exceptions (Peri et al (2015), Hanson and Slaughter (2015), Bound et al. 2015), the literature so far has neglected the question of how skilled immigration has affected native born workers in the STEM fields. How do native workers react to foreign labor competition?

A comprehensive answer to these questions requires multiple inputs. First, we need to estimate the demand for skilled workers across occupations. Second, we need to understand how the native-born workers choose occupations and whether occupational switching can serve as a pressure-valve mitigating and diffusing any consequences of the inflow of skilled migration. In particular, I build a general equilibrium model focusing on dynamic occupational choices with the following key features: (a) skilled natives and immigrants are allowed to be imperfect substitutes or complements, and substitutability or complementarity can vary across occupations; (b) workers are heterogeneous in terms of multi-dimensional innate abilities; (c) workers accumulate occupation specific human capital through learning by doing, and the occupation specific human capital is partially transferable across occupations.

Specifically, this paper studies the wage and welfare implications of skilled immigrants in multi-sector equilibrium settings and explores the occupational mobility responses of native workers. I

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\(^1\)Source: Migration Policy Institute

estimate a two sector model (Computer Science occupations (CS))\textsuperscript{3} v.s. Other-STEM occupations) in which, on the supply side, native workers differ in their abilities for working in either sector. The two dimensions of innate ability are allowed to be correlated. Agents choose their occupations according to their comparative advantage (Roy 1951). This comparative advantage evolves over time because native workers accumulate partially occupation-specific human capital while working in a given occupation (Keane and Wolpin 1997). Since this human capital is only partially transferable, switching occupations is costly. An inflow of migrants can change market prices for different occupations and native workers can respond to these price changes by switching occupations. Thus, native labor supply responds to skilled immigration flows to different occupations.

The supply of foreign workers is assumed to be perfectly inelastic and its level is exogenously determined by U.S. immigration policies. The H-1B visa\textsuperscript{4} for temporary workers places a cap on the total number of skilled immigrants. The lack of portability of the H-1B visa restricts the occupational mobility of skilled immigrants after entering the U.S. labor market. The demand for visas varies year by year according to the U.S. business environment, but caps typically do not. The policy separates the immigration labor supply from the labor demand. This plausible exogenous variation is crucial to identify the demand for skilled workers.

Firms hire both native and foreign born workers. Labor demand shocks, such as the one created by the Internet boom, can be accommodated by two sources: domestic workers in STEM occupations and skilled immigration. Firms use flexible CES production functions where domestic and foreign labor are allowed to be imperfect substitutes or even complements.

I estimate the model with data from the Current Population Survey (CPS), the American Community Survey (ACS), and the Panel Study of Income Dynamics (PSID). The model is identified by combining structural assumptions with exogenous variation in the flow of skilled immigration\textsuperscript{5}.

The estimation is done in two steps. Parameters of the supply side are separately estimated from those of the demand side. In the first step, skill rental rates for native labor are treated as parameters. The individual labor supply is estimated using the simulated method of moments (MacFadden 1989). The estimation of the individual labor supply and occupational choices delivers the time series for the skill rental rates and the measure of effective labor at the individual level.

\textsuperscript{3}Computer Science occupations include computer systems analysts, computer scientists, computer software develop-
er.

\textsuperscript{4}The H-1B is a non-immigrant visa in the United States under the Immigration and Nationality Act, section 101(a)(15)(H). It allows U.S. employers to temporarily employ foreign workers in specialty occupations.

\textsuperscript{5}The full model is estimated following the Jeong, Kim and Manovskii’s (2015) technique.
which can be added up to obtain the aggregate labor supply. In the second step, for the labor demand side, production parameters are estimated using time variations in skill rental rates and aggregate labor inputs. The supplies of skilled immigration are the source of exogenous variation for identifying skilled labor demand.

The model generates moments that are consistent with the key empirical patterns. It generates age-earning profiles that match data well for both occupations and across years, including the flat part approaching retirement. It predicts accurately the occupation employment shares for different birth cohorts over age. In this setup, the occupation-specific human capital in addition to age specific taste shocks makes young workers more likely to switch occupations. Therefore, the model generates a gross occupation mobility pattern that declines with age. Moreover, the model predicts relative skill rental rates\(^6\) for 20 years. This series closely tracks the pattern of Nasdaq composite index in the same period.

The estimates indicate that skilled native and foreign labor are imperfect substitutes in the CS occupation, but are complements in the other-STEM occupations. The difference in elasticity of substitution could potentially be attributed to variations in factors such as task contents and skill requirements across occupations. The complementary could come through task specialization of native and foreign skilled workers within occupations.

Occupation-specific innate abilities are negatively correlated. This implies that workers in both occupation groups are positively selected. In addition there is substantial heterogeneity in innate ability across individuals, which is an important determinant of income inequality. One standard deviation increase in the innate ability is associated with a 23%-35.5% increase in annual wages depending on what sector the individual works in.

Using the estimated model, I consider following policy relevant counterfactual experiments. First, I restrict the total foreign skilled labor supply in the STEM sector to its 1994 level, keeping the occupation mix of immigrants fixed. This experiment attempts to study immigration policies on total quantity restriction, such as variation in the overall H-1B cap. This exercise reveals that even large inflows of foreign skilled workers have only a limited impact on domestic workers. Wages of skilled domestic workers on average increase by 2.41% due to this highly restrictive counterfactual policy.

Second I consider the counterfactual scenario in which the occupation mix of skilled immigra-

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\(^6\)Define as skill rental rate of the CS occupations over that of the Other-STEM occupations.
tion is manipulated. The experiment analyzes policies that favor specific occupations. The point-based immigration system adopted by the Canadian government and the Optional Practical Training (OPT) period used by United States Citizenship and Immigration Services (USCIS) provide workers in certain occupations and fields of study with better access to the country's labor markets. Compared with the results from the first counterfactual experiment, the result suggests that a selective immigration policy based on occupations could achieve larger welfare gains for natives. Optimizing occupation mix of skilled immigrants and favoring occupations where complementarity exists could potentially benefit all natives more compared to a total quantity cap. Workers in the occupations where complementarity exists experience a direct increase in wages due to inflow if skilled immigrants, while others experience positive a spillover effect as a result of occupational mobility.

I then use the estimated model to assess the importance of its key features: substitutability between domestic and foreign workers, general equilibrium with multiple sectors, and choice by heterogeneous agents. First, my estimates indicate that domestic and foreign workers are imperfect substitutes in the CS occupation and are complements in the other-STEM occupation. If one instead falsely assumes that immigrants and natives are perfect substitutes, then one will overestimate the costs immigration imposes on skilled native workers. Second, a partial equilibrium model, unlike the general equilibrium, will ignore any wider impact of foreign computer scientists on other sectors. The quantitative results of this paper demonstrate that a non-trivial number of domestic CS workers switch to the other-STEM occupations. This implies that the consequences of skilled immigration in the CS occupation affect workers in the other-STEM occupation as well. A partial equilibrium model will miss this effect. With a normal downward sloping labor demand curve, the net inflows of native workers into the other-STEM occupation will put downward pressure on wages. Third, unobservable heterogeneity is an important determinant of individual's occupational choices (Keane and Wolpin (1997)). Shutting down heterogeneity in labor will substantially increase occupational mobility. As a result, a model without heterogeneity in labor will overestimate the natives' sensitivity in terms of occupational mobility.

The model could also be used to predict individual's option value of occupational mobility. The computation suggests occupational mobility is an economically meaningful adjustment margin. In general, there is plenty of heterogeneity in individual's valuation. Overall, it is more costly for younger workers to remain in their original occupations when facing foreign competition. Even with only temporary restriction in mobility, younger workers require $40,000 of compensating variation
(CV) on average to maintain the same level of lifetime utility. If native workers were forced to stay in sectors permanently where increasing foreign competition is expected, they would require more than $100,000 as CV. This is because human capital is occupation-specific. Thus, earlier mistakes in occupational choice have long lasting effects. The valuation of free occupational mobility is higher if no one else in the economy is endowed with the same option. Such reallocation of labor across occupations is valuable in terms of welfare.

This paper contributes to a growing body of literature that studies the impacts of skilled immigration on U.S. labor market outcomes \cite{KerrLincoln2010, HuntGauthierLoiselle2010, Hunt2011, Hunt2013, BorjasDoran2012, Moeer2013, Boundetal2015}. Motivated by the empirical evidence documented in \cite{PeriSparer2011, PeriShihSparer2015, DamuriPeri2014}, the main focus of this paper is on the domestic workers' occupational mobility in response to immigration, and consequently the wage impacts. The basic economic arguments suggest that skilled immigrants potentially impose some costs on workers who are close substitutes \cite{Borjas1999}. However, the magnitude of the negative impacts may be substantially mitigated if U.S. skilled workers have good alternatives to occupations that are most impacted by immigrants.

Native's internal migration in response to immigration has been studied before \cite{Card2001, Borjas2006, Piyapromdee2015}. These previous studies find mixed evidence. Card \cite{Card2001} finds that native workers are rather insensitive in terms of geographic mobility. Borjas \cite{Borjas2006} shows that native migration can substantially reduce the negative wage impacts of immigration. Piyapromdee \cite{Piyapromdee2015} builds a spatial equilibrium model in which she finds that the extent to which the geographic mobility reduces the adverse impacts in local labor markets depends on the substitutability between different types of labor and local labor market composition. None of the previous papers are in the context of skilled immigrants. Changes in the geographic settlement of native workers will not be the only behavioral response to immigration. Here I emphasize another adjustment margin - occupational mobility, which is understudied in the literature. I study the impacts of skilled immigration in a multi-sector economy. In the model, domestic workers optimize their occupational choices according to changes in market conditions and their comparative advantages. Switching occupations tends to equalize native wages across occupations and offset the effects of immigration

\footnote{Regression analysis in the literature has found no clear evidence of crowd-out of native employment, and in some cases has found crowd-in. The literature studying the human capital externalities of skilled immigrants has found that immigration through H-1B program leads to large positive impacts on innovation [specifically patenting] in U.S.}
inflows through reallocation.

There are very few structural papers studying natives’ occupational response to foreign competition. The study of Bound et al. (2015) is the only one to my knowledge falling into this category. The authors utilize a calibrated model to analyze the employment and wage adjustment of native computer scientists. They assume a decreasing returns technology in which domestic and foreign computer scientists are perfect substitutes. The partial equilibrium setting in this study focuses on the market for computer scientists and ignores any wider impacts that high-skilled immigration might have on the US economy.

Finally, my model is also related to work studying the human capital formation and occupational mobility. Kambourov and Manovskii (2008, 2009) document two main facts: first, returns to occupational tenure are substantial; second, occupation mobility decreases with age. In this paper, I incorporate both facts into the model. Unlike Kambourov and Manovskii (2009), the occupation specific human capital is not fully depreciated but it is partially transferable across occupations.

In summary, in this paper, I study the occupational mobility of native skilled workers in responses to foreign labor competition in a general equilibrium setting. I explicitly model how the native-born workers choose occupations. Occupational mobility, an understudies adjustment margin in the literature, serve as a pressure valve mitigating and diffusing any consequences of inflows of skilled immigrants. I also estimate the demand for skilled natives and immigrants across occupations using plausible exogenous variations provided by US immigration policies. Using value generated by the structural estimation, I simulate counterfactual scenarios to evaluate two types of immigration policies: (1) a cap on overall skilled immigration, and (2) a selective immigration policy based on occupations. I find that even large inflows of foreign skilled workers have a limited impact on domestic workers. Moreover, a selective immigration policy based on occupations could achieve higher welfare gains for natives compared to an overall cap. Furthermore, I quantify the economic value of occupational mobility for native workers. Had native workers been temporarily constrained to remain in their original occupations during the Internet boom, their lifetime utility would be adversely affected. This restriction would be particularly costly for young workers whose cost is estimated to equal approximately $40000. Early human capital investment decision have lasting effects on individual’s wellbeing.

The paper is structured as follows. Section 2 describes the OPT and H-1B visa program in the U.S. Section 3 specifies the model and Section 4 discusses the data, identification and estimation
procedure. Section 5 presents the results. Section 6 shows counterfactual experiments. I discuss potential model specification issues and limitation of the model in Section 7 and conclude in Section 8.

2 Relevant Immigration Policies and Impacts

The primary visa program under which skilled immigrants enter the U.S. is the H-1B program. The H-1B visa program for temporary workers in 'specialty occupations' was established by the Immigration Act of 1990. H-1B visas require applicants to have at least a bachelor's degree or its equivalent. It effectively restricts the annual flow of skilled foreign new entrants.

The H-1B temporary visa is noteworthy in the current context of the paper not only because it has been a key source of high-skill immigration to the United States in the past two decades, but also because it creates a binding contract between a particular worker and the sponsoring firm. The sponsoring firm files a Labor Condition Application (LCA) to USCIS for a prospective employee. Once the application is approved, it allows foreign skilled workers to stay a maximum of six-year on an H-1B visa. If at the end of the visa period, the worker is unable to adjust his or her visa status into one that allows permanent residence, the H-1B visa holder must leave the country. An important result of this sponsorship is that workers are tied to their sponsoring firms, which to a large extent prevents immigrants from switching occupations. This feature helps to simplify the analysis in the paper. Upon entering the U.S. labor market, skilled immigrants are effectively tied to one particular occupation due to the binding contract. Given the lack of portability of the H-1B visa, foreign workers are very insensitive to changes in wages across occupations. Therefore, the occupational mobility (self-selection) of skilled immigrants after entering U.S. markets is not a concern here.

Since 1990 the United States has capped the number of H-1B visas that are granted each year. The annual cap has fluctuated over the years, and the policy debate typically focuses on whether

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8The 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.

9In LCA's for H-1B workers, the employer must attest that the firm will pay the non-immigrant the greater of the actual compensation paid to other employees in the same jobs or the prevailing compensation for that occupation, and the firm will provide working conditions for the foreign worker that do not cause the working conditions of the other employees to be adversely affected.

10The H-1B allows visa holders to switch employers but the new job has to match the original ones in terms of title, requirements, and background.

11There are exemptions for foreigners who work at universities and non-profit research facilities.
the cap should be increased. During the early 1990s, the initial cap was set at 65,000 visas per year. When first introduced, the cap was rarely reached. By the mid-1990s, the allocation was based on a first come first served principle, resulting in frequent denials or delays on H-1Bs because the annual quota was usually exhausted within a short period of time. The USCIS then employs a lottery mechanism to randomly select qualified petitions. In Figure 1, I show the changes of H-1B visa cap and the estimated population of H-1B holders. The initial cap of 65,000 visas was increased to 115,000 for 1999 and to 195,000 for 2001. The cap then reverted to 65,000 in 2004. The cap is binding recently and the chance of getting an H-1B visa is less than 1. In 2016, the probability of winning the lottery is less than 40% at its “historical low”. The annual flow of the foreign skill workers into U.S. is effectively restricted by the H-1B cap, and the temporary visa only allows visa holders to stay for 6 years. Due to these two facts, I argue that the stock of skilled immigrants is inelastically supplied and policy driven. It could be a plausible source of exogenous variation when identifying the labor demand curves. One maybe concern about the endogeneity of immigration policies in the U.S. However, over years, we see binding caps and news about high tech executives lobby to expand the H-1B program while the cap has not been increased for more than 10 years after it was abruptly cut down by two thirds in 2004.

There are other temporary worker visas close to the H-1Bs: L-1 and TN visas. Both of these programs are less than 10% of the size of the H-1B program for high skilled workers and contain institutional features that limit the firms’ ability to use them to circumvent the H-1B quota. The Department of Homeland Security has argued that limited substitution exists across the H-1B and L-1 visas. Neither visa category shows substantial increases after the H-1B cap was dramatically reduced in 2004.

H-1B can be viewed as an overall quantity cap of skilled immigration, while the optional practical training program (OPT) favors foreign labors with special training and who work in specific occupations. 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 USCIS to work for a certain period of time on a student visa. STEM occupations have a total OPT length of 36 months, which is two years longer than other occupations. 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. Longer OPT length means multiple visa application opportunities. This greatly increases the chance of actually getting a temporary working visa. As a result, a
noteworthy portion of H-1B beneficiaries\footnote{Workers renewing their H-1B visa as well as newly arrived workers} work in STEM occupations, especially computer science related occupations (See the occupational composition of H-1B beneficiaries in Figure 2). In Figure 3, I plot the time series of immigrant\footnote{In the data, I define immigrants as those who does not become U.S. citizens until the age of 18.} fraction in three different groups using March CPS data. The bottom flat line is the fraction of immigrants in the high-skilled labor force. The proportion of foreign workers mildly increased until 2001 and then stabilized afterwards, consisting approximately 12\% of the high-skilled labor force. The proportion of foreign workers in CS is persistently higher than other-STEM sector, both of which are higher than non-STEM occupations. Policies like OPT favoring STEM occupations are responsible for this pattern. One of the reasons I choose to study CS and other-STEM occupations is because they are the occupation groups that are most influenced by skilled immigrants for the past 20 years.

3 A Model of Dynamic Labor Supply and Demand of STEM Workers

To analyze the effects of skilled immigration on native workers in different occupations, I extend the static Roy model to dynamic general equilibrium settings.

To begin, in this model, there are two types of labor: immigrants and native labor. All agents work in STEM occupations. The supply of foreign labor in each occupation is assumed to be exogenous as discussed in the policy part. Native workers in each period choose either work as computer scientists or work in other-STEM occupations according to their comparative advantages. Native workers differ in their innate ability and their comparative advantages evolve over time since they accumulate occupational-specific human capital when engaged production activity (working in one occupation).

For the labor demand (production) side, firms maximize profits and decide how much native labor to hire and what are the skill rental rates. Both representative firms use a flexible CES production function treating native and immigrant labor as two different inputs in production.

The focus of this structural paper is the labor market adjustment underlying the native workers’ behavior response. With different intensities of immigration inflows, changes in labor market conditions for native vary across occupations. Rational natives observe changes in market conditions,
form expectations about career prospects, and then adapt to immigration shocks by re-optimizing their occupational choices.

I begin this section by specifying native labor supply decisions, foreign workers labor supply, labor demand, and then finally present the equilibrium conditions.

### 3.1 Labor Supply

#### 3.1.1 Native Labor Supply

Natives enter the labor market at age 22 with a bachelor’s degree. At the beginning of each period between age 22 and 65 (the exogenous retirement age), individuals choose \( d \in \{cs, ncs\} \), working either as computer scientists \( (d = cs) \) or in other-STEM occupation \( (d = ncs) \) in order to maximize the expected present value of their lifetime utility.

#### Individual Human Capital Formation, Wages, and Preferences

An individual enters the labor market with full knowledge of his or her own innate ability\(^{14}\) modeled as a realization from a bivariate normal distribution.

\[
\begin{pmatrix}
\epsilon_{cs} \\
\epsilon_{ncs}
\end{pmatrix}
\sim N(\mu, \Sigma)
\]

The initial ability endowments are occupation specific. The two dimensions of the innate ability are allowed to be correlated.

Once starting work, individuals accumulate occupation specific human capital when engaged in a productive activity (working in one occupation). This occupation specific human capital is partially transferable across occupations.

The human capital evolves endogenously with age \( a \) based on individual’s occupational choices. The occupation specific human capital depends on occupational tenures \( (x_{cs}^a, x_{ncs}^a) \) and the general work experience \( x_a \), where \( x_a = x_{cs}^a + x_{ncs}^a \).

\[
\begin{align*}
H_{cs}^a &= \exp[\alpha_1 x_{cs}^a + \alpha_2 x_{ncs}^a + \alpha_3 x_a^2 + \alpha_4 x_a^3 + \epsilon_{cs}] \\
H_{ncs}^a &= \exp[\alpha_5 x_{cs}^a + \alpha_6 x_{ncs}^a + \alpha_7 x_a^2 + \alpha_8 x_a^3 + \epsilon_{ncs}]
\end{align*}
\]

\(^{14}\)Even though I call this innate ability, it actually captures more than unobserved ability. Since the educational decision and investment prior to work phases are not explicitly modeled in the model, they can be captured by these ability types.
One feature of the model is that even though no explicit cost of switching occupation is introduced, the way human capital is modeled imposes implicit switching costs. With $\alpha_1$ greater than $\alpha_2$, workers with long tenures in other-STEM occupation experience wage losses when switching to CS occupation.

I assume labor market is competitive with no search friction. Thus wages are determined by the product of current equilibrium rental rates ($\Pi_{t}^{cs}$ and $\Pi_{t}^{ncs}$) and individuals’ occupation specific human capital ($H_{a}^{cs}$ and $H_{a}^{ncs}$).

$$ W_{a,t}^{s} = \Pi_{t}^{s} H_{a}^{s} \quad (2) $$

$s \in \{cs, ncs\}$

The market is assumed to be complete. Individuals can fully insure against risks, so no precautionary saving is required. As a result, agents can be modeled as if they are risk neutral. They have linear utility $^{16}$ from wages and age specific taste shocks $\eta_{a}^{17}$.

$$ u_{a,t}^{cs} = W_{a,t}^{cs} + \eta_{a} \quad (3a) $$
$$ u_{a,t}^{ncs} = W_{a,t}^{ncs} \quad (3b) $$

As shown in equation (4), taste shocks are independent draws from a family of normal distributions whose variance decreases along with age.

$$ \eta_{a} \sim N \left(0, \sigma_{\eta_{a}}^{2}\right) \quad (4) $$

$$ \sigma_{\eta_{a}}^{2} = \sigma_{\eta}^{2} \exp(-\gamma a) $$

This parsimonious specification of taste shocks together with the occupation specific human capital generate patterns of occupational mobility similar to those documented in Kambourov and...
Manovskii (2009). The model generates decreasing gross occupational mobility with age.

**Individual Occupational Choices**

Followed the notation of Lee and Wolpin (2006), let $\Omega_{a,t}$ be the vector of state variables at age $a$ and time $t$, variables known then that determine the remaining expected present value of lifetime utility. Given the structure of the model, the state space at any age $a$ includes the current equilibrium skill rental rates ($\Pi_t$), future expectation of equilibrium skill rental rates up to age 65 ($\Pi_t(\epsilon)$), current occupation tenures ($x_{cs}^a$, $x_{ncs}^a$), innate ability ($\epsilon$), and the current realization of taste shocks ($\eta_a$). Given the information set $\Omega_{a,t}$, agents choose between two mutually exclusive alternatives in the action space $d = (cs, ncs)$. The relevant history of career choices and past realizations of taste shock are summarized by current occupational tenures. Then the Bellman equations of the two alternative value functions at age $a$ (between 22 and 64) at time $t$ are as follows.

\[
V^{cs}(\Omega_{a,t}) = W^{cs}_{a,t} + \eta_a + \beta E V(\Omega_{a+1,t+1}|d = cs, \Omega_{a,t}) \quad (5a)
\]
\[
V^{ncs}(\Omega_{a,t}) = W^{ncs}_{a,t} + \beta E V(\Omega_{a+1,t+1}|d = ncs, \Omega_{a,t}) \quad (5b)
\]

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

\[
V^{cs}(\Omega_{65,t}) = W^{cs}_{65,t} + \eta_{65} \quad (6a)
\]
\[
V^{ncs}(\Omega_{65,t}) = W^{ncs} \quad (6b)
\]

In each period, native workers choose the greater of $V^{cs}$ and $V^{ncs}$.

\[
V(\Omega_{a,t}) = \max \{ V^{cs}, V^{ncs} \} \quad (7)
\]

**Evolution of the State Variable**

The state space of a domestic worker at age $a$ and time $t$ is
\[ \Omega_{a,t} = \{a, a_{c}^{s}, a_{n}^{ncs}, \epsilon, \eta_{a}, \Pi_{t}, \Pi_{t}(e) \} \]

where \( \Pi_{t}(e) \) represents the expectation of future equilibrium skill rental rates.

The evolution of age \( a \), innate ability \( \epsilon \), and taste shock \( \eta_{a} \) is trivial. Since innate ability \( \epsilon \) is permanent heterogeneity, it is constant along the entire career path; the taste shocks \( \eta_{a} \) are independent draws; age \( a \) evolves in a deterministic way. Occupational tenures \( x_{a}^{s} \) and \( x_{a}^{ncs} \) evolve endogenously. If the native worker spends one period in sector \( s \) (\( d = s \)), this individual accumulates tenure according to the rule,

\[ x_{a+1} = x_{a}^{s} + 1(d = s). \]

The current skill rental rates \( \Pi_{t} \) are determined by labor market clear condition, which will be discussed in detail in the model equilibrium part.

Another important component of the state space is agent’s expectations of future equilibrium skill rental rates \( \{\Pi_{\tau}(e)\}_{\tau=t+1}^{\infty} = \{\Pi_{\tau}^{cs}(e), \Pi_{\tau}^{ncs}(e)\}_{\tau=t+1}^{\infty} \). For simplicity and tractability, I assume that agents form deterministic expectation, a perfect foresight model.

\[ \Pi_{\tau}^{s}(e) = \hat{\Pi}_{\tau}^{s}(o) \forall \tau > t s \in \{cs, ncs\} \tag{8} \]

where \( \hat{\Pi}_{\tau}^{s}(o) \) denote the observed market skill rental rates that are directly measured using CPS data. In this current model, \( \hat{\Pi}_{\tau}^{s}(o) \) are perfect anticipated by the workers\(^{18}\).

Lee and Wolpin (2006) have a rational expectations equilibrium\(^{19}\); however, in this paper I construct a model with perfect foresight expectation - the equilibrium skill rental rates do not have to coincide with the expectation.

Workers form expectations about skill rental rates rather than aggregate productivities. This is because even though those two are closely related, skill rental rates contain more information and

\(^{18}\)I also considered the alternative assumption that all agents in the economy assume naively that the current skill rental rates will last forever \( \Pi^{s}_{\tau}(e) = \Pi^{s}_{t} \forall \tau > t s \in \{cs, ncs\}. \) They then are surprised by changes in skill rental rates on a less frequent basis (the MIT shocks). This static expectation assumption yields time paths for wages and employment that are quite similar to the ones under the current perfect foresight assumption.

\(^{19}\)In a rational expectations equilibrium, current, past values and future expectation of the aggregate shocks and of the human capital rental rates, which are common to all agents, as well as the idiosyncratic elements of the state space associated with the occupation decision problem of each agent in the economy (age, occupational tenure, preference and innate ability) will determined equilibrium skill rental prices. The expectation should coincide with the equilibrium results which are also time invariant. This requires solving for another layer of fixed point.
are more relevant to individual’s occupational choices. Prices reflect information about the future sequences of the aggregate technology shocks, flows of immigrations, and cohort sizes.

**Aggregate Native Labor Supply**

There is no leisure choice in this model. However, individual labor supply in efficiency units differs due to the heterogeneity in individual human capital \((H_{cs}^{a} \text{ and } H_{ncs}^{a})\). The occupation specific human capital is also the individual’s labor supply in efficiency units. To get the total labor supply for each occupation, I first aggregate the labor supply for age group \(a\), \(NS_{a,t}^{s}\):

\[
NS_{a,t}^{s} = \int \int \Gamma^{s}(\Omega_{a,t})H_{a}^{s}(x_{cs}^{a}, x_{ncs}^{a}, \epsilon)dF(x_{cs}^{a}, x_{ncs}^{a}, \epsilon|a,t)dF(\eta_{a})
\]

\((9)\)

\(\Gamma^{s}(\Omega_{a,t})\) is an indicator variable that occupation \(s\) is chosen at age \(a\) and year \(t\). For age group \(a\) in year \(t\), there is a joint distribution of the innate ability and the occupational tenure \(F(x_{cs}^{a}, x_{ncs}^{a}, \epsilon|a,t)\) which summarizes all relevant information about the entire history of skill rental rates, taste shocks and expectations of career prospects. Jointly with the distribution of the current taste shock \(F(\eta_{a})\), \(F(x_{cs}^{a}, x_{ncs}^{a}, \epsilon|a)\) determines the aggregate labor supply for age group \(a\).

Since cohort population size also differs, to compute the aggregate labor supply, \(NS_{t}^{s}\), I give each cohort aggregate labor supply \((NS_{a,t}^{s})\) a weight proportional to his birth cohort size, \(w_{a,t}\). As a result, the aggregate labor supply of one occupation at time \(t\) is

\[
NS_{t}^{s} = \sum_{a=22}^{a=65} w_{a,t} NS_{a,t}^{s}
\]

\((10)\)

Where the weight is the cohort population size which I measure using the CPS data by \(w_{a,t} = \frac{N_{a,t}}{\sum_{i=22}^{65} N_{i,t}}\).

Similarly, the model predicts the fraction of natives working in CS sector in age group \(a\) and year \(t\) has the following expression,

\[
P_{cs}^{a,t} = \int \int \Gamma_{cs}(\Omega_{a,t})dF(x_{cs}^{a}, x_{ncs}^{a}, \epsilon|a,t)dF(\eta_{a})
\]

\((11)\)
3.1.2 Immigration Labor Supply

The supplies of immigrants in each sector are assumed to be perfectly inelastic, and the actual quantity is determined exogenously by immigration policies. In the CPS and ACS data, we observe annual incomes for full-time full-year skilled workers as well as their nationality. The skill rental rate $\Pi_t^*$ paid to foreign labor is measured directly by the average annual income of new foreign entrants. New entrants have no previous work experience, and the mean of innate abilities is normalized to 0.

For each skilled immigrants, his or her labor supply in efficiency units is back out by

$$H_{i,t}^* = \frac{W_{i,t}^*}{\Pi_t^*}.$$  

Total foreign labor supply in occupation $s$ ($M_t^s$) is aggregated over the immigrant population.

3.2 Labor Demand

Firms in both occupations hire two types of labor, native labor $N_t^s$ and foreign labor $M_t^s$. For simplicity and constrained by data availability, I assume that capital is separable from labor. Representative firms solve static profit maximization problems in every period. No dynamic structure is imposed on the demand side.

Firms use general CES production technologies that are occupation specific. The profit maximization problem of the representative firm in occupation $s$ is:

$$\max_{\{N_t^s, M_t^s\}} Z_t^s ((1 - \delta^s) (N_t^s)^{\rho^s} + \delta^s (M_t^s)^{\rho^s})^{\psi^s/\rho^s} - \Pi_t^s N_t^s - \Pi_t^* M_t^s$$

(12)

The functional form is very flexible. $\psi^s$ is the parameter that governs the curvature of the production function (return to scale parameter), which is also closely related to the demand elasticity of skilled labor. $\rho^s$ relates to the substitutability between the two types of labor. All the above parameters will be estimated from the data. The production function is general enough to allow these two types of labor being substitutes or even complements.

The FOCs with respect to native labor deliver the implicit demand functions for native skilled labor.

$$\Pi_t^s = Z_t^s \psi^s (1 - \delta^s) ((1 - \delta^s) + \delta^s (\frac{M_t^s}{N_t^s})^{\rho^s})^{\psi^s/\rho^s - 1} (N_t^s)^{\psi^s - 1}$$

(13)

The native labor demand $ND_t^s$ is implicitly determined by equation (13). The parameters of
interest are $\psi_s$, $\rho_s$, and $\delta_s$, which inform us of the fundamentals of occupation specific production technologies. If $\frac{\psi_s}{\rho_s} > 1$, the skill rental rate for natives goes up when foreign labor increases in this sector. If this is the case, then native and immigrant workers are complements in production.

### 3.3 Equilibrium

A dynamic general equilibrium can be characterized by a system of equations representing the agent’s labor supply decision (value functions, choice functions, agent’s expectation), the firm’s labor demand decision (demand functions, technology process), and market clear conditions. In particular, the equilibrium skill rental rate series $\{\Pi_t\} = \{\Pi_t^{cs}, \Pi_t^{ncs}\}$ in this model has to satisfy the following conditions:

1. Based on the skill rental rates $\{\Pi_t\}$ and future expectation $\{\Pi_t(e)\}$, the native labor supply $NS_t$ is the aggregation (equation 9 - 10) of individual labor supply decision, which is fully described by equation 5 - 8.

2. Firms maximize profit given skill rental rates $\{\Pi_t\}$. The labor demand $ND_t$ is determined in equation 13.

3. $\{\Pi_t\}$ clears the skill market in every period.

$$NS_t = ND_t \text{ for all } t$$

where $NS_t = \{NS_t^{cs}, NS_t^{ncs}\}$ and $ND_t = \{ND_t^{cs}, ND_t^{ncs}\}$.

### 4 Data, Identification and Estimation Method

#### 4.1 Data

Given the nature of the model, the ideal data would be of longitudinal type with a long time span containing detailed records about citizenship, education, occupation, fields of study, annual income, labor market participation. Moreover, ideally the sample should be large enough to cover enough observations in STEM occupations. Unfortunately, there doesn’t exist this kind of a data set\(^\text{20}\). As a compromise, I will combine two large repeated cross-sectional datasets (CPS and ACS), with one

\(^{20}\)The NLSY79 is a longitudinal data long time span. However, the subjects of this study were typically born between 1957-1964. There are not enough observations in STEM occupations with at least a bachelor’s degree. The SIPP data coverage is from 1984-2008 with a short panel structure (4-year).
longitudinal dataset (PSID) in the estimation process. Data from multiple sources are necessary because identification of the full set of parameters requires information on individuals’ occupational choices, outcome wage distributions conditional on age and occupational choice, and also on gross occupational mobility.

To get the necessary information about the wage distribution and career prospects, I use the CPS data. The span of the data, from 1964 to present, is the longest among comparable surveys. Furthermore, the annual frequency of the March CPS data fits the timing of the current model. The sample is constructed following the work of Lemieux (2006).

CPS samples about 60,000 U.S. households annually. However, only a very restricted subsample – the highly educated\(^{21}\) full-time full-year\(^{22}\) STEM workers – is studied in this paper. Especially, when computing the conditional wage distribution for each age group, I encounter the small sample problem. The problem is severe at the beginning of the career path and near the retirement age. In Table 2, I list the maximum and minimum sample size over 20 years for each occupation and age cell. For CS workers when approaching retirement age, barely any observations are left. This provides the motivation to incorporate the ACS and the census data in the analysis. The ACS has much larger sample size, consisting of about 1% of total U.S. population every year. However, the ACS starts only from 2001 covering a shorter sample period. In 2000, I will use the 5% census data. The principle here is to use the ACS and census whenever they are available and use the CPS otherwise. Both sources of data will be used to extract information about the conditional wage distribution and the employment share of each occupation.

PSID data due to its longitudinal characteristic will be used to get information on the age profile of occupational mobility between CS and other-STEM occupation. I will follow the method proposed by Kambourov and Manovskii (2008) which uses the Retrospective Occupation-Industry Supplemental Data Files to correct for classification errors in occupation coding. The pattern of gross occupational mobility I find is very similar to the one in Kambourov and Manovskii (2008) at the one digit level. Occupational mobility declines sharply as people age. The estimated model does well in accounting for native workers’ wage dynamics, occupational choices, and inter-occupational flows.

\(^{21}\)Defined as a Bachelor’s degree or higher.

\(^{22}\)Those workers 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 Estimation by Simulated Method of Moment

I estimate parameters of the model by minimizing the distance of simulated moments to their empirical counterparts. The moments matched describe the gross occupational mobility, occupation employment share, and wage distributions over the life cycle and across cohorts. During the estimation process, I combine different data sources, which all have different sample sizes. The standard asymptotic results don’t apply here. In order to get the correct inference on the estimates, I follow the modification of the standard asymptotic results proposed in (2016). The new asymptotic distribution explicitly addresses the issue with multiple samples. See Appendix D for details.

4.2.1 Choice of Moments

The data moments to be matched are as follows where $a$ is between 22 to 65 and $t$ covers the period from 1994 to 2013:

\[
p_{a,t} = \text{proportion of age } a \text{ native STEM workers working in CS sector in year } t.
\]

\textit{Age Profile of Occupation Employment Share}

\textit{Conditional Wage Distribution}

1. First moments: the mean wage of occupation $s$, in age group $a$ and year $t$, $\bar{W}_{a,t}^s$.
2. Second moments: the variance of wages of occupation $s$, in age group $a$ and year $t$, $\text{var}_{a,t}^s$.

\textit{Age Profile of Gross Occupational Mobility}

\[
\text{Mob}_a = \text{fraction of age } a \text{ workers switching between CS and other-STEM occupations.}
\]

4.2.2 Model-Data Comparison

There is a discrepancy between model and data being used in the estimation part. This occurs because I fit a life-cycle model using repeated cross-sectional data. The model presented in section 3 is a life cycle choice model. But the moments being targeted, $p_{a,t}$ for example, is also confounded with cohort effects. In data, people at age 65 in the year of 2000 entered labor market in 1956. They faced very different market conditions when making their educational and earlier occupational choices. Consequently, their human capital investment decisions are different from those of workers age 65 in the year of 2015. A single cohort model is not capable of capturing the empirical data patterns.
To address the issue, in the estimated version of the model, I explicitly model multiple birth cohort groups. Different cohort groups have the same initial ability distribution, and human capital is formed in a similar fashion; but they differ in their labor market experience. To match the data moments, it is necessary to solve for the optimal career decision rule for each birth cohort, i.e., the cohort-specific set of value functions. Specifically, different birth cohorts solve life-cycle choice problems subject to different path of skill rental rates. In Appendix E, I show how to combine the simulation results of different cohort groups to match the empirical moments.

4.2.3 Estimation Procedure

The parameter space $\Theta$ in the model can be naturally divided into two subsets $[\Theta^s|\Theta^d]$. $\Theta^s$ contains parameters that determine the native labor supply decision, including parameters governing human capital formation, individual preferences, and ability heterogeneity. $\Theta^d$ includes parameters entering the occupation-specific production functions. The supply and the demand side are treated as two separate parts. The key elements connecting these two components are the equilibrium skill rental rates. I use a two-step estimation procedure that separates the supply side estimation from that of the demand side. The two-step estimation is less efficient, but it significantly reduces the computational requirements.

I assume that over the recent 20 years, fundamentals of the labor supply side of native skilled workers have remained unchanged. The innate ability distribution, preferences, and human capital production function remain unaltered. Variations in the conditional wage distribution and occupational employment share are attributed to changes in skill rental rates\textsuperscript{23}. In the first stage, skill rental rates in both occupations across years are treated as free parameters along with the fundamentals mentioned above. The first stage selects the fundamental parameters governing labor supply side and 20 year’s skill rental rates that match natives’ conditional wage distribution, occupational employment share, and gross occupational mobility. The estimation of the first stage delivers the time series for the skill rental rates and the measure of effective labor supply at the individual level, which can be added up to obtain the aggregate labor supply.

Next, in the second stage I combine the first stage outputs $\hat{\Pi}_s^t$ and $\hat{N}_s^t$ with observed quantities for immigrants ($\hat{\Pi}_s^t$ and $\hat{M}_s^t$) to estimate the production function using maximum likelihood. The pro-

\textsuperscript{23}In the traditional demand and supply framework, labor supply curve is fixed over the recent two decades. Any skill rental price variation is simply movements along the supply curve. Consequently, The labor supply side is well identified.
duction parameters are estimated using time variation in skill rental rates aggregate labor quantities. The supplies of skilled immigration are the source of exogenous variation for identification.

4.2.4 Recover the Deterministic Expectation

As mentioned in the model section, agents can perfectly anticipate the future skilled rental rates, which is directly measured in the data. \( \hat{\Pi}^s_\tau(o) \) series are recovered using the method known in the human capital literature as the flat spot method (Heckman et al., 1998). This method is based on the fact that most optimal human capital investment models have the feature that at some point in the working life-cycle, optimal net investment is zero (Bowles and Robinson, 2012). Human capital of a given cohort over these years is constant. For a cohort in the flat spot area of their human capital profile, any changes in wages purely reflect changes in skill rental rates. By applying the flat spot method, the rental rate series are directly identified from CPS data. In Figure 4, I plot the evolution of skill rental rates in both sectors. Note these two series are subject to normalization. For the illustration purpose of Figure 4, the skill rental rates in 2010 are normalized to unity in both sectors. The detailed data cleaning and smooth techniques are discussed in Appendix C.

4.3 Identification

In this section, I illustrate how some of the crucial parameters are identified.

The identification of the innate ability can be considered as an application of Heckman and Honore (1990) in a dynamic setting. In their discussion, under the normality assumption of the ability distribution, the mean and the covariance matrix of the ability type can be identified by using a single cross-sectional data. The data should contain occupational choices and conditional wage distributions. In the application of this paper, I maintain the normality assumption of abilities and choose to target occupational choices and conditional wage distributions in the estimation process. Additionally, I also explore time variations of the targeted moments. The variation of skill rental rates over years provides an additional source of identification. In particular, the occupational choices of new entrants are directly related to the ability distribution. Sufficient variations in skill rental rates and the resulting changes in occupational employment share over years help to explore the innate ability distribution more. Meanwhile, the conditional wage dispersion maps to the dispersion of ability distribution.
Between year shifts of the income profiles reveal information about changes in skill rental rates, which will eventually map to the technological processes. The identification of human capital formation comes jointly from the variations in occupational choices when market skill rental rates change and the life-cycle wage dynamics. When rental rates change, the net flow of workers between occupations gives information about the transferability of the occupational specific human capital. Within one year, the skill rental rates are the same for all native workers. Wage difference among native workers attributes mainly to different returns to occupational tenures and to the total labor market experience. The flat part of the income age profile helps to pin down the coefficients in front of the higher order polynomials of the labor market experience.

The identification of taste shock parameters mainly comes from the gross occupational mobility. The magnitude of the gross mobility over age reflects partially the variance of the taste shock.

For the labor demand side, I estimated all the parameters once with maximum likelihood method. In this part, I will illustrate step by step how the model pins down each parameter in regression form for illustration purpose. The inputs of demand side estimation are the skill rental rates and the equilibrium labor quantities in efficiency units for both domestic and foreign workers. For native workers, skill rental rates $\tilde{\Pi}_t^s$ and aggregate labor supply $\hat{N}_t^s$ are either directly estimated or aggregated using estimates from the individual labor supply, whereas skill rental rates $\tilde{\Pi}_t^\star$ and aggregate labor supply $\hat{M}_t^\star$ of immigrants are directly measured from data. Given the CES functional form, the share parameter $\delta^s$ and the parameter related to substitutability $\rho^s$ can be identified by exploring time variations between relative quantity demanded and the relative rental rates. Regression version of the identification of $\delta^s$ and $\rho^s$ is given by the estimation equation 14

$$\log\left(\frac{\tilde{\Pi}_t^s}{\Pi_t^\star}\right) = \log\left(\frac{1-\delta^s}{\delta^s}\right) + (\rho^s - 1) \log\left(\frac{\hat{N}_t^s}{\hat{M}_t^\star}\right) + \mu_t$$

To identify the return to scale parameter $\psi^s$ and the technology process $Z_t^s$, I impose one identification assumption on the $Z_t^s$ process. I assume $Z_t^s$ is a log stationary process. Let $\bar{z}^s$ and $\Delta_t^s$ denote the long-run average of $\log(Z_t^s)$ and the deviation from the long-run average respectively. $\bar{z}^s$ and $\psi^s$ are separably identifiable, where $\hat{y}_t^s$ and $\hat{x}_t^s$ are function of known parameters and quantities.24

\[\hat{y}_t^s = \frac{1}{\rho^s} \log\left(1 - (\delta^s)^s\right) \hat{N}_t^s + (\delta^s)^s \hat{M}_t^\star \rho^s, \quad \hat{x}_t^s = \frac{\hat{N}_t^s}{(1-\delta^s)^s(N_t^s)^{\rho^s}}\]
\[
\log(\hat{y}_t^s) = (\hat{z}_t^s + \log \psi^s) + \psi^s \hat{x}_t^s + \Delta_t^s
\] (15)

Once we identify \(\hat{z}_t^s\) and \(\psi^s\), the technology process \(Z_t^s = \exp(\hat{z}_t^s + \Delta_t^s)\) is identified observation by observation as well. In all the counterfactual experiments, representative firms know the technology processes in both sectors.

5 Results

In this paper, I fixed the annual discount factor to the value 0.95 which is within the reasonable range in literature.

5.1 Estimation Results

In Table 3, I present the estimates of \(\Theta^s\), the parameters from labor supply side. All parameters are statistically significant at 1% level. For the parameters related to returns to occupational tenure, the first year of the CS tenure augments CS human capital by about 7.56% with little attenuation in the rate of increase at higher years of experience. The first year of other-STEM tenure increases other-STEM skill by 8.51% \(^{25}\). Both sectors value tenures in other occupations but to a lesser extent. An additional year of CS (other-STEM) working experience augments other-STEM (CS) skill by less than 6.95% (7.60%). The value of estimates implies that the two occupations are close alternatives measured by the transferability of human capital. This actually suggests that when facing foreign labor competition, native CS workers will choose other-STEM occupations as their alternative occupations. Transferability of occupation specific human capital varies cross occupation groups. In Keane and Wolpin (1997), the white-collar sector is found to discount tenures in the blue-collar occupations a lot.

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 returns to

\(^{25}\)Holding everything else being constant, Kambourov and Manovskii (2008) find smaller returns to occupation tenures. They find one year of occupational tenure are associated with a 2.4% - 4% increase in wage. The major reason of the difference is that in Kambourov and Manovskii’s (2008) specification they also include industry tenure, job tenure, and general labor market experience. In this model, without job and industry tenure, occupational tenure should account more for individual’s wage growth.
occupation tenures are smaller. And it reaches a lower plateau faster compared to other-STEM occupations.

These two unobservable abilities are mildly negatively correlated with a correlation coefficient -0.17. This implies that workers in both sectors are positively selected. Since other-STEM occupation actually is an aggregate of multiple occupations, it has a larger variance in ability. In addition, there is substantial heterogeneity in innate ability across individuals, which is an important determinant of income inequality. One standard deviation increase in the innate ability is associated with a 23% and 35.5% increase in annual wages for CS and other-STEM occupation respectively.

The estimates of the labor demand side are presented in Table 4. Both sectors display decreasing return to scale with the estimated values between 0.58-0.6. The more interesting result is the substitutability between foreign and domestic labor. For CS sector, immigrants and natives are substitutes with an elasticity of substitution $\frac{1}{1-\rho} = 6.9$, suggesting that impacts of immigrants will be very limited in the CS occupation. This value is slightly higher than the estimates in Ottaviano and Peri (2012) obtained by estimating nested CES production function. They find that the median of elasticities of substitution between comparable skilled immigrants and native is around 6.6. On the other hand, in the other-STEM occupation, complementarity exists between native and foreign workers. This indicates an influx of foreign workers result in wage gains for native workers, and consequently a crowding-in effect rather than crowding-out effect on native employment. This could operate through task specialization within one occupation. Bound et al (2015) assume that domestic and foreign workers are perfect substitutes with decreasing return technology. Skill immigrants in their specification, by construction, crowd out native workers and impose negative effects on wages. I use more flexible sector specific production functions allowing for both crowding-in and crowding-out effects.

5.2 Sample Fit

5.2.1 In-sample Fit

Figure 5 to 6, based on a simulation of 500 individuals, graphically depict the fit of the basic model in the year 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
third polynomial in human capital formation function help the simulated profile to fit better when approaching retirement. The variance of log wage presents the U shape pattern which has already been documented many times in the literature. There is no mechanism in the current model that generates this U-shape. As a result, the simulated data only match the level rather than the age profile of the wage dispersion.

The model with multiple cohort groups is able to match the fraction of domestic workers choosing to be computer scientists over age. The parsimonious taste shock specification with occupation specific human capital helps to capture the sharp decrease in occupational mobility over age.

For the remaining 19 years, the model fit the targeted moment well. Figures vary slightly year from year. But there is no qualitative difference. Overall the model is able to capture the patterns of conditional wage distributions, employment share, and gross occupational mobility.

5.2.2 Out of Sample Fit

As mentioned in the estimation procedure part, skill rental rates are treated as free parameters. The estimation procedure picks skill rental rates that best match conditional wage distributions and employment shares over 20 years.

I take the ratio of the two skill rental rates \( \frac{\pi_{c,t}}{\pi_{nc,t}} \) and plot this time series. I put the Nasdaq composite index aside in Figure 7. The model predicted relative skill rental rate basically reproduces the Nasdaq patterns. The relative skill rental rate peaked around 2000 before the dot-com bust hit. After the bust, it was gradually recovering until 2007 when the financial crisis occurred. Recently it has stayed on an uphill track for about 6 years. The pattern of relative skill rental rate mimics closely the Nasdaq composite index. The correlation coefficient between these two series is 0.81.

Taking the changes in the relative skill rental rate as given, which are the fundamentals that drive natives’ choices of fields of study and occupations, how sensitive the natives are in response

I also estimate another version of this basic model. Rather than specifying a human capital formation equation with third polynomial in labor market experience, in the other vision, I specify a random accumulation process for occupation specific human capital. In that process, human capital is accumulated in a stochastic way that the probability of acquiring an additional unit of occupation specific human capital is a decreasing function of occupational tenure. If the native worker spends one period in sector \( s (d_s = 1) \), this individual randomly accumulates experiences according to the following rule.

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

My estimates indicate the accumulation process stops around age 45-50 with minor differences across occupations which is consistent with the findings of the life-time income dynamic (the flat spot area) in literature. This version performs equally well. The random accumulation process also captures well the curvature of wage profiles.
to these changes? In Figure 8 I plot the share of 22-year-old native workers who choose to be a computer scientist from 2000-2013 with the model predicted relative skill rental rates over the same time. There is no strong correlation. But when I lag the relative efficiency wage series by 3 years (1997-2010), there appears a stronger correlation. The reason why there is a 3 year lag period is because in the current model I don’t model the college major choices. College graduates choose their fields of study before they enter the labor market. This lag period suggests that the current market condition, rather than expectation, matters for individual’s major choice.

After the initial moves (choosing fields of study), natives remain alert to price variations as well. However, switching occupation becomes less favorable and frequent in the latter part of one’s career. The reason is that given the previous occupational choices, agents have already accumulated a fair amount of occupation specific human capital, making them less sensitive to price shocks. There are two points in Figure 10 which draw my attention. First, there is a level effect that cohort groups who enter the market faced with higher relative skill rental rate remain to have a higher proportion of CS workers in the subsequent decision periods. The 1978 cohort finished college in 2000 at the peak of the Internet boom. This cohort stays unambiguously higher than the 1986 cohort who entered the labor market at the lowest point of the relative skill rental rate series. Second, the correlation coefficients between the fraction of CS workers and the relative skill rental rate vary by birth cohort. The correlation coefficient is higher for younger workers. Younger workers are more sensitive to price changes in terms of occupational mobility.

<table>
<thead>
<tr>
<th>Correlation Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative Efficient Price</td>
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</table>

27The 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.

28This provides some limited evidence that supports Khan’s (2010) conclusion about long-term labor market consequences of graduating from college in a bad economy. Here at least we can say graduating at different phases of industry cycle will have a lasting effect on occupational choices.
6 Counterfactual Exercises

6.1 Policy Relevant Exercises

Next, I analyze the effect of changes in the stock of immigrants and the effects of changes in the immigration occupational mix. The outcomes of interest are the equilibrium skill rental rates and employment share of native STEM workers. In this set of analysis, native STEM workers can freely switch occupations.

In the first counterfactual exercise, I simulate the counterfactual scenario in which the stock of foreign CS is fixed at its 1994 level whereas the stock of skilled immigrants in the other STEM occupation follows its actual observed path\textsuperscript{29}. The purpose of this exercise is to assess that to what extent the rapid growth in the recruitment of foreign computer scientists affected outcomes of native workers in the STEM sectors.

Figure 11 graphically depicts the counterfactual exercise and its results. In the top right panel, I present the resulting impact on the skill rental rate for CS workers. In the counterfactual economy, the log skill rental rate for CS workers would be higher. As illustrated in the bottom left panel, the native labor supply in the CS occupation would also be higher. One advantage of a general equilibrium model is that it enables me to study broader effects of foreign computer scientists, for instance, the impact on the labor market of the other-STEM occupation. In the second row of Table 5, I quantitatively evaluate these effects.\textsuperscript{30} Had the immigrant CS workers been fixed at its pre-boom level, the skill rental rate for CS workers would have increased by 2.52\%. The cap placed to the total labor supply of foreign CS workers would also benefit natives working in the other-STEM occupation. The skill rental rate would have increased slightly by 1.37\%. This spill-over effect is primarily attributed to the selection behavior of native skilled workers. When experiencing less competition from immigrants in the CS occupation, skill rental rate 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 occupation. This leads to increases in the native labor supply in the CS occupation, decreases in the native labor supply and consequently increases in the equilibrium rental rates in the other-STEM occupation. The counterfactual simulation confirms this channel. On average the native labor supply in the CS occupation would grow by 5.24\% while the native labor

\textsuperscript{29}Bound et al. (2015) adopt the same counterfactual settings as this one.

\textsuperscript{30}The number reported is the 20 year average of percentage changes between counterfactual data and the real data.
supply in the other-STEM occupation would reduce by only 2.81%. The asymmetricity in labor supply changes across sectors implies that those who switch are only marginally better working in other-STEM occupations under the old prices.

Bound et al. (2015) perform the same counterfactual exercise and find that rental rates increase by 2.8-3.8% while native labor supply increases by 7%-13.6% in the CS occupation. I find instead a more muted effect. According to my simulations, the rental rate increases by 2.5% and 1.4% in the CS and in the other STEM occupation respectively. Three major modeling factors are responsible for delivering this limited effect. First, native and foreign workers are imperfect substitutes as opposed to Bound et al. (2015)'s model. This limits the immigration-induced competition. As a result, my model only generates small price changes in the CS occupation and an even smaller effect on the other-STEM occupation. Second, natives are heterogeneous in terms of their labor supply (occupation specific human capital). Those who would switch in the counterfactual simulation are not as productive as always-takers in the CS sector. When we measure the labor supply in efficiency units, we see it only increases by 5% in this counterfactual scenario as opposed to 11.3% when measured in number of workers. Also, the occupation specific human capital added in the model would restrict the occupation mobility further.

The second experiment, presented in the first row of Table 5, rather than only putting restrictions on foreign CS workers, reduces labor supply for both the CS and the other-STEM occupation to their 1994 levels. Skill rental rates for both occupations would still increase, but the magnitudes are smaller compared to the first counterfactual discussed before. The reason is that the skill rental rate in the other-STEM occupation has the following expression (equation 16). It is an increasing function of immigration labor supply, given \( \delta > \rho \).

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

(16)

Since \( \frac{\psi}{\rho} - 1 > 0 \), complementarity exists. As a result, the marginal product of skilled native workers in the other-STEM occupation actually decreases when the foreign labor is restricted to a lower level. Comparing these two counterfactual results, we learn that restriction on foreign labor supply in sectors where complementarity exists can have negative impacts on domestic workers. The skill rental rates increase by 2.41% and 1.22% for the CS and the other-STEM occupation.
respectively. Compared to the first experiments, though the total quantity of foreign labor is smaller in this case, domestic workers are actually worse off.

The different quantitative results from the previous counterfactual exercises demonstrate first the importance of a general equilibrium model when assessing the impacts of skilled immigrants. If the occupation mobility mechanism identified by this paper is a viable channel and native workers are sensitive in terms of occupational mobility, the occupations where native workers move to matter and need to be modeled explicitly. Meanwhile, to have a comprehensive evaluation of the effects of the skilled immigrants, the indirect impact on the destination occupations should also be properly measured.

Second, the previous two experiments also shed light on the welfare impact of two kinds of immigration policies, the overall cap on quantity and the selective policy based on occupations and fields of study. A selective immigration policy based on occupations and fields of study could result in larger welfare gains for natives. For example, Canada employs the point-based systems that grant more entry to workers in special occupations. The OPT program in the U.S. functions in a similar manner that grants more entry to workers in STEM fields. On the other hand, the H-1B program resembles an overall cap that controls the total number of skilled workers entering the U.S. labor market. Optimizing occupation mix of skilled immigrants, favoring occupations where complementarity exists or where natives are less substitutable, could potentially benefit all natives more. The success of the selective immigration policy based on occupations hinges on the accurate estimate of sector production functions. Identifying the correct occupations is the key.

6.2 Mechanism Related Exercises

6.2.1 Explore the Demand Parameters

The occupation specific production function is crucial here. This raises the question of how robust these results are to variations in how the production function is specified. In this part, I explore counterfactual economies in which the labor demand parameters differ in various ways from the basic model estimates. I conduct two sets of exercises in this section. First, I use my estimates of the other-STEM occupation, but change the parameters of the CS occupation. For comparability, I use the same parameters as those employed in Bound et al (2015). In Bound et al (2015), immigrants and native workers are assumed to be perfect substitutes ($\rho = 1$), and skilled immigrants are more
productive than natives (equation 17). The comparable share parameter $\delta$ takes a value of 0.52. I then explore different curvature parameters ($\psi = 0.75, 0.50, 0.25$), which relate to different demand elasticities. Later, I explore to what extent the variation in the parameter determining the magnitude of immigration impacts.

\[ Y^{CS} = Z_t((1 - \delta^{CS})N_t^{CS} + \delta^{CS}M_t^{CS})^{\psi^{CS}} \]

The production function in equation (17) implies a downward sloping labor demand in the CS occupation. By construction, this production function generates crowding out effect of foreign computer scientists. Quantitatively how strong this crowding out effect is depends on the demand elasticity of skilled labor. This elasticity is given in the following equation.

\[ \eta^{CS} = -\frac{1}{1 - \psi} \]

When there is a sudden rise of foreign skilled workers in the CS occupation, the less elastic the labor demand is, the greater the negative effects will be. On the contrary, if skilled labor demand is more elastic, the increase in immigrant labor supply can be absorbed with minimal crowding out effects. When I vary $\psi$’s value, the demand elasticity varies from -1.3 to -4.0, which is within the plausible range in the literature.

The production function in equation 17 rules out the possibility that foreign computer scientists might be a sufficient spur to innovation; it could, in fact, positively affect both wages and employment on domestic workers. The results from the counterfactual economies discussed above are presented in Panel A of Table 6.

In a second set of counterfactual exercises, for which the results are shown in Panel B of Table 6, I force both sectors to use the same production technology where native and foreign labor are perfect substitutes. I also explore different demand elasticities of skilled labor. For all the above counterfactual exercises, I consider the same scenario that only the recruitment of foreign computer scientists is fixed at its 1994 level.
When comparing results in the column where $\psi = 0.5$ \(^{31}\) from Table 6 to the baseline results in Section 6.1, it is obvious that in both panels A and B, the magnitudes of impacts induced by skilled immigration are larger. This is because skilled immigrants and natives are considered to be perfect substitutes in the CS occupation in panel A and B. Perfect substitution amplifies the potential negative impacts of high-skilled immigrants.

Comparing results within each panel, as $\psi$ increases, labor demand becomes more elastic. With immigration shocks of the same size, more elastic labor demand is capable of better absorbing the foreign supply shock, resulting in smaller wage drops. Smaller wage drops generate a very limited crowding out effect.

Another important message learned from Table 6 is through comparing results in the same column across panels. The two panels differ in the production technology used in the other-STEM occupation. Different results across panels reiterate one point made earlier - to be able to better assess the impacts of high skilled immigrants in the U.S. economy, a general equilibrium model is more appropriate. When workers move occupations in response to immigration shocks, the potential impacts are mitigated and diffused. The effectiveness of the diffusion mechanism relies on the labor demand of the alternative occupations. In the current context, the more elastic the native labor demand is in the other-STEM occupation, the better 'buffer' the economy provides against immigration shocks. With large immigration inflows in the CS occupation, native workers react by switching towards the other-STEM occupation where the market price becomes more favorable. The more elastic the native skilled labor demand is in the other-STEM occupation, the smaller skill rental rate reduction is caused. Small reduction in skill rental rates indicates that more native workers who now lose comparative advantages to work as computer scientists can find better 'shelters' (with more favorable market conditions). Meanwhile, more natives leaving the CS occupation further neutralizes the negative shocks by maintaining wages at a higher level.

The demand elasticity of skilled native labor in the other-STEM occupation has the following expression\(^{32}\).

\[^{31}\psi = 0.5\] is comparable to results in sector 6 because my estimates $\psi^{CS} = 0.58$ predicts approximately the same labor demand in CS sector.

\[^{32}\]The formula that uses inverse demand function to derive the demand elasticity is valid when the inverse demand function is monotone. The local monotonicity holds at least for those points where I compute various elasticities.
In Table 7, I evaluate the above expression using quantities in 1994. In column 1, the labor demand of the other-STEM occupation is more elastic in the lower panel. This means that the counterfactual economy in the lower panel can better 'absorb' the immigration-induced shocks. The quantitative results confirm my conjecture. For the immigration shocks of the same size, the economy in the lower panel experiences more occupational mobility responses. The native labor supply grows by 5.99% in the lower panel as opposed to 4.74% in the upper panel. However, wage fluctuations are attenuated in the economy with more elastic other-STEM occupation. Changes in skill rental rates of both sectors are smaller in the lower panel. The same argument also applies to the second column. However, in the third column, the labor demand of the other-STEM occupation in the lower panel is less elastic. As a result, the price system in the lower panel economy is more fragile and more volatile to immigration shocks. Fewer natives are able to re-optimize their occupations. The interaction between the CS and the other-STEM occupation is important when evaluating the impacts of increasing foreign computer scientists over the past two decades.

In summary, there are two points learned from the counterfactual experiments in this part. First, to precisely assess the impacts of skilled immigration, accurate sector production parameters are required. The crucial parameters in the CES production function are the substitution elasticity and return to scale parameters. Second, a general equilibrium model capturing the interaction between the CS and the other-STEM occupation is more appropriate. We have seen that the interaction has a non-negligible impact on natives’ mobility responses. The extent to which the potential negative impacts are diffused relates to the demand elasticity in alternative occupations where native workers move to.
6.2.2 Heterogeneous Effects and Valuations of Occupational Mobility

Throughout the paper, I argue that the occupational mobility mechanism identified in this paper is an important adjustment margin that is understudies in the literature. But economically speaking, how important is the mechanism for each individual? Does an agent’s valuation of this mechanism vary with individual characteristics? To answer questions of this sort, I quantify the individual option valuation of occupational mobility using compensating variations (CV). CVs are the dollar amount agents require to maintain the same level of lifetime utility if they are constrained to remain in their original occupation regardless of the changes in market conditions.

Over the Internet boom (1994-2000), native workers are constrained in their original occupations. When skill rental rates change, I first identify individuals who exercise this option, those who benefit from occupational mobility.

The age composition of potential switchers is computed using a simulation of 20000 native workers. More than 80% of those switchers are younger than 40 (see table 8). About 35% of the 22-26 year-old workers will switch occupations over this period. However, less than 2% of workers approaching the end of their career respond. Fewer older native workers find it beneficial to switch occupations because the human capital investment has been made and the implicit switching cost is too high. Younger workers are more sensitive in terms of occupational mobility.

Economically speaking, how important is the option of occupational mobility? In this case, even with temporary restrictions (six periods) on occupational mobility, younger workers require more than $45,000 on average as CVs. Human capital is occupation specific in this model. Early work experiences and human capital investment have long lasting effects. If young workers are permanently forced to stay in occupations where increasing foreign competition is expected, they would demand more than $100,000 to compensate for not being able to re-optimize.

Next, I compute the average CVs for identified switchers by age group. The average CV decreases as individual age, as shown in Figure 13. The CV drops from $50,000 for new entrants to zero for workers who are about to retire. Overall, it is more costly for younger workers to stick to their previous occupations when market conditions become less favorable. Young workers have a longer career path. Career concerns about choosing the ‘right’ occupations play a big role. Individual’s valuation of occupational mobility is higher when no one else is endowed with the option to switch.
There is plenty of heterogeneity. Within one age group, on the two-dimensional space of occupation specific human capital, workers located along the relative rental rate line require for high expected CVs. For age group \(a\), given the two-dimensional human capital distribution \(H_a = \begin{pmatrix} H_{aCS} \\ H_{aNCS} \end{pmatrix}\), the expression for expected CVs is

\[
ECV(H_a) = E(CV|\text{mob} = 1, H_a)P(\text{mob} = 1|H_a) + E(CV|\text{mob} = 0, H_a)P(\text{mob} = 0|H_a)
\]

where \(\text{mob} = 1\) if one chooses to switch occupations when the market condition changes. When \(\text{mob} = 0\), agents will not exercise their options, which implies \(E(CV|\text{mob} = 0, H_a) = 0\).

In Appendix F, I derive general expressions to compute the expected CVs for native workers. I then use the expression to compute the distribution of expected CVs for new entrants when foreign labor supply changes. As shown by the contour map in Figure 14, individuals who do not have dominant advantages in any one of the occupations demand high CVs. Along the relative skill rental rate line, workers are the most sensitive to changes in market conditions, exercise their option of switching most frequently. As a result, they place the highest valuation on the occupational mobility.

7 Discussion

This section addresses some of the potential issues about the model specification.

In the current model, I only consider a binary choice within the STEM domain over the CS and the other-STEM occupation. This framework can be extended to include occupations at a more detailed level without much substantial modification of the basic model. However, I choose to focus this paper on the STEM occupations because native STEM workers have been experiencing the strongest inflow of skilled foreign labor. And in order to identify the parameters, I use information about conditional wage distributions of narrowly defined age and occupation cells. The sample size is already small at the current broad occupational groups. It is impossible to look at occupation choices at a more detailed level. With large administrative datasets, such as the Danish Integrated Database for Labor Market Research (IDA), the basic model can be extended to include more detailed occupations.\(^{33}\)

\(^{33}\)Foged and Peri (2015) track the labor market outcomes of low-skilled natives in response to an exogenous inflow of low-skilled immigrants in Danish labor market and find that an increase in the supply of refugee-country immigrants
With the current available data, the non-STEM occupation is a potential third choice. Whether to include the non-STEM occupations depends on how frequently do workers switch between the STEM and the non-STEM occupation. Is non-STEM occupation considered as a good alternative where domestic workers move to? The task contents of the STEM occupation differ a lot from those of the non-STEM one. And STEM occupation requires years of special training. The implicit switching cost can be very high between these two occupation groups. To answer questions above, I use the linked monthly CPS data from 1994-2014 to explore individual’s occupational mobility patterns between the STEM and the non-STEM occupation. The clean technique proposed by Moscarini and Thomsson (2007) is applied here to get rid of classification errors. Table 9 panel A indicates that if non-STEM workers switch occupations, about 94% of them switch to a different occupation within the non-STEM category. For STEM workers, conditional on switching occupations, 62.8% of them move to the non-STEM category. This is due to the fact that managerial occupations are classified as non-STEM occupation. Moving to managerial positions in the same industry is occupation upgrading. Both the cause and implication of the vertical occupational mobility are different from the horizontal mobility discussed in this paper. Once the occupational mobility toward managerial positions in the same industry is adjusted and treated as mobility within the same occupation group. The binary choice captures more than 2/3 of the total switches for STEM workers.

The previous results talk about the gross occupational mobility. In Figure 15, I show the employment shares of the STEM workers and the CS workers. The employment share of STEM workers in the U.S. skilled labor force is stable, about 4% over the past two decades, which indicates that no structural or systematic changes occurred during this period that make the STEM occupation more favorable for natives. However, the employment share of the CS workers within STEM category increases by nearly 2/3 over the same period. These patterns suggest that the STEM occupation as a whole do not become more attractive to native workers; the CS occupation becomes more popular among STEM workers. It is the selection within STEM occupation attributes to the observed increase in the CS employment share.

The simple binary choice model seems naive at first, in fact, it is capable of capturing the most salient features and most relevant margin.

pushes less educated native workers to pursue less manual-intensive occupations.
8 Conclusion

Immigration is a major policy issue and concern in the U.S. Most of the previous literature has focused on the low-skilled immigration. In this paper, I focus on high-skilled immigrants who play a qualitatively and quantitatively important role nowadays in the U.S. labor market. This paper quantifies the impacts of skill immigration on native workers in STEM occupations. I estimate demand for skilled labor across occupations in a general equilibrium setting and explicitly model the native workers’ occupational mobility in response to foreign labor competition.

Despite the public concerns, my results indicate that a large inflow of skilled immigrants has muted impacts on natives with similar skills. For some occupations, for example the other-STEM occupation, complementarity exists. Increases in the supply of foreign labor actually have positive impacts on welfare. Even when native and foreign labor directly compete with each other in some occupations (CS), native workers are not perfect substitutable. Moreover, as native workers optimize their occupational choices, the potential adverse impacts of foreign labor competition are mitigated and diffused.

The estimated model is used to assess two types of immigration policies, an overall quantity cap and a selective program based on fields of study and occupations. Optimizing the occupational mix of skilled immigrants and favoring occupations where complementarity exists benefit natives more compared to an overall quantity cap. The success of the policy hinges on the accurate estimates of occupation specific production functions. I emphasize in this paper that the general equilibrium framework is important. It allows the model to analyze the overall welfare impact of high-skilled immigration. Even when some occupations are not directly affected by the increasing foreign labor supply, they are relevant. Because they determine the economy’s ability to absorb immigration shocks through natives’ occupational movement. Individuals value the option of occupational mobility. Had native workers been constrained to remain in their original occupations, their life-time utility would be adversely affected. This restriction would be particularly costly for young workers.

While the model incorporates mobility between different types of occupations according to comparative advantages, a model explicitly accounting for vertical occupational movement is also desirable. D’Amuri and Peri (2014), Peri and Sparber (2009) document that natives tend to upgrade their jobs in response to low-skilled immigration. They take on more complex and communication-intensive tasks and leave manual tasks to immigration. This protects them from the direct foreign
competition. In the context of high-skilled immigration, do inflows of foreign skilled labor push more natives within the same occupation to managerial positions? By moving up the job ladder, natives potentially gain more. Does the speed of vertical mobility differ across occupations? If it does, what drives the differential? Adding this margin provides a more comprehensive assessment of the impacts of skill immigrants.
References


39


### Appendix A

**Table 1: Fraction of Immigrants**

<table>
<thead>
<tr>
<th>Year</th>
<th>Immigrants as a fraction of Skilled Worker</th>
<th>Immigrants as a fraction of Computer Scientists</th>
<th>Immigrants as a fraction of Other-STEM workers</th>
</tr>
</thead>
<tbody>
<tr>
<td>1970</td>
<td>2.10%</td>
<td>2.37%</td>
<td>3.63%</td>
</tr>
<tr>
<td>1980</td>
<td>5.43%</td>
<td>7.09%</td>
<td>9.72%</td>
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<tr>
<td>1990</td>
<td>6.89%</td>
<td>11.06%</td>
<td>10.71%</td>
</tr>
<tr>
<td>2000</td>
<td>8.41%</td>
<td>18.59%</td>
<td>12.69%</td>
</tr>
<tr>
<td>2010</td>
<td>12.77%</td>
<td>27.82%</td>
<td>18.21%</td>
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</table>
Table 2: Sample Size by Age and Occupation Group (1994-2013)

<table>
<thead>
<tr>
<th>Age</th>
<th>CS min</th>
<th>CS max</th>
<th>STEM min</th>
<th>STEM max</th>
<th>Age</th>
<th>CS min</th>
<th>CS max</th>
<th>STEM min</th>
<th>STEM max</th>
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<td>39</td>
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<td>39</td>
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<td>0</td>
<td>12</td>
<td>4</td>
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1 For each age group, there are 20 samples for 1994-2013.
Table 3: Estimates of Native Labor Supply

<table>
<thead>
<tr>
<th></th>
<th>Computer Science</th>
<th>Other STEM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>val. std. err</td>
<td>val. std. err</td>
</tr>
<tr>
<td>CS Exp.</td>
<td>0.0756 (0.0012)</td>
<td>0.0760 (0.0016)</td>
</tr>
<tr>
<td>Other STEM Exp.</td>
<td>0.0695 (0.0013)</td>
<td>0.0851 (0.0011)</td>
</tr>
<tr>
<td>Total Exp$^2$ /100</td>
<td>-0.2009 (0.0020)</td>
<td>-0.2028 (0.0024)</td>
</tr>
<tr>
<td>Total Exp$^3$ /1000</td>
<td>0.0124 (0.0014)</td>
<td>0.0141 (0.0010)</td>
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Covariance Matrix

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<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>unobs. Heterogeneity</td>
<td>0.0561 (0.0060)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.0143 (0.0037)</td>
<td>0.1263 (0.0066)</td>
</tr>
</tbody>
</table>

Taste Shock

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>Shrinking</td>
<td>0.0998 (0.0067)</td>
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<tr>
<td>Variance</td>
<td>26.975 (2.9435)</td>
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</table>

Table 4: Estimates of Industry Production Function

<table>
<thead>
<tr>
<th></th>
<th>Computer Science</th>
<th>other-STEM</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>val.</td>
<td>val.</td>
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<tr>
<td>Share</td>
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<td>0.4229</td>
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<tr>
<td>Rho</td>
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<td>0.4914</td>
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<tr>
<td>Return to Scale</td>
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<td>0.6085</td>
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Table 5: Fixed Immigrant Labour Supplies at Their 1994 Level

<table>
<thead>
<tr>
<th></th>
<th>$\Delta \Pi_{cs}$</th>
<th>$\Delta \Pi_{npps}$</th>
<th>$\Delta N_{cs}$</th>
<th>$\Delta N_{npps}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M_{cs}$ Fixed &amp; $M_{npps}$ Fixed</td>
<td>2.41%</td>
<td>1.22%</td>
<td>5.49%</td>
<td>-2.96%</td>
</tr>
<tr>
<td>$M_{cs}$ Fixed &amp; $M_{npps}$ Old Path</td>
<td>2.52%</td>
<td>1.37%</td>
<td>5.24%</td>
<td>-2.81%</td>
</tr>
</tbody>
</table>

Table 6: Summary Results from Counterfactual Simulation With Different Production Parameters

| Panel A $\rho_{cs} = 1$ While other-STEM sector Using Estimated Production Function |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
| $\psi_{cs} = 0.75$              | $\psi_{cs} = 0.50$ | $\psi_{cs} = 0.25$ | Basic            |
| $\Delta \Pi_{cs}$               | 2.28%            | 3.44%            | 3.70%            | 2.51%            |
| $\Delta \Pi_{npps}$             | 1.24%            | 2.00%            | 2.01%            | 1.37%            |
| $\Delta N_{cs}$                 | 4.74%            | 5.57%            | 7.66%            | 5.24%            |
| $\Delta N_{npps}$               | -2.55%           | -2.90%           | -4.07%           | -2.81%           |

| Panel B Same Production Function in Both CS and other-STEM sector ($\rho=1$) |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
| $\psi = 0.75$                   | $\psi = 0.50$   | $\psi = 0.25$   | Basic            |
| $\Delta \Pi_{cs}$               | 2.01%            | 3.15%            | 4.61%            | 2.51%            |
| $\Delta \Pi_{npps}$             | 0.72%            | 1.66%            | 2.55%            | 1.37%            |
| $\Delta N_{cs}$                 | 5.99%            | 6.91%            | 7.11%            | 5.24%            |
| $\Delta N_{npps}$               | -3.31%           | -3.73%           | -3.90%           | -2.81%           |
Table 7: Elasticities of Counterfactual Simulation With Different Production Parameters

<table>
<thead>
<tr>
<th>Panel A</th>
<th>$\rho_{cs} = 1$ While other-STEM sector Using Estimated Production Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\psi=0.75$</td>
<td>$\psi=0.50$</td>
</tr>
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<td>CS</td>
<td>NCS</td>
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<table>
<thead>
<tr>
<th>Panel B</th>
<th>Same Production Function in Both CS and other-STEM sector ($\rho=1$)</th>
</tr>
</thead>
<tbody>
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<td>$\psi=0.75$</td>
<td>$\psi=0.50$</td>
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<td>CS</td>
<td>NCS</td>
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<td>Elasticity</td>
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Table 8: Age Composition of Switchers

<table>
<thead>
<tr>
<th>Age Group</th>
<th>Fraction as % of Total Switcher</th>
<th>Accumulative %</th>
</tr>
</thead>
<tbody>
<tr>
<td>22 – 26</td>
<td>34.63%</td>
<td>34.63%</td>
</tr>
<tr>
<td>27 – 21</td>
<td>27.83%</td>
<td>62.46%</td>
</tr>
<tr>
<td>32 – 36</td>
<td>19.23%</td>
<td>81.69%</td>
</tr>
<tr>
<td>37 – 41</td>
<td>9.52%</td>
<td>91.21%</td>
</tr>
<tr>
<td>42 – 46</td>
<td>4.76%</td>
<td>95.97%</td>
</tr>
<tr>
<td>47 – 51</td>
<td>2.45%</td>
<td>98.41%</td>
</tr>
<tr>
<td>52 – 65</td>
<td>1.59%</td>
<td>100%</td>
</tr>
<tr>
<td>total</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>

The age composition is computed using simulation of 500 native workers.
Table 9: Composition of Monthly Occupational Mobility

<table>
<thead>
<tr>
<th></th>
<th>STEM</th>
<th>Non-STEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>STEM</td>
<td>37.2%</td>
<td>62.8%</td>
</tr>
<tr>
<td>Non-STEM</td>
<td>7.4%</td>
<td>92.6%</td>
</tr>
</tbody>
</table>

B: Adjusted Composition

<table>
<thead>
<tr>
<th></th>
<th>STEM</th>
<th>Non-STEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>STEM</td>
<td>66.7%</td>
<td>33.3%</td>
</tr>
<tr>
<td>Non-STEM</td>
<td>7.4%</td>
<td>92.6%</td>
</tr>
</tbody>
</table>

The monthly occupation switch probability is computed using linked monthly CPS data from 1994-2013. The row corresponding to occupation groups in month t. The column corresponding to occupation groups in month t+1.

Figure 1: H-1B Petition Cap and Estimated H-1B Population

Note: Population stock is constructed using estimations of inflows (visa granted) and outflow (deaths, permanent residency, or emigration) of H-1B workers. In later years, the number of visa granted could exceed the visa cap due to exemptions for foreigners who work at universities and non-profit research facilities.
Figure 2: Occupations of H-1B Worker Beneficiaries in 2010

Figure 3: Fraction of Immigrants
Figure 4: Evolution of Skill Rental Prices

Other-STEM Rental Rate

CS Rental Rate

Source: CPS. Correlation Coefficient=0.70.

In 71-76, the observations are discarded because sample size is too small (n<2).
Figure 5: Wage Distribution Fit (Year 2000)

(a) Log CS Wage Profile

(b) Log Other-STEM Wage Profile

(c) Std of CS

(d) Std of Other-STEM

Log Annual Earnings in Thousands

Simulation vs Actual Wage for CS

Simulation vs Actual Wage for Other STEM

Simulation vs Actual Std for CS

Simulation vs Actual Std for Other STEM
Figure 6: Occupational Choices and Mobility Fit (2000)

(a) Fraction of Native CS Workers

(b) Gross Occupational Mobility
Figure 7: Model Predicted Prices v.s. Nasdaq Index

(a) Model Predicted Relative Prices

(b) Nasdaq Composite Index

Source: Yahoo Finance
Figure 8: Response of New Entrants

Figure 9: Lagged Response of New Entrants

Figure 10: Cohort Response

Source: American Community Survey
Figure 11: Fixed Foreign Computer Scientists at 1994 Level

- Labor Supply of Immigrants
- Efficient Rental Rate For Native CS
- Labor Supply of Native CS
- Labor Supply of Native Other-STEM

Graphs and data points showing trends over time, with Efficiency Units on the y-axis and years from 1994 to 2014 on the x-axis. The graphs display actual and counterfactual data for STEM, CS, and other-STEM supply.
In 2000, efficiency labor supply of foreign CS workers is restricted to its 1994 level. Those who will respond to this shock by switching occupations are identified. For this period, the switchers are forced to stay in their previous occupation. Conditional on being switchers, the average CVs are computed for each age group.
Figure 14: Contour Map of Expected CVs For Workers Aged 22

Figure 15: Employment Share of STEM and CS Workers

Source: March Current Population Survey
Skilled Labour is defined as full-time workers with Bachelor's degree or higher
Appendix B

Detailed Description of Data Cleaning

For the data cleaning, I first restrict the analysis applying only to the skilled labor force, defined as those who have a Bachelor’s degree or higher and are currently in the labor force. The status ‘in labor 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 omitted in the discrete choice model, I further restrict the sample to full-time full-year workers whose total hours worked (the product of usual hours 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 hours worked. Then the hourly wage rate is employed to deal with possible outliers. Individuals with hourly wage rate lower than 7 dollars 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 consistently 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 in OCC1990.

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 labor 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 second measure suffers from the small sample problem because most of the answers are not available.

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34 The level of federal minimum wage
Appendix C

Recover Skill Rental Rates Series Using Flat Spot Method

The estimation follows the method proposed by Bowlin and Robinson (2012). I made the assumption of competitive markets for each human capital type. The wages for any individual $i$ of a particular occupation are given by

$$W_{i,t}^s = \Pi_t^s H_{i,t}^s.$$  

This implies that within each occupation the change in wages between $t$ and $t+1$ is given by

$$\frac{W_{i,t+1}^s}{W_{i,t}^s} = \frac{\Pi_{t+1}^s H_{i,t+1}^s}{\Pi_t^s H_{i,t}^s}.$$  

Therefore, the price change is given by

$$m_t^s = \frac{\Pi_{t+1}^s}{\Pi_t^s} = \frac{W_{i,t+1}^s}{W_{i,t}^s} \frac{H_{i,t+1}^s}{H_{i,t}^s}.$$  

The flat spot method estimates the price change by restricting estimation to observations where human capital levels do not change over time, i.e. where $\frac{H_{i,t}^s}{H_{i,t+1}^s} = 1$. As a result, the changes in observable wages are equivalent to the changes in skill rental rates. Here for the choice of flat spot region, I follow Bowlin and Robinson (2012) and choose 51-62 as the suitable range for college graduates. 4 time series are recovered using the ACS and CPS.

Smooth Series

The CPS covers the entire period of interest. However, series obtaining by CPS are noisier than that obtained by the ACS due to differences in sample size. I develop a statistical way to obtain smooth series. Let us denote $x_o^o$ the skill rental rate of occupation $o$ from the CPS, and $y_o^o$ the skill rental rate of occupation $o$ from the ACS, where $o \in \{cs, ncs\}$.

Let us assume both $x_o^o$ and $y_o^o$ are noisy measures of some process $\theta_o^o$ that governs the fundamentals in the evolution of skill rental rates.
where $\epsilon_t$ and $\epsilon_t$ are autocorrelated innovations with different variances (with different noise levels). $x_t^o$ is considered to be a noisier measure because the CPS has a relatively smaller sample size than the ACS. The CPS sample size is small for the CS sector especially in the early 1970s only.

Figure D.1: Evolution of Sector Efficiency Wages (CPS)

![Efficiency Wage Graph](image)

about 10 to 20, and this number gradually increases to 300 as the industry grows. In Figure D.1 I plot $x_t^o$s recovered using the CPS. We can observe that the rental rates for both occupations are extremely volatile in early periods. And CS series is even more volatile in general compared to that of the other-STEM sector. The 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 fundamentals, but with a shorter time span as depicted in Figure D.2. The purpose of the smooth adjustment is to propose a statistically valid method to retrieve meaningful patterns 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 the CPS sample is to impose a functional form on $\theta_t^o$ and also some error structures on $\epsilon_t$ and $\epsilon_t$. From now on I will focus discussions on one occupation and thus the occupation notation $o$ is suppressed.
I fit the ACS and CPS series to fourth polynomials of the deterministic time trend $t$ with AR(1) error terms respectively. If the assumptions above are reasonable, the fitted series from the CPS and ACS would show improvements in their correlation coefficient compared to the unadjusted series.

As presented in Table D.1, both adjusted series show an increase of approximately 30% in the correlation coefficients. The correlation coefficients for the CS and the other-STEM occupations
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 $\frac{\sigma^2_u}{\sigma^2_v}$ equals approximately to 10.

Next, I apply the model to the full CPS sample (1972-2013). For the CS sector, the first 5 years of observations are discarded for the concern of small sample size. The smooth series and their original series are shown in Figure 4.

**Solution Method Using** \( \left\{ \frac{\Pi^s_{t+1}(o)}{\Pi^s_t(o)} \right\} \)

Using the flat spot method, I obtain the series of observed skill rental rates \( \{m^s_t\} = \{\frac{\Pi^s_{t+1}(o)}{\Pi^s_t(o)}\} \). Now I assume the ratio of skill price series is fully anticipated by agents.

\[ \Pi^s_t(e) = \Pi^s_t(o) = m^s_t m^s_{t+1} \ldots m^s_{\tau} \Pi^s_{\tau}, \forall \tau > t \]

This relationship yields a sequence of skill rental rates that can be written solely in terms of \( \Pi^s_t \). The value of \( \Pi^s_t \) is determined by equating labor supply and demand in period \( t \).

**Appendix D**

**Asymptotic Distribution of the SMM Estimators with Multiple Samples**

The asymptotic distribution of the SMM estimators used in this paper follows results of Gorlach (2016).

The criterion function to be minimized has the follow general functional form:

\[
M(\theta) = D(\theta)'WD(\theta) = (m^d - m^s(\theta))'W(m^d - m^s(\theta))
\]

Where \( m^d \) denotes the data moments, \( m^s(\theta) \) is the simulated moments using the model. \( \theta \) is the parameters of interest and \( W \) is any weighting matrix.

Important assumptions need to be made in addition to the assumptions required by the usual asymptotic theory of M-estimators:
Additional Assumption 1: Different samples used are drawn independently. This implies that any cross-sample moments are zeros and the weighting matrix $W$ will be block diagonal.

Additional Assumption 2: The sample size $N_\zeta$ of the dataset $\zeta$ used increases at a proportional rate

$$\lim_{N_1 \to \infty} (N_1/N_\zeta) = \lambda_\zeta$$

$$N_1 \to \infty$$

$$N_\zeta \to \infty$$

with $0 < \lambda_\zeta < \infty$ for all samples $\zeta$, which means that none of the samples is irrelevant relative to the others.

Additional Assumption 3: The simulated sample size $N^*_\zeta$ increase at a rate such that

$$\lim_{N_\zeta \to \infty} (N_\zeta/N^*_\zeta) = n_\zeta$$

$$N_\zeta \to \infty$$

$$N^*_\zeta \to \infty$$

with $0 < n_\zeta < \infty$ for all sample $\zeta$.

The application of the central limit theorem then yields the asymptotic distribution for the parameter $\hat{\theta}$:

$$\sqrt{N_1}(\hat{\theta} - \theta) \to N(0, (\frac{\partial D'}{\partial \theta})(\hat{\theta})W\frac{\partial D}{\partial \theta}(\hat{\theta}))^{-1}$$

$$\left(\Sigma \lambda_\zeta (1 + n_\zeta) \frac{\partial D'}{\partial \theta}(\hat{\theta})W\lambda_\zeta \text{var}(m^\zeta)W_\zeta \frac{\partial D}{\partial \theta}(\hat{\theta})\right)$$

$$\left(\frac{\partial D'}{\partial \theta}(\hat{\theta})W\frac{\partial D}{\partial \theta}(\hat{\theta})\right)^{-1}$$

Appendix E

Addressing the Cohort Effects

I assume that individuals form deterministic expectations of skill rental rates. Each person in each cohort solves the decision problem under the deterministic path of skill prices. However, the skill price series that each cohort faces is different. Therefore, it is necessary to solve for the optimal
career decision rule for each cohort, i.e., for the cohort-specific set of value functions.

I assume each year the native labor force consists three birth-cohort groups: young, middle-aged and old workers\textsuperscript{35}. The reason that I only consider three cohort groups is simply for the computational feasibility. For each group, the average birth year is computed and assigned as a group characteristic. Taking old cohort group in the year 2000 as an example, old workers are on average 57 years old who entered the labor market in 1965. When native workers enter the labor market, they are assumed to be capable of correctly forecasting the career prospects under the perfect foresight assumption. These three cohort groups solve different dynamic choice problems (DDP) since they experience different phases of the industrial development. Then in a particular year, the combined income age profile of these three cohort groups as well as the choice age profiles to match data moments computed using cross-sectional data. The following graph takes the year 2000 again as an example to show graphically how to construct the combined income age profile using the simulated data from three DDP problems. All other model specifications are identical to the basic model.

Figure D.4: Illustration of the Perfect Foresight Model

\textsuperscript{35}Each group of workers has 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.
Appendix F

Derive Expression for Expected CV

By the law of iterated expectation, the calculation of CV breaks down into two parts.

\[ \mathbb{E}(CV(H_a)) = \mathbb{E}(CV|mob = 1, H_a)P(mob = 1|H_a) + \mathbb{E}(CV|mob = 0, H_a)P(mob = 0|H_a) \]

Assume that the skill rental rates change from \( \begin{pmatrix} \Pi_{cs}^{old} \\ \Pi_{ncs}^{old} \end{pmatrix} \) to \( \begin{pmatrix} \Pi_{cs}^{new} \\ \Pi_{ncs}^{new} \end{pmatrix} \). For an individual age \( a \) with occupation specific human capital \( \begin{pmatrix} H_{cs}^a \\ H_{ncs}^a \end{pmatrix} \), I derive the expected CV given \( H_a \). Let \( d_{old} \) and \( d_{new} \) denote this individual’s choice of occupation under old and new market conditions. \( mob = 1 \) if occupational mobility is plausible when market conditions change. \( mob = 1 \) either when \( \{d_{old} = ncs, d_{new} = cs\} \) or when \( \{d_{old} = cs, d_{new} = ncs\} \) occurs. When \( mob = 0 \), individuals will not exercise their options of occupational mobility anyway, which implies \( \mathbb{E}(CV|mob = 0, H_a) = 0 \).

This implies that

\[ \mathbb{E}(CV(H_a)) = \mathbb{E}(CV|mob = 1, H_a)P(mob = 1|H_a) \] (21)

Since \( \{mob = 1\} = \{d_{old} = ncs, d_{new} = cs\} \cup \{d_{old} = ncs, d_{new} = cs\} \), use again the law of iterated expectation.

\[ \mathbb{E}(CV|mob = 1, H_a) = \]

\[ \mathbb{E}(CV|d_{old} = ncs, d_{new} = cs, mob = 1, H_a)P(d_{old} = ncs, d_{new} = cs|mob = 1, H_a) \]

\[ + \mathbb{E}(CV|d_{old} = cs, d_{new} = ncs, mob = 1, H_a)P(d_{old} = cs, d_{new} = ncs|mob = 1, H_a) \] (22)

\( \{d_{old} = ncs, d_{new} = cs\} \) and \( \{d_{old} = ncs, d_{new} = cs\} \) are two mutually exclusive events. This implies
\[ P(mob = 1|H_a) = P(d_{old} = ncs, d_{new} = cs|H_a) + P(d_{old} = ncs, d_{new} = cs|H_a). \]

\[ P(d_{old} = ncs, d_{new} = cs|mob = 1, H_a) = \frac{P(d_{old} = ncs, d_{new} = cs|H_a)}{P(mob = 1|H_a)} \]  

(23)

Substitute equation (22) and (23) into (21).

\[ E(CV|H_a) = E(CV|d_{old} = ncs, d_{new} = cs, H_a)P(d_{old} = ncs, d_{new} = cs|H_a) + E(CV|d_{old} = cs, d_{new} = ncs, H_a)P(d_{old} = cs, d_{new} = ncs|H_a) \]  

(24)

\[ P(d_{old} = ncs, d_{new} = cs|H_a) = P(V_{cs}^{old} < V_{ncs}^{old}, V_{cs}^{new} < V_{ncs}^{new}|H_a) \]

The value functions derived in the model part are as follows.

\[ V_{cs}^{old} = \Pi_{cs}^{old}H_a^{cs} + \eta_a + \beta E V'_{old}(d_{old} = cs) \]

\[ V_{ncs}^{old} = \Pi_{ncs}^{old}H_a^{ncs} + \beta E V'_{old}(d_{old} = ncs) \]

\[ d_{old} = ncs \text{ when } V_{cs}^{old} < V_{ncs}^{old} . \] This implies

\[ \eta_a^{old} < (\Pi_{ncs}^{old}H_a^{ncs} + \beta E V'_{old}(d_{old} = ncs)) - (\Pi_{cs}^{old}H_a^{cs} + \beta E V'_{old}(d_{old} = cs)). \]

By the same computation, \( d_{new} = cs \) implies

\[ \eta_a^{new} > (\Pi_{ncs}^{new}H_a^{ncs} + \beta E V'_{new}(d_{new} = ncs)) - (\Pi_{cs}^{new}H_a^{cs} + \beta E V'_{new}(d_{new} = cs)). \]

The taste shocks under the old and new skill rental rates are independent draws from the same normal distribution.

\[ P(d_{old} = ncs, d_{new} = cs|H_a) = P(V_{cs}^{old} < V_{ncs}^{old}|H_a)P(V_{ncs}^{new} < V_{cs}^{new}|H_a) \]  

(25)

\[ = \Phi\left(\frac{\Pi_{ncs}^{old}H_a^{ncs} + \beta E V'_{old}(d_{old} = ncs) - (\Pi_{cs}^{old}H_a^{cs} + \beta E V'_{old}(d_{old} = cs))}{\sigma_{\eta_a}}\right) \]

\[ \times \Phi\left(\frac{\Pi_{ncs}^{new}H_a^{ncs} + \beta E V'_{new}(d_{new} = cs) - (\Pi_{cs}^{new}H_a^{cs} + \beta E V'_{new}(d_{new} = ncs))}{\sigma_{\eta_a}}\right) \]
\( \mathbb{E}(CV|d_{old} = ncs, d_{new} = cs, H_a) = \mathbb{E}((\Pi_{new}^{cs} H_a^{ncs} + \eta_a + \beta \mathbb{E} V'_{new}(d_{new} = cs)) - (\Pi_{new}^{ncs} H_a^{ncs} + \beta \mathbb{E} V'_{new}(d_{new} = ncs))|d_{new} = cs, H_a) \) \hspace{1cm} (26)

Taste shock is normally distributed as \( \eta_a \sim N(0, \sigma_{\eta_a}^2) \).

\( \mathbb{E}(\eta_a|\eta_a > (\Pi_{new}^{ncs} H_a^{ncs} + \beta \mathbb{E} V'_{new}(d_{new} = ncs)) - (\Pi_{new}^{cs} H_a^{cs} + \beta \mathbb{E} V'_{new}(d_{new} = cs))) = \eta_a \cdot \frac{\phi\left( \frac{(\Pi_{new}^{ncs} H_a^{ncs} + \beta \mathbb{E} V'_{new}(d_{new} = ncs)) - (\Pi_{new}^{cs} H_a^{cs} + \beta \mathbb{E} V'_{new}(d_{new} = cs))}{\sigma_{\eta_a}} \right)}{1 - \phi\left( \frac{(\Pi_{new}^{ncs} H_a^{ncs} + \beta \mathbb{E} V'_{new}(d_{new} = ncs)) - (\Pi_{new}^{cs} H_a^{cs} + \beta \mathbb{E} V'_{new}(d_{new} = cs))}{\sigma_{\eta_a}} \right)} \) \hspace{1cm} (27)

Substitute equation (27) into (26).

\( \mathbb{E}(CV|d_{old} = ncs, d_{new} = cs, H_a) = (\Pi_{new}^{cs} H_a^{cs} + \beta \mathbb{E} V'_{new}(d_{new} = cs)) - (\Pi_{new}^{ncs} H_a^{ncs} + \beta \mathbb{E} V'_{new}(d_{new} = ncs)) + \eta_a \cdot \frac{\phi\left( \frac{(\Pi_{new}^{ncs} H_a^{ncs} + \beta \mathbb{E} V'_{new}(d_{new} = ncs)) - (\Pi_{new}^{cs} H_a^{cs} + \beta \mathbb{E} V'_{new}(d_{new} = cs))}{\sigma_{\eta_a}} \right)}{1 - \phi\left( \frac{(\Pi_{new}^{ncs} H_a^{ncs} + \beta \mathbb{E} V'_{new}(d_{new} = ncs)) - (\Pi_{new}^{cs} H_a^{cs} + \beta \mathbb{E} V'_{new}(d_{new} = cs))}{\sigma_{\eta_a}} \right)} \) \hspace{1cm} (28)

\( P(d_{old} = cs, d_{new} = ncs|H_a) = \Phi\left( \frac{(\Pi_{new}^{ncs} H_a^{ncs} + \beta \mathbb{E} V'_{new}(d_{new} = ncs)) - (\Pi_{new}^{cs} H_a^{cs} + \beta \mathbb{E} V'_{new}(d_{new} = cs))}{\sigma_{\eta_a}} \right) \) \hspace{1cm} (29)

\( \mathbb{E}(CV|d_{old} = cs, d_{new} = ncs, H_a) = (\Pi_{new}^{ncs} H_a^{ncs} + \beta \mathbb{E} V'_{new}(d_{new} = ncs)) - (\Pi_{new}^{cs} H_a^{cs} + \beta \mathbb{E} V'_{new}(d_{new} = cs)) + \eta_a \cdot \frac{\phi\left( \frac{(\Pi_{new}^{ncs} H_a^{ncs} + \beta \mathbb{E} V'_{new}(d_{new} = ncs)) - (\Pi_{new}^{cs} H_a^{cs} + \beta \mathbb{E} V'_{new}(d_{new} = cs))}{\sigma_{\eta_a}} \right)}{\Phi\left( \frac{(\Pi_{new}^{ncs} H_a^{ncs} + \beta \mathbb{E} V'_{new}(d_{new} = ncs)) - (\Pi_{new}^{cs} H_a^{cs} + \beta \mathbb{E} V'_{new}(d_{new} = cs))}{\sigma_{\eta_a}} \right)} \) \hspace{1cm} (30)

\( \phi \) and \( \Phi \) are the pdf and cdf function for the standard normal distribution respectively.