Abstract

This paper analyzes the dynamic effects of immigration on worker outcomes by estimating an equilibrium model of local labor markets in the United States. The model includes firms in multiple cities and multiple industries which combine capital, skilled and unskilled labor in production, and forward-looking workers who choose their optimal industry and location each period as a dynamic discrete choice. Immigrant inflows change wages by changing factor ratios, but worker sector and migration choices can mitigate the effect of immigration on wages over time. I estimate the model via simulated method of moments by leveraging differences in wages and labor supply quantities across local labor markets to identify how wages and worker choices respond to immigrant inflows. Counterfactual simulations yield the following main results: (1) a sudden unskilled immigration inflow leads to an initial wage drop for unskilled workers which decreases by over half over 20 years; (2) both workers’ sector-switching and migration across local labor markets play important roles in mitigating the effects of immigration on wages; (3) a gradual immigration inflow leads to significantly smaller effects on native wages than a sudden inflow of the same magnitude.

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1 Introduction

Immigration to the United States has increased dramatically over past decades, leading to significant changes in the US labor market. While most economic research has analyzed immigration’s long run effects on unemployment and wages, public debate on immigration often centers on native job loss and worker displacement, phenomena which are often transitory in nature. Surprisingly, there is little economic research on the dynamic adjustment processes of workers to immigrant inflows.

There may be substantial differences in the long and short run effects of immigration. In the long run, reallocation of labor across sectors or geographic regions can mitigate the effect of immigration on wages. In the short run, however, natives may face considerable costs as a result of immigrant inflows. If natives cannot change sectors or migrate immediately, they may experience a wage decrease. If they do switch sectors, they may take a wage cut as they adjust to the new sector. Finally, they may also face other nonpecuniary costs that accompany finding a new job in another sector or moving to another city.

In this paper, I use a dynamic equilibrium model to quantify the effects of immigrant inflows on wages and the distribution of workers across local labor markets and sectors. Firms across sectors and locations combine capital, skilled labor, and unskilled labor in constant elasticity of substitution (CES) production functions. Immigrant inflows increase the ratio of unskilled to skilled workers, thus depressing wages for unskilled workers. Forward-looking agents may choose to change sectors or migrate in response to immigrant inflows but may suffer a wage cut or nonpecuniary cost as a result. Both migration and sector switching can mitigate the effect of immigration on wages: in-migration of skilled workers or out-migration of unskilled workers can reverse the effect of immigration on factor ratios within cities. Alternatively, sector switching leading to increases in the size of industries which intensively use unskilled workers can cause within-sector factor ratios to approach their initial values. The persistence of the wage effects of immigration therefore depend on the extent and speed of sector switching and migration.

One of the primary benefits of my framework is the transparency with which the key parameters are identified. To estimate labor demand, I identify exogenous shifts in immigrant labor supply across sectors and local labor markets by modifying the “ethnic enclave” instruments employed by Card (2009); immigrant supply shocks from sending countries create variation in the relative supplies of labor. Furthermore, I exploit variation in relative wages of sectors across local labor markets to estimate labor supply. Preference parameters are identified via different sectoral choices of similar agents who face different wages as a result
of living in different labor markets. For example, wages for unskilled native workers in the service sector have remained stagnant over the past 30 years in Los Angeles while growing by over 30% in San Jose.\footnote{Calculations of average log wages from 1980 census and 2010 aggregated ACS.} The responsiveness of workers to wages is identified off the proportion of agents that switch into the service sector in Los Angeles compared to San Jose as wage changes differentially over time.

Estimating a dynamic model with switching costs across multiple local labor markets requires panel data on sector choices and wages, a large sample of workers in each labor market, and panel data on migration decisions. The main dataset I use in estimation, the Current Population Survey Merged Outgoing Rotation Groups (CPS MORG), satisfies the first two of these requirements. The dataset includes wages and industry choices for the same individual over two consecutive years and is also large: my estimation sample includes almost 600,000 individuals from 12 local labor markets. I supplement this data set with data from the National Longitudinal Survey of Youth 1979 (NLSY79) and the American Community Survey (ACS). I use the NLSY79 data to capture long run wage dynamics and I use the ACS data to identify cross city migration flows.

I use the estimated model to simulate a sudden influx of unskilled immigrants which increases the immigrant share of unskilled workers by 10%. Immediately following the shock unskilled agents experience roughly a 3% decrease in their wages while skilled wages increase by 1%. Unskilled workers respond to the immigration by migrating to areas less affected by immigration, while both unskilled and skilled workers switch into unskilled intensive sectors. Over time, as a result of these adjustments, the effect of immigration on wages decrease by over one half. I then use the model to decompose the roles played by sector-switching and migration in mitigating the effects of immigration on wages. The model-based decomposition shows that both of these margins of adjustment play important roles in an economy’s adjustment to immigration: without either sector switching or migration responses the long run effects of immigration on unskilled native wages would be roughly 50% larger.

Next, I show that the negative wage effects of immigration can be decreased substantially by smoothing the immigrant inflow over 10 years. As immigrants enter the labor markets, workers simultaneously switch into unskilled intensive industries and migrate across labor markets. Therefore, within sector factor ratios remain relatively constant throughout the immigration and the effect of immigration on wages are small. Finally, I introduce a policy which both dramatically increases the number of immigrants admitted into the US each year and requires unskilled immigrants pay a fraction of their income each year after being
admitted under the program. The revenue raised from this visa fee is transferred to unskilled natives. I show that under this policy, large increases in immigration can lead to income gains for both skilled and unskilled natives.

This paper is related to a large empirical literature on the effects of immigration on receiving country wages (e.g. Card (2001), Borjas (2003), LaLonde and Topel (1991b), Ottaviano and Peri (2012)). My paper extends this line of research by measuring the effects of immigration on wages in a dynamic setting, rather than at a single point in time. My model produces long run effects of immigration on native wages that are consistent with existing papers in this literature. However, my results show that the wage effects of immigration are over two times larger than this immediately after an immigration inflow. A smaller literature utilizes “natural experiments” to measure the effects of immigration immediately after a sudden immigration inflow (Card (1990), Cohen-Goldner and Paserman (2011), Monras (2015), Borjas (2015), Dustmann, Schönb erg and Stuhler (2016)). Consistent with the majority of studies in this literature, I find that immigration inflows lead to large effects on native wages in the short run but that these effects dissipate over time.

This paper also expands on a literature on native responses to immigrant inflows by modeling and estimating workers’ dynamic migration and sector choice responses to immigrant inflows. Studies on native responses to immigrant inflows generally employ static models and measure natives responses to immigration over 10 year periods (Piyapromdee (2014), Lewis (2003), Dustmann and Glitz (2015), and Peri and Sparber (2009)). This extension allows me understand the importance of these adjustments in mitigating the effect of immigration on wages over time. Specifically, I find that, without these adjustments, the long run effects of immigration on unskilled wages would be twice as large and that both migration and sector switching play important roles in how an economy adjusts to immigration shocks.

Additionally, the results of this paper can shed light on conducting immigration policy in a dynamic setting. Recent literature, including Card (2009), Ottaviano and Peri (2012) and Borjas and Monras (2016), have emphasized that the skill mix of immigrants is an important determinant of the extent to which immigrant inflows affect native wages. My results show that the timing and intensity of an immigrant inflow are also important determinants of the effects of immigration. Therefore, holding the total number and composition of immigrants fixed, a policy maker can drastically reduce the negative impact of immigration on unskilled native wages by smoothing the inflow of immigrants over time. My paper is the first to quantify this intuitive result.

Methodologically, this paper is related to a series of papers which estimate dynamic equilibrium models of occupation or industry choice (Ashournia (2015), Dix-Carneiro (2014),
Lee (2005), Johnson and Keane (2013), Traiberman (2016), Lee and Wolpin (2006) and Llull (2016)). My paper differs from the literature in that I model a migration decision in addition to the industry or occupation choice. Migration is an important margin to consider given the disparity in immigrant inflows across cities. Additionally, this paper differs from this literature in that it uses local labor market variation to identify the key parameters of the model. Previous dynamic equilibrium models of occupation or industry choice have relied on time series variation and functional form assumptions to separately identify worker’s responsiveness to wages from the wage determination process. Instead, I utilize variation in labor supply and labor demand across local labor markets to identify these effects. Identification strategies which leverage differences across local labor markets have been utilized extensively in reduced form studies (see Bartik (1991) or Card (2001), for example), however, to my knowledge this is the first paper to utilize a local labor market approach to identify a dynamic labor market equilibrium model. The strategy I develop here could readily be employed in other studies.

In the next section I review the literature on short run effects of immigration and on native migration and sectoral choice responses to these inflows. In Section 3 I describe the model. Section 4 introduces the data I use in estimation while Section 5 describes the estimation procedure. I present the estimation results in Section 6 and the counterfactual simulations in Section 7. Section 8 concludes.

2 Background and Related Literature

While the majority of studies on the impact of immigration on native wages have focused on the long run, a few studies have attempted to estimate the effects of immigration on native wages in the short run. Cohen-Goldner and Paserman (2011) analyze the short and medium run effects of immigration from the former Soviet Union to Israel on wages and employment levels. They find that immigration lead to a substantial wage decrease for natives immediately after the immigration inflow that dissipated in 4-7 years. In a seminal paper, Card (1990) examines the effects of the sudden influx of low skilled Cuban immigrants caused by the 1980 Mariel boatlift on native workers in Miami. Surprisingly, he finds almost no effects on native wages or unemployment in Miami compared to a group of comparison cities. However, in a recent reappraisal of the Card study, Borjas (2015) argues that the Mariel boatlift did, in fact, have large effects on the wages of native high school dropouts in the years immediately following the boatlift. The wage effects completely disappear by
1990, 10 years after the shock. He attributes the discrepancy between he and Card’s results on his focus on high school dropouts, rather than all workers with high school education or less, and on a more careful choice of comparison cities. Monras (2015) analyses the effects of the sudden increase in Mexican immigration to the US caused by the Mexican Peso Crisis in 1994. He finds that states which received relatively more Mexican migrants after the crisis experienced substantial decreases in unskilled wages immediately following the crisis. Similar to Borjas (2015) and Cohen-Goldner and Paserman (2011), he finds that the wage effects dissipate quickly; Monras argues that wage effects are larger in the short run because workers migrate to cities less affected by immigration over time.

Papers measuring the extent to which immigration leads to migration responses of native workers have found a variety of results. Card and DiNardo (2000) use an instrumental variables strategy to test whether inflows of immigrants into an MSA lead to outflows of natives. Their results show that immigrant inflows are associated with inflows of native workers. Borjas (2006) challenges these results, arguing that for every ten immigrants that live in a state, two fewer natives chose to live in that state.

Sectoral adjustments are another mechanism which could mitigate the wage effects of immigration over time. According to the Rybczynski theorem, a small open market with multiple sectors can absorb changes in factor endowments by shifting production towards sectors which intensively employ factors whose supply is expanding (Rybczynski (1955)). If sectors fully absorb the change in factor endowments such that factor ratios in each sector are unchanged, factor prices will be unchanged after the change in factor endowments.

A series of papers have attempted to quantify the importance of Rybczynski effects in mitigating the wage impact of immigration by measuring changes in industry structure in a local labor market in response to immigration of low skilled immigrants. Lewis (2003) uses local labor market data from the United States to measure the extent to which changes in relative factor endowments as a result of immigration are absorbed by the expansion of unskilled intensive industries. He finds that unskilled intensive industries grow in response to unskilled immigrant inflows. However, while the Rybczynski theorem predicts that long run sector factor ratios will be identical to pre-shock factor ratios, Lewis finds that within sector factor ratios change considerably in the ten year periods he considers. Dustmann and Glitz (2015), using firm level data from Germany, and Card and Lewis (2007) and Gonzalez and Ortega (2011), using data from the US and Spain, respectively, perform a similar exercise and find qualitatively similar results. Lewis (2004) studies changes in industry production levels in Miami following the Mariel boatlift of 1980. He finds that, compared to similar cities, Miami experienced a decline in skilled manufacturing production and a statistically insignificant
increase in unskilled intensive apparel production in the years following the boatlift. The ratio of unskilled to skilled workers within industries remain above their pre-boatlift levels in the 16 years following the boatlift.

A related literature tests for factor price equalization across local labor markets. Bernard, Redding and Schott (2013) test for relative factor price equality across labor markets in the U.S. by comparing relative wage bills of different types of workers within industries across labor markets. Their test rejects relative price equalization across US cities. In this paper I explore how frictions to sector or geographic mobility can lead to sluggishness in the adjustments of factor ratios to shocks prevent factor price equalization.

Finally, a macroeconomic literature analyzes the effects of immigration in a dynamic setting. Ben-Gad (2008), Ben-Gad (2004) and Hazari and Sgro (2003), among others, use neoclassical growth models to analyze the effects of immigration on the path of consumption and output. Klein and Ventura (2009) analyze the dynamic reallocation of labor and capital across countries using a two-location growth model. Xu (2015) uses a multi-country model endogenous growth model to analyze the effects of high skilled immigration on global innovation. Lee (2015) uses a two country model to simulate the effects of doubling the H1-B visa quota on U.S. output. None of these models include sector choice and local labor market choice, the two main margins of adjustments I focus on in this paper.

3 Model

I propose a dynamic equilibrium model of wage determination, sector choice, human capital accumulation and migration. The basic mechanism is straightforward. Inflows of immigrants affect wages by changing factor ratios. Workers can respond to immigrant inflows by switching sectors or migrating, but crucially pay switching costs for doing so. Over time, these adjustments allow the within sector factor ratios to approach their initial levels. Therefore, the effects of immigration on the wage structure will depend not only on the initial change in factor ratios caused by immigration, but also on how quickly the factor ratios adjust over time as a result of worker sector choices and migration.

Specifically, firms in each sector combine capital, skilled labor and unskilled labor in constant elasticity of substitution production functions. Labor is measured in human capital units: workers of the same skill level can have heterogeneous productivity based on their age, immigrant status and work history. I assume perfectly competitive markets, and hence human capital prices are equal to the marginal products of human capital and are determined.
by the relative quantities of capital and the labor inputs in each sector.

Sector and location choice are sequential dynamic discrete choices; at the beginning of each year workers choose between working in one of the productive sectors or engaging in home production. Agents who choose a productive sector receive a wage and accumulate human capital via learning-by-doing. At the end of the period, agents may choose whether to remain in their current labor market, or to migrate to any of the other labor markets.

The model incorporates two frictions to sector switching and one friction to migration. Agents who switch sectors pay a nonpecuniary switching cost and a permanent cost to their human capital stock while agents who migrate pay a nonpecuniary cost. The speed at which agents respond to wage changes, and thus the speed at which factor ratios return to their initial values, will depend largely on the magnitude of these switching costs; if switching costs are large, agents will respond slowly to immigration and thus the effects of immigration on wages will be long-lasting.

Many papers have documented that gross industry and location flows are an order of magnitude larger than net flows. Kambourov and Manovskii (2008), for example, note that roughly 10% of US workers change between 1-digit industries each year, while yearly net mobility is only about 1-3%. To accommodate this feature in my model, I assume agents receive a vector of sector preference shocks and location preference shocks each period. The presence of these shocks implies that gross flows across sectors and locations will exceed net flows.

3.1 Labor Demand

The economy consists of a set of labor markets, $J$, and a set of industries $N$. Each industry in labor market $j$ is populated by many homogeneous firms. The production function for a firm operating in industry $n$ and labor market $j$ in year $t$ is given by:

$$Y_{njt} = A_{njt} K_{njt}^{(1-\alpha_n)} L_{njt}^{\alpha_n}$$  \hspace{1cm} (1)

where $A_{njt}$ is city-industry productivity, $K_{njt}$ is capital, $L_{njt}$ is a CES aggregate combining unskilled and skilled labor, and $\alpha_n$ is a parameter.

The CES aggregator $L_{njt}$ is given by

$$L_{njt} = \left( \theta_{njt} L_{njtS}^\zeta + (1-\theta_{njt}) L_{njtU}^\zeta \right)^{1/\zeta}$$  \hspace{1cm} (2)

Workers of a given skill level can vary in quantity of human capital units they possess based
on their age, immigrant status and work history. $L_{njts}$ and $L_{njtu}$ are measured as the sum of total human capital supplied by skilled and unskilled workers, respectively. I define skilled workers as individuals who have attended some college or more. Agents with no college experience are defined as unskilled. $\theta_{njt}$ is the relative productivity of skilled labor, and $\sigma = \frac{1}{1-\zeta}$ is the elasticity of substitution between skill levels in each sector. Notice that the factor intensity parameters (the $\theta$s) and productivity (the $A$s) are allowed to vary by time, industry, location and city, while the elasticity of substitution is fixed across industries.\(^2\)

The direct effect of immigration on relative wages of skilled and unskilled workers in a given sector will depend on the degree to which immigration changes the ratio of skilled to unskilled workers in a sector and on the elasticity of substitution. If the ratio of unskilled to skilled human capital is higher for immigrants than for natives, immigration will place downward pressure on unskilled wages and upward pressure on skilled wages. A lower elasticity of substitution implies that skilled and unskilled workers are less substitutable in production and thus a change in the factor ratios will have a larger effect on the price ratio.

Differences in factor intensities ($\theta$’s) across sectors play a crucial role in an economy’s adjustment to immigration. When immigrant inflows increase the ratio of unskilled to skilled workers, proportional increases in the size of the industries which intensively use unskilled labor (industries with low $\theta$) allow within-sector factor ratios to return to their initial levels.

Conditional on education, natives and immigrants are assumed to be perfect substitutes in production. I make this assumption for a number of reasons. First, allowing for imperfect substitution between natives and significantly increases the computational burden of estimating the model as it doubles the number of human capital prices that need to estimated. Secondly, the dataset is not large enough to reliably estimate human capital prices for immigrants specific to each city, year, industry and skill level. Finally, the previous literature suggests that, conditional on education, the elasticity of substitution between immigrants and natives at a local labor market level is large: Card (2009) estimates an elasticity of substitution between immigrants and natives of 40 for unskilled workers.\(^3\)

\(^2\)I have experimented with allowing the elasticity of substitution to vary by sector. My identification strategy for the elasticity of substitution relies on using skill biased immigration flows to instrument for changes in the skill ratio. However, immigration inflows into skilled intensive industries are weak instruments because the immigrants and natives in these sectors tend to have similar skill ratios. Therefore I assume only one elasticity of substitution.

\(^3\)Ottaviano and Peri (2012), using national level data from the United States, find an elasticity of substitution of 20. The differences in estimates of this parameter between studies which use local labor market data and national level data can be partially attributed to the fact that immigrants tend to settle in cities and work in sectors in which previous immigrants live and work. Therefore previous immigrants will have a larger exposure to immigrants inflows than native workers. These differences in exposure are not accounted for in studies that use national level data.
Another option is to allow for imperfect substitution between four skill groups: high school dropouts, high school graduates, workers with some college and college graduates. However, Ottaviano and Peri (2012) the elasticity of substitution between high school dropouts and graduates and between agents with some college and college graduates is high. Card and Lemieux (2001) have also suggested a specification which allows for imperfect substitution between workers with different levels of experience. However, ignoring this effect makes little difference in determining the effect of immigration on native wages as immigrants tend to have a similar age distribution as natives (Ottaviano and Peri (2012), Card (2009)).

As the market is perfectly competitive, the firms choose labor quantities such that the marginal productivity of the labor inputs are equal to the human capital prices. Let \( r_{njte} \) represent the price of one unit of human capital supplied by workers of skill group \( e \in \{S,U\} \). Then:

\[
\begin{align*}
    r_{njtS} &= \frac{P_{nt}Y_{njt}^{\alpha_n}}{L_{njt}^{1-\zeta}} \left(1 - \theta_{njt}\right) L_{njt}^{\zeta-1} \\
    r_{njtU} &= \frac{P_{nt}Y_{njt}^{\alpha_n}}{L_{njt}^{1-\zeta}} \left(1 - \theta_{njt}\right) L_{njt}^{\zeta-1}
\end{align*}
\]

where \( P_{nt} \) is price of the output good.\(^4\)

The firm chooses capital such that the marginal revenue product of capital is equal to the rental price of capital. For the baseline simulations, I assume capital to be perfectly mobile and traded at an exogenously set price \( \bar{r}_tK \).\(^5\) Taking the first order condition of the production function with respect to capital and solving for the capital labor ratio yields:

\[
\frac{L_{njt}}{K_{njt}} = \left(\frac{\bar{r}_tK}{P_{nt}A_{njt} (1 - \alpha_n)}\right)^{1/\alpha_n}
\]

which implicitly defines demand for capital \( K_{njt} \) as a function of the labor supply aggregate \( L_{njt} \), the price of capital \( \bar{r}_tK \), the goods price \( P_{nt} \), TFP \( A_{njt} \), and the parameter \( \alpha_n \). Note that the capital labor ratio is only a function of exogenously set prices and parameters and is not a function of capital or labor levels.

Plugging in this formula for the capital labor ratio into the marginal revenue products of labor for each skill group yields:

\(^4\)As I do not have access to goods prices at a local labor market level, I assume that all goods are tradeable across local labor markets and thus prices do not vary across cities \( j \).

\(^5\)I test the robustness of my counterfactuals to this assumption in the counterfactuals section.
\[ r_{njtS} = \tilde{A}_{njt} \ell_{njt}^{1-\zeta} \theta_{njt} \lambda_{njtS}^{\zeta-1} \]
\[ r_{njtU} = \tilde{A}_{njt} \ell_{njt}^{1-\zeta} (1 - \theta_{njt}) \lambda_{njtU}^{\zeta-1} \]

where
\[ \tilde{A}_{njt} = \alpha_n P_{nt} A_{njt} \left( \frac{\bar{r}_{tK}}{P_{nt} A_{njt} (1 - \alpha_n)} \right)^{\alpha_n/(1-\alpha_n)} \]

The expressions in 4 are useful for both simulation and estimation purposes as they do not depend on the quantity of capital, and therefore the econometrician can calculate labor demand and wages without knowledge of the level of physical capital. Therefore, labor demand can be estimated without data on physical capital.

### 3.2 Labor Supply

I model industry choice and location choice as a sequential dynamic discrete choice problem. For tractability, I assume that agents cannot borrow or save, so consumption is equal to wages in each period. Agents are endowed with an initial location, a level of skill \( e \in \{S, U\} \) and an immigrant status \( m \). Workers enter the model upon finishing their schooling or upon immigrating from abroad. I do not model the decision to immigrate from abroad or choice of education level.\(^6\) All agents are assumed to retire at age 65.

At the beginning of each period, agents receive a vector of industry preference shocks and choose between working in one of the productive industries or engaging in home production. Workers who choose a productive sector receive a wage and accumulate human capital. At the end of the period workers receive a vector of location preference shocks and may choose to stay in their current location or to migrate to another labor market.\(^7\)

In what follows, I describe each portion of the labor supply model in chronological order: 3.2.1 describes the flow utility associated with each sector choice, 3.2.2 describes the human capital accumulation process, 3.2.3 describes the flow utility associated with each location choice and 3.2.4 connects the three steps into a dynamic programming problem.

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\(^6\)Modeling the decision to immigrate is difficult for both computational and data reasons. Hunt (2012) finds that natives may increase schooling attainment in response to immigrant inflows.

\(^7\)A flow chart showing the timing of the model is included in the appendix.
3.2.1 Sector Choice Flow Utility

At the beginning of each year, agents can either work in one of the industries in the set \( N \), or engage in home production. Let \( v^\text{Sec}_n(\cdot) \) represent the agent’s sectoral choice flow utility conditional on choosing sector \( n \in \{N \cup \{Home\}\} \). The agent receives utility from goods consumption and amenities. I assume that amenity utility can be represented as the sum of an industry amenity, \( \gamma_{n,e} \), a location amenity \( \gamma_{j,e} \), a switching cost \( \phi_e(n, n_{t-1}) \), and an idiosyncratic preference shock \( \varepsilon_{int} \). We can therefore write the flow utility function as:

\[
v^\text{Sec}_n(\cdot) = \beta^w_{e,m} W_{int} + \gamma_{n,e} + \gamma_{j,e} + \phi^\text{Sec}_e(n, n_{t-1}) + \varepsilon_{int}
\]

\( \beta^w_{e,m} \) is a parameter which measures the weight agents place on consumption relative to the idiosyncratic preference shock, whose variance is normalized across agents. The value of \( \beta^w_{e,m} \) is allowed to vary across skill levels and immigration status, allowing for the possibility that different types of agents vary in their responsiveness of their sector choices to wages. \( \gamma_{n,e} \) and \( \gamma_{j,e} \) allow for the possibility that different sectors and cities differ in the amenity value they provide. For example, workers might find it more difficult to work in manufacturing than in the service sector, or might find it more enjoyable to live in San Francisco than in Cleveland. These amenity terms are allowed to vary by an agent’s skill level.

The agent pays the sector switching cost, \( \phi^\text{Sec}_e(n, n_{t-1}) \), if she chooses an industry that she was not employed in in the previous year. The switching cost captures the idea that workers may pay a utility cost when they have to search for and begin work at a new job. Finally, the preference shock, \( \varepsilon \) allows for idiosyncratic differences in agents’ preferences over sectors and cities. I assume the \( \varepsilon \)'s are jointly distributed extreme value type 1.

Agents wages are given by the product of their human capital and the price of human capital in their sector of choice. Wages for agent \( i \) in sector \( n \) can therefore be written as:

\[
W_{int} = r_{njte} H_{it}
\]

where \( r_{njte} \) is the human capital price that is determined in equilibrium and \( H_{it} \) is individual \( i \)'s human capital level in period \( t \). The process of human capital accumulation is described in the next section.
3.2.2 Human Capital Accumulation

The main dataset I use for wages, the Merged CPS, only includes two observations for each agent. As such, I do not observe the agent’s level of experience in each of the sectors and therefore cannot identify a model with multi-dimensional human capital. Instead, I assume one-dimensional human capital that is imperfectly transferred when an agent switches sectors. Conceptually, each year an agent is engaged in the same sector, their human capital will increase via learning by doing. However, if an agent switches sectors, her human capital will grow at a slower rate or may decrease. These differences in the rate of human capital growth capture the human capital cost to switching sectors.

Formally, let \( h_{it} = \log H_{it} \). When an agent works for the first time, her level of human capital is determined as a linear combination of her characteristics. Additionally, I assume that after an agent chooses their sector, she receives a human capital shock, \( \nu \). I therefore write the initial level of human capital as:

\[
h_{it} = \beta_{n}^{new} X_{it}^{new} + \nu_{int} \tag{6}
\]

where \( n \) is the sector chosen by the agent, \( X_{it}^{new} \) is a vector of the agent’s characteristics, \( \beta_{n}^{new} \) is a vector of parameters, and \( \nu_{int} \) is the human capital shock in chosen sector. The human capital shock is distributed as: \( \nu_{int} \sim N(0, \sigma_{n,e}^{\nu,new}) \). This shock accounts for idiosyncratic differences in human capital and wages that are not accounted for by an agent’s observable characteristics.

After entering the labor market, human capital accumulates as a function of the chosen sector, the sector they have most recently worked in, and the human capital shock of their chosen sector. For an agent most recently employed in sector \( n_L \) who chooses to work in sector \( n \) in the current period, human capital accumulates according to the following autoregressive process:

\[
h_{it} = \delta_{e} h_{it-1} + \alpha_{e,n,n}^{n,n_L} + \beta_{n} X_{it} + \nu_{int} \tag{7}
\]

where \( \nu_{int} \) is the human capital shock in the chosen sector and is distributed as: \( \nu_{int} \sim N(0, \sigma_{n,e}^{\nu}) \). \( \delta_{e} \) measures serial correlation in worker productivity. \( \alpha_{e,n,n_L}^{n,n_L} \) measures both the rate of human capital growth from learning by doing and the degree of transferability of human capital across sectors. Because of learning by doing, we expect \( \alpha \) to be large for agents who remain the same sector \( (n = n_L) \), and we expect it to be smaller for agents who switch sectors because of the human capital costs of switching sectors. \( X_{it} \) is a vector of worker characteristics.
If an agent is engaged in home production, her human capital depreciates according to:

\[ h_{it} = \delta_e^{Home} h_{it-1} \]  

(8)

Although the one dimensional human capital assumption may seem stark, the model is able to replicate many of the wage patterns present in the data. First, as \( \alpha \)'s are allowed to vary by current and previous industry, the model can replicate the average wage losses workers experience when they switch sectors.\(^8\) Second, the model allows for persistent human capital differences that are not explained by observables. As \( \nu \) is modeled as a permanent human capital shock, and not as a transitory wage shock or as measurement error, agents with higher wages in period \( t \) will on average have higher wages in \( t + 1 \), even conditional on all observables and industry choices.

Another potential concern is my assumption that an agent receives the human capital accumulation shock after choosing her sector. Another option would be to assume that agents observe their a vector of human capital shocks before they make their sector choice. Pursuing this approach would greatly increase the difficulty of estimating the model. Under my current assumption that the shocks are received after the sector choice is made there is no selection on unobservables into sectors, so I can estimate human capital prices and human capital accumulation parameters without solving the whole dynamic model. If I assume that human capital shocks are observed before the sector choice is made, I allow for the possibility of selection on unobservables and thus would need to simulate the full dynamic model for each guess of the human capital prices. Given the large number of human capital prices I estimate, estimating the prices in this way would be impossible. Additionally, as the human capital accumulation function accounts for previous sector, education level, immigration status, and lagged human capital, the bias caused by not accounting for selection on unobservables will be relatively small.

3.2.3 Location Choice Flow Utility

After choosing a sector, working, and accumulating human capital, the agent receives a vector of location preference shocks. The agent may then choose to remain in the same labor

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\(^8\)The one dimensional human capital specification will be especially problematic if "return switching" were common—that is, that agents switch into sectors into which they have accumulated. In the extreme case in which there is no return movement, all workers switching into an industry will have exactly 0 industry specific human capital so the one-dimensional human capital assumption in this setting would be innocuous. Using data from the PSID Retrospective Occupation-Industry Supplmental Data Files, Kambourov and Manovskii (2008) find that, after switching from a 1 digit industry, 30% return to the same 1 digit industry within 4 years.
market or to migrate to any other labor market in the set J or to an outside option location. If the agent migrates to another labor market she pays a moving cost. Let \( u_{j'}^{\text{Loc}} \) denote an agent’s location flow utility conditional on choosing location \( j' \). Agents receive utility from preference shocks and also pay a moving cost if they switch locations:

\[
u_{j'}^{\text{Loc}} = \phi_e^{\text{Loc}}(j' \neq j) + \sigma^t i_{ij't}
\]

where \( \phi_e^{\text{Loc}} \) is a moving cost parameter which is paid if their choice of \( j' \) is not equal to their location at the beginning of the period. \( i_{ij't} \) is a location preference shock which is assumed to be distributed extreme value type 1, and \( \sigma^t_e \) is a scale parameter.

### 3.2.4 Dynamic Programming

Worker choices are not only a function of current human capital prices, but also a function of their expectations of future prices. I assume all agents have perfect foresight of the path of future human capital prices but are unable to predict the future values of their preference and human capital shocks.

Let \( V_n \) represent the value function at the beginning of the period conditional on choosing \( n \in \{N \cup \{\text{Home}\}\} \). The state space at the beginning of the period consists of the agent’s observables: age, education, immigrant status, location, sector or home production choice in the previous period, sector most recently employed in, and human capital level; and an unobserved vector of preference shocks \( \epsilon \).\(^9\) Let \( \Omega = (j, t, e, m, age, n_{t-1}, n_L, h_{t-1}) \) denote the subspace of the state space that is observable to the econometrician. The choice specific value function is the sum of expected sectoral choice flow utility, expected location choice flow utility and expectation of the next year’s value function:

\[
V_n(\Omega, \epsilon) = \mathbb{E}_\nu \left[ v_n^{\text{Sec}}(\Omega, \epsilon) + \mathbb{E}_e \left( v_{j'\epsilon}^{\text{Loc}}(\Omega, e) + \beta \mathbb{E}_{\epsilon'} \left[ V(\Omega', \epsilon') | n, j^* \right] \right) \right]
\]

where the first expectation is the over current year’s human capital shock, the second expectation is over location preference shocks, and the final expectation is over next year’s sectoral preference shocks. \( j^* \) is the optimal location choice at the end of the period and is described below.

At the beginning of the period, the agent chooses \( n \) to maximize lifetime utility. We can

\(^{9}\)The sector most recently employed in will differ from the choice in the previous period if the agent was engaged in home production last period. The choice in the previous last period is an argument in the agent’s flow utility function as it dictates when the agent pays sectoral switching costs. The sector most recently employed in is an argument in the human capital accumulation function.
therefore write an agent’s decision, \( n^* \) as:

\[
n^* = \arg\max_{n \in \{N \cup \{\text{Home}\}\}} V_n(\Omega, \varepsilon)
\]

An agent’s value function is the maximum of the choice specific value functions:

\[
V(\Omega, \varepsilon) = V_{n^*}(\Omega, \varepsilon)
\]

At the end of the period, the agent chooses their next location \( j^* \) after receiving the vector of location preference shocks \( \iota \). The state space at the time of location choice consists of the agent’s observables, \( \Omega \), and the vector of location preference shocks, \( \iota \). The agent chooses \( j^* \) by solving the discrete choice problem:

\[
j^* = \arg\max_{j' \in \{J \cup \{\text{Outside}\}\}} u^{L_{ij}}_{j'}(\Omega, \iota) + \beta \mathbb{E}_{\varepsilon'}[V(\Omega', \varepsilon') | n, j']
\]

I estimate \( \mathbb{E}_{\varepsilon'}[V(\Omega', \varepsilon') | n, j' = \text{Outside}] \), the expected value of moving to the outside option, as a flexible function of the state space variables.

### 3.3 Equilibrium

A perfect foresight equilibrium is a set of labor quantities and human capital prices such that: 1) firms choose the optimal quantities of capital and human capital inputs given prices, 2) agents make choices each year to maximize lifetime expected utility, 3) labor supply equals labor demand in each sector, city and year, and 4) agents’ expectations about human capital prices are equal to realized human capital prices. In what follows, I first define the conditions for labor market clearing given a set of expectations on prices. Next I define the fixed point in equilibrium prices and expectations which defines the perfect foresight equilibrium.

#### 3.3.1 Labor Market Clearing

Quantities demanded of labor inputs \( L^D_{njtU} \) and \( L^D_{njtS} \) are implicitly defined as functions of human capital prices by the first order conditions of the firm’s profit function:
To constitute an equilibrium, these labor demand quantities must be consistent with the labor supply quantities determined by the agents’ maximization problem. Let the vector $\tilde{r}$ represent an agent’s expectations of human capital prices in all years and industries. Abusing notation, write $n^*_i$ as agent $i$’s optimal choice in period $t$ given current prices $r_{njte}$ and expectation $\tilde{r}$:

$$n^*_i (r_{njte}, \tilde{r}) = \arg\max_{n \in \{N \cup \{Home\}\}} V_{i,n} (r_{njte}, \tilde{r})$$  \hspace{1cm} (11)

Labor supply is the sum of total human capital provided by agents who optimally choose a sector in each labor market and year:

$$L^S_{njte} (r_{njte}, \tilde{r}) = \sum_{i \in I} \mathbb{I} (n^*_i (r_{njte}, \tilde{r}) = n) \mathbb{I} (j_i = j) \mathbb{I} (e_i = e) H_{it}$$  \hspace{1cm} (12)

Labor market clearing for a given vector of expectations $\tilde{r}$ implies $L^S_{njte} (r_{njte}, \tilde{r}) = L^D_{njte} (r_{njte})$ for all sectors $n$, cities $j$, years $t$ and skill levels $e$.

### 3.3.2 Perfect Foresight Equilibrium

Denote the vector of realized equilibrium prices in all cities, sectors, years and skill levels for a given vector of expectations as $r^* (\tilde{r})$.

Under the perfect foresight assumption, equilibrium prices are equal to expectations of prices. Perfect foresight equilibrium prices $r^{**}$ are therefore a vector of prices such that

$$r^* (r^{**}) = r^{**}$$  \hspace{1cm} (13)

In simulations, I must therefore find the vector of labor quantities and prices such that agents’ expectations of future prices are consistent with realized prices. To find this fixed point, I follow the algorithm described in Lee (2005): I first choose a guess for the vector of expectations of human capital prices. I then calculate realized equilibrium prices and choices in each sector, each year, under the assumption that agents have these expectations of prices. After calculating this equilibrium, I update the expectation guess with the realized prices. I
<table>
<thead>
<tr>
<th>Service</th>
<th>Manufacturing</th>
<th>Professional</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retail Trade</td>
<td>54.1%</td>
<td>Educational</td>
</tr>
<tr>
<td>Construction</td>
<td>19.2%</td>
<td>Other professional</td>
</tr>
<tr>
<td>Transportation</td>
<td>13.8%</td>
<td>Health Services</td>
</tr>
<tr>
<td>Personal Services</td>
<td>7.9%</td>
<td>Business</td>
</tr>
<tr>
<td>Repair Services</td>
<td>3.4%</td>
<td>Public Admin</td>
</tr>
<tr>
<td>Private Household</td>
<td>1.6%</td>
<td>Hospitals</td>
</tr>
</tbody>
</table>

Table 1: This table shows the six largest individual industries which make up the aggregated industries used in structural estimation.

<table>
<thead>
<tr>
<th>(a) Unskilled Workers</th>
<th>(b) Skilled Workers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Service</td>
<td>Manufacturing</td>
</tr>
<tr>
<td>Native</td>
<td>Immigrant</td>
</tr>
</tbody>
</table>

Figure 1: Distribution across industries by education level and immigration status.

then calculate the new equilibrium given the new set of expectations and repeat this process until the realized prices are equal to the prices expectations.

4 Data

The main dataset for my analysis is the Current Population Survey Merged Outgoing Rotation Groups (CPS MORG). I supplement the CPS MORG data with data from the 1979 National Longitudinal Survey of Youth (NLSY79) and the American Community Survey (ACS). Generally speaking, I use the CPS MORG for moments on sector transitions and wages across local labor markets, I use the NLSY79 for moments on long term wage dynamics and I use the ACS for moments on cross city migration flows.

Every household in the CPS is interviewed for four consecutive months, not interviewed for eight months, then interviewed again for four more months. In the fourth and eighth month a household is asked additional questions about weekly earnings and hours worked.
Table 2: Summary statistics across the three industries. Standard deviations are displayed in parenthesis. Log wages are the log of weekly wages in the week of the interview. Agent types gives the percentage of workers in each industry who belong to each immigration status-skill level type.

<table>
<thead>
<tr>
<th></th>
<th>Service mean</th>
<th>Manufacturing mean</th>
<th>Professional mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>38.9</td>
<td>42.2</td>
<td>41.7</td>
</tr>
<tr>
<td></td>
<td>(11.9)</td>
<td>(10.6)</td>
<td>(11.2)</td>
</tr>
<tr>
<td>Log Wage</td>
<td>2.8</td>
<td>3.1</td>
<td>3.2</td>
</tr>
<tr>
<td></td>
<td>(0.6)</td>
<td>(0.6)</td>
<td>(0.6)</td>
</tr>
<tr>
<td>Stay</td>
<td>73.8</td>
<td>75.3</td>
<td>84.1</td>
</tr>
</tbody>
</table>

Agent Types

<table>
<thead>
<tr>
<th></th>
<th>Service</th>
<th>Manufacturing</th>
<th>Professional</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Skill Imm</td>
<td>9.6</td>
<td>10.5</td>
<td>12.1</td>
</tr>
<tr>
<td>High Skill Native</td>
<td>39.8</td>
<td>48.0</td>
<td>65.7</td>
</tr>
<tr>
<td>Low Skill Native</td>
<td>31.7</td>
<td>23.2</td>
<td>16.7</td>
</tr>
<tr>
<td>Low Skill Imm</td>
<td>18.8</td>
<td>18.4</td>
<td>5.5</td>
</tr>
</tbody>
</table>

I therefore use these fourth and eighth month interviews to construct a panel of two yearly wage, employment status and industry observations for each household. In what follows I will refer to the interview in the fourth month as the first interview and the eighth month’s interview as the second interview.

The CPS is a survey of residential locations, not individuals; if an individual moves in the time between his first and second interview, she is not followed to her new location. Instead, the new resident in this location will be interviewed. I use the following algorithm to identify whether an individual in the second interview is the same as the individual interviewed in the first interview. I first match agents based on their household identifier (HHID), individual identifier (LINENO), and household number (HHNUM), a variable that is used to identify situations in which the original tenant is replaced by a new tenant. In the absence of recording errors, these three variables should uniquely identify individuals. However, as Madrian and Lefgren (2000) note, recording errors leading to false positives are common—when a new tenant moves in, she is occasionally assigned the same identifiers as the old tenant. Therefore, I also enforce that two individuals must share the same gender and month of interview and have an age increase of 0 to 2 years between the two interviews in order to be considered the same individual.

Agents who are present in the first interview but are not present for the second interview

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10See Madrian and Lefgren (2000) for a discussion of the pros and cons of various algorithms for matching individuals in the CPS
can help to identify agents who migrate. However, respondents may not appear in the second interview for a number of reasons in addition to migration—for example, they may not be present at home or may have moved to another location within the city. As a result, the number of people who are not present for the second interview is much greater than the amount of migration observed in other datasets. To correct for this, I calculate the 1 year migration rates by age, immigration status, education level and origin using data from the ACS and can calculate an error rate—the probability that an agent is not interviewed but has not migrated to a different city. I assume that the probability of not being present in the second interview despite still living in the labor market is constant across agents conditional on age, immigration status, education level and origin city. Therefore I randomly select and drop from the sample agents based on their group specific error rate.

Wages are calculated as weekly earnings at the current job divided by usual hours worked. Workers who are unemployed or not in the labor force are considered to be engaged in home production. In order to remove workers with implausibly low wages, I drop any workers who report that they are working but report wages below the national minimum wage. I multiply top coded earning and hourly observations by 1.5 and deflate wages using CPI from the BLS.

I use CPS MORG data from 1993-2014, as data on immigration status are not available before 1993. I define the set of cities, $J$, as the 12 Core Based Statistical Areas (CBSAs) with the most observations in the CPS. To make CBSAs comparable over time, I combine any CBSAs that are combined later in the data. This leaves me with 580,069 observations from the CPS MORG, each which consists of two consecutive years of wages and industry choices for agents who do not move.\footnote{This constitutes 35\% of the national sample.}

I aggregate into three industries: manufacturing, service, and professional. Table 1 shows the most common industries within aggregate industries and table 2 shows summary statistics for the three industries. The professional industry employs the most skilled workers, with 77\% of its workers having at least some college education. Next is manufacturing; 58\% of manufacturing workers are defined as skilled. The service industry employs the fewest skilled workers; less than 50\% of its workers have attended college.

\textit{Kambourov and Manovskii (2013)} note that the coding scheme used for the CPS may lead to spurious industry changes. If many of the industry switches I observe in the data are spurious, I will underestimate the costs of switching sectors. To deal with this, I first note that many 3-digit occupations are highly concentrated in a single industry. For example, 97\% of “Textile Operators” are employed in the manufacturing industry and 99\% of “Mail
Carriers for the Postal Service” are employed in the transportation/communications industry. I therefore calculate an agent’s implied industry if she is employed in an occupation in which 70% of more of the agents are employed in the same industry. Then, if an agent reports switching industries, but her implied industry does not change, I replace both of her industry observations with her implied industry. I find that applying this correction decreases the measured level of switching in my data from 14.8% to under 11.7%.

As a test, I apply a similar correction at the 1 digit SIC level. As I am using a more disaggregated definition of industries, for this exercise I assume occupations with over 50% of their agents in the same 1 digit industry are associated with an implied industry. I find that performing this correction decreases the measured level of year to year industry switching from over 18% to 14%. In comparison, Kambourov and Manovskii (2008) find that industry switching at a 1 digit level increased from 7% to 12% from 1968 to 1997.

I use NLSY79 data from 1979 to 2012. Respondents in the NLSY79 were interviewed yearly from 1979 to 1994, and every even numbered year following that. Each interview, they are asked about their current employment status, and the hourly rate of pay and industry of their current job. I use these questions to construct wage and industry variables in each year they are interviewed. The respondent also provides a history of her labor force status for every week since the previous time they were interviewed. I use this information to determine an agent’s labor force status in years in which they are not interviewed. I do not observe wages or industry choices for agents in odd numbered years after 1994. However, as I only use the NLSY79 to measure wage growth for agents who return from unemployment, I can still use agents who are employed in even numbered years but unemployed in odd numbered years to estimate these moments.

I use ACS data downloaded from the Integrated Public Use Microdata Series (IPUMS). From 2005 onwards, the ACS included a respondent’s Public Use Microdata Area (PUMA) of residence one year ago in addition to the current PUMA of residence. I use these data to measure CBSA to CBSA migration flows.

5 Estimation

The set of parameters to be estimated include the labor demand, worker preferences and human capital accumulation parameters. Theoretically, I could estimate all of parameters simultaneously via simulated method of moments. However, this approach is computationally infeasible as I would need to solve for the perfect foresight equilibrium at each guess of the
Instead I pursue a three-step approach which allows me to recover the majority of the parameters without simulating the model. In the first step I estimate the human capital prices and human capital accumulation parameters using individual wage data from the CPS MORG. In the second step, I use the human capital prices I estimated in the first step to estimate the labor demand parameters via two stage least squares. These first two steps allow me to recover all of the labor demand and human capital parameters quickly and without the need to simulate the model. In the third step, I estimate the remaining parameters via simulated method of moments. As I have already estimated the equilibrium human capital prices in the first step, I do not need to solve for the perfect foresight equilibrium at each parameter guess.

In what follows, I discuss each of the three steps in detail and how the parameters are identified. I also discuss in detail an endogeneity issue that arises when identifying labor demand and the instrumental variables I use to deal with this issue.

5.1 Step 1: Human Capital Prices and Human Capital Accumulation

In the first step I estimate the human capital prices and human capital accumulation parameters using data from the CPS MORG.

I obtain the estimating equations for these parameters by plugging human capital prices into the human capital accumulation equations. Let \( w = \log W \). The estimating equation for agents entering the labor market is:

\[
w_{\text{int}} = \log(r_{njte}) + \beta_n^{\text{new}} X_{it}^{\text{new}} + \nu_{\text{int}}
\]

Log wages, \( w_{\text{int}} \), and worker characteristics, \( X_{it}^{\text{new}} \), are observed by the econometrician. Given the assumptions made on the distribution of \( \nu_{\text{int}} \) and the assumption that \( \nu_{\text{int}} \) is realized after agents make their sector decision, \( \nu_{\text{int}} \) is uncorrelated with all the right hand side variables. Therefore, the full set of human capital prices, the parameters \( \beta_n^{\text{new}} \), and the variance of the human capital shock for entrants, \( \sigma_{n,e}^{\nu,\text{new}} \) are identified.

Log wages for agents most recently employed in sector \( n_L \) currently working in \( n \) can be written as:

\[
w_{\text{int}} = \log(r_{njte}) + \delta_e \left( w_{\text{int}_{L}} - \log(r_{nL,jL_{L}}) \right) + \alpha_{e}^{n,nL} + \beta_n X_{it} + \nu_{\text{int}}
\]
As $\nu_{int}$ is uncorrelated with the right hand side variables, the full set of human capital prices are can be identified from data on wages from labor market entrants while the remaining parameters can be identified from wage data on all agents.

Conceptually, human capital prices, $r_{njt}'s$, are identified by the average wages of market entrants and by differences in average wages for all workers across labor markets and across time. Human capital growth terms, $\alpha_{n,nt}^{e,nL}$ are identified by individual level yearly wage growth, conditional on the current sector and the sector worked in the previous period. The serial correlation terms, $\delta_e's$, are identified by differences in wage growth rates conditional on the initial level of human capital. For example, a large depreciation rate implies wages grow quickly for agents with low levels of human capital but slowly for similar agents with high human capital.

I estimate these equations via maximum likelihood using agents entering the market and agents employed two periods consecutively in the CPS MORG. This allows me to estimate all of the human capital prices and all of the human capital accumulation parameters except for the depreciation rates of human capital for unemployed agents, $\delta_{e,home}$.

### 5.2 Step 2: Labor Demand Parameters

Having estimated the human capital prices in the previous step, I now turn to estimating the labor demand parameters. I will start by highlighting an identification issue that results because of the correlation between labor supply and factor intensities. I will then introduce the instrument I use to deal with this identification issue.

From 3, we can write the ratio of log human capital prices as:

$$\log \left( \frac{r_{njtS}}{r_{njtU}} \right) = -\frac{1}{\sigma} \log \left( \frac{L_{njtS}}{L_{njtU}} \right) + \log \left( \frac{\theta_{njt}}{1 - \theta_{njt}} \right)$$

(14)

One problem with estimating equation 14 is that $\log \left( \frac{\theta_{njt}}{1 - \theta_{njt}} \right)$ will be correlated with $\log \left( \frac{L_{njtS}}{L_{njtU}} \right)$: increases in $\theta_{njt}$ will increase wages for skilled workers and thus increase the number of skilled agents. I deal with this issue by introducing a supply shifter—an instrument which affects labor supplies but is assumed to be uncorrelated with unobserved demand parameters.

Differencing and letting $\varphi_j + \varphi_n + \varphi_t + \eta_{njt} = \Delta \log \left( \frac{\theta_{njt}}{1 - \theta_{njt}} \right)$ gives our estimating equation:

$$\Delta \log \left( \frac{r_{njtS}}{r_{njtU}} \right) = -\frac{1}{\sigma} \Delta \log \left( \frac{L_{njtS}}{L_{njtU}} \right) + \varphi_j + \varphi_n + \varphi_t + \eta_{njt}$$

(15)

Even with this decomposition of the factor intensity terms into city, sector and time effect,
endogeneity is still an issue; changes in $\eta_{njt}$ will lead to changes in the labor supply ratio. To deal with this issue, I modify the instrumental variables strategy developed by Card (2009) to predict sector-specific immigrant inflows. Card utilizes the insight that current migrants from a given country tend to settle in similar locations as previous migrants from that country. He therefore uses the lagged geographic distribution of immigrant to predict current inflows of immigrants. I extend the Card instrument by first noting that immigrants from different countries vary considerably in their distributions across industries. Additionally, these differences are persistent over time: figure 2 shows that the industry distribution of new unskilled immigrants from Mexico and China are very persistent between the 1980 census and the 2007 ACS. Therefore to predict the number of immigrants entering a given sector, I can use lagged industry structure in addition to lagged geographic distribution of immigrants.

To motivate the instrument, let $I_{njte}$ denote the total immigrant inflows of skill level $e$ into sector $n$, sector $j$ in year $t$. $I_{njte}$ will be correlated with $\Delta \log \left( \frac{L_{njtS}}{L_{njtU}} \right)$—inflows of skilled immigrants will increase the ratio of total skilled to unskilled workers—but may also be correlated with $\eta_{njt}$—immigrants will to choose to locate in cities and sectors with positive demand shocks. Note that the immigrant inflow into a specific city and sector can be decomposed into the sum of immigrants across origin countries as follows:

$$I_{njte} = \sum_g I^t_{gte} \times \omega^t_{gnje}$$  

where $g$ indexes origin countries of immigrants, $I^t_{gte}$ is total immigrant inflows of skill level $e$ from country $g$ in year $t$ into all labor markets in the United States and $\omega^t_{gnje}$ is the fraction of these total immigrant inflows who choose city $j$ and sector $n$. When the immigrant inflows are decomposed in this manner, there are two reasons why $I_{njte}$ may be correlated with local labor demand shocks $\eta_{njt}$. First, local demand shocks may lead to increases in the total inflow from a given country, $I^t_{gte}$. For example, a positive demand shock in the manufacturing industry in Los Angeles may lead to an increase in the total number of Mexican immigrants coming to the United States. Second, the fraction of immigrants from a given country that come to a given city and sector, $\omega^t_{gnje}$, may also be correlated with local shocks.

To deal with these concerns, I replace total inflows from a given country with total inflows

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12 Lafortune, Tessada et al. (2010) document a similar pattern with occupation choice of immigrants. The authors attribute persistence in occupation choice for immigrants as evidence of the important of migrant networks in finding jobs.

13 The instrument is consistent with the model because I have assumed that immigrants initial location, sector and time of migration are exogenous.
Figure 2: Panels (a) and (b) show the number of recent immigrants from Mexico and China in US cities measured as a fraction of the receiving city’s population. Panels (c) and (d) show the number of recent unskilled immigrants from Mexico and China in sectors measured as a fraction of the receiving sector’s population. Data from the 1980 census and 2007 aggregated ACS.
to every other city in the United States, and I replace current fractions of immigration coming to a city and sector with the lagged fraction. Specifically, I write predicted sector-specific immigration inflows of skill level $e$ into sector $n$, city $j$ as:

$$\tilde{I}_{njte} = \sum_g I_g(-j)te \omega_{gne}^{1980} \omega_{gj}^{1980}$$

where $g$ indexes countries, $\omega_{gne}^{1980}$ is the proportion of total immigrants from country $g$ and skill level $e$ employed in industry $n$ in 1980, $\omega_{gj}^{1980}$ is the proportion of total immigrants from country $g$ living in location $j$ in 1980, and $I_g(-j)te$ is the year $t$ national inflow of immigrants from country $g$ with education $e$ to all locations except for $j$. For example, to predict the number of Mexican immigrants coming to the manufacturing industry in Houston in 2010, I multiply the fraction of Mexicans in 1980 who were employed in manufacturing and the fraction in 1980 who lived in Houston by the total number of Mexicans immigrating to every US city besides Houston in 2010. I then sum over all countries to obtain the total predicted inflow of immigrants.

For these instruments to be valid, it must be that $\text{corr}\left(\tilde{I}_{njte}, \eta_{njt}\right) = 0$. Conceptually, identification relies on the assumption that current total inflows of immigrants to other US cities from a given country are uncorrelated with current local labor market shocks. In the example above, this is equivalent to assuming that the total number of Mexicans coming to all cities besides Los Angeles is driven by a shock in Mexico—a recession in Mexico, for example—and not by a technology shock in Los Angeles.

In practice I find that these instruments perform better in predicting industry specific immigration inflows than the traditional Card instruments, which only interact lagged geographic distribution with current immigrant inflows. My instrument, instead, interacts both lagged geographic distribution and lagged industry distribution with current immigration inflows. As the industry distribution of workers from a given country is persistent over time, including the industry distribution allows me to more accurately predict industry specific immigration inflows. For example, suppose there is a shock in China that leads to an influx of unskilled Chinese immigrants. The traditional Card instrument predicts that San Francisco will see a much larger immigrant inflow than Philadelphia. However, my instrument also predicts that the service industry in San Francisco will see a larger increase in unskilled workers compared to the manufacturing industry in San Francisco because unskilled Chinese immigrants are more likely to be employed in the service sector. Figure 3 displays a scatterplot between actual sector specific inflows and the predicted values from using the either...
Figure 3: Scatterplots of predicted values when using the traditional Card instruments compared to the sector-specific instruments. Each dot represents a city-year-sector combination. The vertical axis is the inflow of immigrants as a proportion of the sector’s population in the data. The horizontal axis is the predicted proportions when using the two instrumental variables strategies.

the Card instrument of the sector-specific instruments and figure 4 displays the density of the residuals from these regressions. We can see that my modified immigrants have more predictive power than the original instruments.

5.3 Step 3: Choice Parameters

Having estimated the human capital accumulation parameters and equilibrium human capital prices, I proceed to estimate the remaining parameters via indirect inference (Gourieroux, Monfort and Renault (1993)). From the three datasets, I choose a set of moments which describe the main patterns of worker sorting and wage growth over cities and time. These data moments are stored in a vector $M^{data}$. Then, for a given guess of choice parameters, $\Lambda$, I simulate the choices and wages of a sample of agents over the sample period and calculate the same moments for the simulated data. These simulated moments are stored in a vector $M^{sim}(\Lambda)$. The ultimate goal is to find the vector of parameters which minimize the distance
between the data moments and the simulated moments. Specifically, the distance between data and simulated moments as a function of a parameter vector is calculated as:

$$\Psi(\Lambda) = (M^{data} - M^{sim}(\Lambda))^\top \Gamma (M^{data} - M^{sim}(\Lambda))$$

where $\Gamma$ is a positive definite matrix. In practice I calculate $\Gamma$ as the diagonal elements of the inverse covariance matrix of $M^{data}$.

One major benefit of the three step estimation approach is that, as I already estimated the equilibrium human capital prices in the previous steps, I do not need to calculate the perfect foresight equilibrium at every guess of the parameter vector. Instead, I only need to simulate worker choices taking the human capital prices as given. This significantly reduces the computational burden of estimating the model.

I include the following moments from the CPS in the distance function to be minimized: 1) average wages by education level, immigrant status, city, year, industry and previous industry; 2) average wages for entrants by education, city, industry and year; and 3) choice probabilities of sector, home production and outmigration by education level, immigrant status, age, city, year and previous industry. From the NLSY79, I include average wage
loss from previous year employed for agents who have been not employed for one or two consecutive years for each skill level. From the ACS, for each skill level I include the number of agents who migrate to each of the $J$ labor markets as a fraction of the total number of agents who migrate.

One main challenge of estimating the choice parameters is separately estimating the sector amenities and switching costs from the value of consumption, $\beta^w$. Separate identification is facilitated by the use of multiple local labor markets in estimation. $\beta^w$ is largely identified by the correlation of average wages and choices across cities and over time. For example, a higher $\beta^w$ implies that if New York has higher relative wage growth in the professional sector compared to Chicago, then people in New York are more likely to switch into the professional industry than people in Chicago. The switching costs are identified by the number of agents who switch sectors each year and the amenity parameters are identified by the number of agents who choose each sector after accounting for switching costs and wage differences across sectors.

A similar argument applies for separate identification of the city level amenities, $\gamma_j$'s, moving cost, $\phi^{Loc}$, and the standard deviation of the location preference shock, $\sigma^i$: $\sigma^i$ is identified by the responsiveness of migration flows to across city wage changes, the $\gamma_j$'s are identified by the location choice probabilities that are not explained by wage differences and $\phi^{Loc}$ is identified by the total amount of migration after accounting for differences in expected utility across locations.

### 5.4 Initial Conditions

As described earlier, I use data from 1994 to construct the simulation sample and use data from 1993 to form the pre-sample period. If an agent is employed in either of these periods, I can infer the agent’s entire state space. However, if an agent is not employed in both of these periods, I cannot infer the agent’s most recent industry or level of human capital.\(^{14}\) I therefore estimate the distribution of initial values using the strategy described in Wooldridge (2005) and employed in Dix-Carneiro (2014). I assume the distribution of last industry for these agents depends on the agent’s education level, immigrant status, age and the distribution across industries of all agents in the agent’s labor market. For a given agent the probability of having $n_L$ as their most recent industry is given by:

\(^{14}\)Agents who are not working in both years constitute 14% of my sample
\[
\Pr (n_L = n | j, m, e, a) = \frac{\pi^1_{n,e,m} + \pi^2\mu_{j,m,e,n} + \pi^3_{n\text{age}}}{\sum_{n' \in N} (\pi^1_{n',e,m} + \pi^2\mu_{j,m,e,n'} + \pi^3_{n'\text{age}})}
\]

(19)

where \(j\) is agent \(i\)’s city, \(m\) is immigrant status, \(e\) is skill level and \(\mu_{j,m,e,n}\) is the proportion of agents in city \(j\) of education \(e\) and immigrant status \(m\) who are employed in sector \(n\).

I model the distribution of lagged human capital as an ordered probit where the latent variable depends on age, last industry, migrant status and education level. I estimate the parameters of both of these probability models jointly with the preference parameters in the final stage of estimation.

### 6 Results

#### 6.1 Labor Demand

Table (3) summarizes the labor demand estimates. The elasticity of substitution between high and low skilled labor is 2.49. I am not aware of any studies that estimate industry specific elasticities of substitution using local labor market variation. Dix-Carneiro (2014) estimates national level sector specific elasticities using data from Brazil and finds elasticities of substitution between 1.1 and 1.6 across industries. Card (2009), using local labor market in the US and a similar instrumental variables strategy as this paper, estimates an elasticity of substitution for a single sector economy as between 2.3 and 4, depending on his specification.

The next rows show the mean and standard deviation of factor intensity of skilled labor (\(\theta s\)) in each industry across all cities and years and figure 5 shows the distributions of the estimated skilled labor intensities in the three industries. The average factor intensity of skilled labor is highest in the professional industry, followed by the manufacturing industry. We can also see that the standard deviations of the three relative productivity parameters are relatively small.

Figure 6 displays isoquants for an arbitrary level of production in the three industries given the average estimated skilled labor intensities. As expected, we can see that the service industry is the most unskilled intensive industry, professional is the most skilled intensive industry, and manufacturing sits between the two.
Table 3: Labor Demand Parameters. The production function is given by:

\[ Y_{njt} = A_{njt} K_{njt}^{\alpha_n} L_{njt}^{\alpha_n} \]

where CES aggregator \( L_{njt} \) is given by:

\[ L_{njt} = \left( \theta_{njt} L_{njtS}^\zeta + (1 - \theta_{njt}) L_{njtU}^\zeta \right)^{1/\zeta}. \]

The standard error of the estimate of the elasticity of substitution is displayed in parentheses and the standard deviation of skilled labor intensity across cities and over time is displayed in parentheses.

<table>
<thead>
<tr>
<th>( \sigma ): Elasticity of Sub.</th>
<th>2.49</th>
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<td></td>
<td>(0.88)</td>
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<table>
<thead>
<tr>
<th>( \theta ): Average Skilled Labor Intensity</th>
<th>Service</th>
<th>Manu.</th>
<th>Professional</th>
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<tr>
<td>0.54</td>
<td>0.64</td>
<td>0.71</td>
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<tr>
<td>(0.033)</td>
<td>(0.050)</td>
<td>(0.028)</td>
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Figure 5: Density of estimated skilled labor intensity in the three industries over time and across cities. The mean and standard deviation of the estimated skilled labor intensities are displayed in Table 3.
Figure 6: Isoquants for an arbitrary level of production for each of the three industries. The isoquants are constructed according to the estimated elasticity of substitution and the average skilled labor intensity in each of the three industries.

6.2 Human Capital Accumulation

Table 4 shows the estimated human capital accumulation parameters. I assume the vector of worker characteristics for market entrants, $X_{new}$, consists of a dummy variable for immigrants. I estimate that unskilled immigrants on average have lower human capital upon market entry compared to unskilled natives and that skilled immigrants on average have similar levels of human capital as skilled natives when they enter the labor market. I assume the vector of worker characteristics for workers already in the market, $X$, consists of the worker’s age and the worker’s age squared. The estimates show that human capital is an increasing, concave function in age.

The $\alpha$ terms measure differences in human capital growth rates across sectoral transitions, after accounting for the growth rate of human capital from age. The human capital parameter estimates show that human capital is imperfectly transferred across sectors. $\alpha$’s for unskilled agents are generally negative for workers who switch sectors and positive when they remain in manufacturing or professional sectors. Agents who switch from the service sector see the largest decrease in human capital while agents who remain in the manufacturing sector or remain in the professional sector have largest increases in human capital.
The patterns for skilled agents are similar. $\alpha$’s for skilled agents who remain in the same sector are positive while those for agents who switch from the service sector to the other two sectors are negative. Somewhat surprisingly, the $\alpha$’s for agents who switch from the professional to the manufacturing sector or from the manufacturing to the professional sector are also positive. Therefore, skilled agents can easily transfer their human capital between these two sectors.

For both unskilled and skilled agents, the variance of human capital shocks is similar across sectors. Labor market entrants have slightly higher variance in their human capital shocks than agents already in the market. The term measuring serial correlation in worker productivity, $\delta$, is less than one for both unskilled and skilled agents, implying that agents with low levels of human capital accumulate human capital faster than agents with high human capital.

### 6.3 Choice Parameters

I set the discount rate, $\beta$, to .95. The parameters estimates are displayed in table (5). I do not report amenity values of the cities ($\gamma_j$s).

We see that immigrants are more responsive to wages than are natives and that skilled natives are much more responsive to wages than unskilled natives. These results of responsiveness to wages are largely consistent with estimates of responsiveness of location choices to wage differentials across locations. Bound and Holzer (2000) find that the location choices of skilled workers are much more responsive to local demand shocks than unskilled workers. Cadena and Kovak (2016) also find that high skilled workers are more responsive to demand shocks in their location choices. They also find that among low skilled workers, Mexican immigrants are substantially more responsive than natives.

One useful way to interpret these parameters is as a partial equilibrium derivative of choice probabilities with respect to wages. To see this, let $\Pi_n(\Omega)$ represent the probability that an agent with observables $\Omega$ chooses industry $n$. Given that the preference shock vector $\varepsilon$ is distributed as extreme value, we can write:

$$\Pi_n(\Omega) = \frac{e^{\tilde{V}_n(\Omega)}}{\sum_{n' \not\in \{N \cup \{Home\}\}} e^{\tilde{V}_{n'}(\Omega)}}$$

where $\tilde{V}_n(\Omega) = V_n(\Omega, \varepsilon) - \varepsilon_{int}$ is the choice specific value function minus the sectoral preference shock. By taking the derivative of $\Pi$ with respect to wages $W_{int}$ and rearranging, we obtain the following expression for $\beta^w$:
Table 4: Human Capital Parameters: Standard errors are calculated as the diagonals of the inverse hessian.
\[ \beta_w^m = \left( \frac{\partial \Pi_n(\Omega)}{\partial W_{int}} \right) \frac{1}{\Pi_n(\Omega) - \Pi_2^2(\Omega)} \]

The term in parenthesis is the partial equilibrium derivative of the choice probability with respect to wages. For example, conditional on working in the manufacturing sector in the previous year, 7% of unskilled workers are employed in the service sector. Therefore, increasing unskilled service wages for one year in one city by 1$ an hour would lead to roughly a 
\[ .08 \times (.07 - .07^2) = .005 \]
increase in the proportion of unskilled natives in that city choosing the service sector and a 
\[ .15 \times (.07 - .07^2) = .01 \]
increase in the proportion of unskilled immigrants, conditional on working in the manufacturing sector last year.\(^{15}\)

The next three parameters display the amenity values of the three sectors. The amenity value for the service sector is largest for unskilled workers while the professional sector has the highest amenity value for skilled workers.

The next two rows show the costs of switching sectors and switching locations. It is important to note that in addition to these switching cost terms, agents who switch sectors or migrate receive a different wage, different amenities and different preference shocks. These switching costs terms should therefore be interpreted as the expected flow utility of a randomly selected agent who is forced to switch sectors or migrate, ignoring amenity and wage differences across sectors and locations. These terms cannot be interpreted as the utility cost of agents conditional on switching; workers will only move or switch sectors if it is beneficial for them to do so.

For unskilled workers, the sector switching cost is 4.27. An unskilled native who was chosen at random and forced to switch sectors would therefore need to see a one year wage increase of $53 dollars an hour, equal to 3 times average wages, in order to be compensated for the switching cost. For skilled natives, the sector switching cost is estimated to be 4.49, equal to roughly a 37$ increase in hourly wages, or a 120% increase in wages.

The migration costs are of a slightly larger magnitude, at 7.58 and 8.08 for unskilled and skilled workers, respectively. This implies that a randomly chosen unskilled native would need to see a one-year wage increase of $94 an hour, 5.5 times the average wage, in order to be compensated for the move. The average skilled native would need to be compensated $67 dollars an hour or 2.2 times the average wage.

The size of these moving costs is consistent with those found in sector choice and migration literature. Dix-Carneiro (2014) finds that the nonpecuniary moving costs of switching sectors range from 1.4 to 10.6 times annual wages, depending on the sectors between which an agent

\(^{15}\)An average unskilled worker in the service sector makes about $17 an hour.
is switching. Kennan and Walker (2011), find that the cost of moving between states for the average unskilled worker is equal to over $300,000 is present value. As with the switching costs estimated in my model, the switching cost terms estimated in both these papers should be interpreted as the expected utility cost of a randomly chosen worker who is forced to move, not as the utility cost of workers who actually choose to move.

6.4 Model Fit

The effects of immigration on wages will depend crucially on the frictions workers face to sector and location switching. If frictions are large, the economy will adjust slowly to immigration and the effect on wages will be long-lasting. To assess the reliability of the switching costs I have estimated, I compare the transition rates across options in the data and the model’s simulation in figure 7. The model does well at replicating the level of persistence in sector choice observed in the data.

Furthermore, the exposure of workers to immigrant inflows will depend on their distribution across industries. Figure 8 shows the distribution of agents across industries conditional on their immigrant status and education level. The model does reasonably well at replicating these moments.

7 The Dynamic Effects of Unskilled Immigration

In this section I use the estimated model to simulate the effects of a unskilled immigration shock. Given the ongoing debate on the effects of immigration on workers in the United States, these counterfactuals are policy relevant. In particular, this model allows me to quantify the effects of immigration on wages in the dynamic setting, something that has been given limited attention by the literature. Additionally, I can use the model to examine the efficacy of various labor market and immigration policies.

For each simulation, I calculate the effect of immigration on average wages by skill level and immigrant status. In addition to wages, immigration can affect agents’ nonpecuniary utility. Specifically, if immigration changes the distribution of workers across sectors or locations, workers will receive different amenity utilities, pay switching costs, and receive different preference shocks. For example, an agent working as in Dallas in the professional sector may switch sectors and move to Providence in response to immigration. Because she has switched sectors and moved, she must pay a switching cost, \( \phi_{\text{Sec}} \), and a moving cost \( \phi_{\text{Loc}} \). Additionally, as she is living in a different city and working in a new sector, she receives
<table>
<thead>
<tr>
<th></th>
<th>Unskilled</th>
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<th>Skilled</th>
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<td></td>
<td>Natives</td>
<td>Imm.</td>
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<tr>
<td>I. Wages</td>
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<tr>
<td>$\beta^w$</td>
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<td>(0.002)</td>
<td>(0.001)</td>
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<td>II. Amenities</td>
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<tr>
<td>$\gamma_{Serv}$</td>
<td>-0.29</td>
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<td></td>
<td>(0.002)</td>
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<td>$\gamma_{Man}$</td>
<td>-0.74</td>
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<td>$\gamma_{Pro}$</td>
<td>-0.35</td>
<td>-0.79</td>
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<td>III. Switching Costs</td>
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<tr>
<td>$\phi_{Sec}$</td>
<td>-4.27</td>
<td>-4.49</td>
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<td></td>
<td>(0.032)</td>
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<tr>
<td>$\phi_{Loc}$</td>
<td>-7.58</td>
<td>-8.08</td>
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<td>(0.064)</td>
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<td>IV. Location Shock</td>
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<tr>
<td>$\sigma^Move$</td>
<td>0.96</td>
<td>1.19</td>
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<td>(0.002)</td>
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Table 5: Choice Parameters: Standard errors are calculated by a bootstrapping procedure in which I re-sample the preference and human capital shocks at each draw. The sectoral choice flow utility is given by: $v_{n}^{Sec} (\cdot) = \beta^w_{e,m} W_{int} + \gamma_{n,e} + \gamma_{j,e} + \phi_{e}^{Sec} (n, n_{t-1}) + \varepsilon_{int}$

The location choice flow utility is given by: $v_{j'}^{Loc} = \phi_{e}^{Loc} (j, j') + \sigma^t_{ij't}$
Figure 7: Model Fit: Transition Rates. Each graph shows the proportion of workers choosing each industry conditional on their previous industry. The light blue bars show the proportion in the data while the red bars show the proportion in the simulation.
Figure 8: Model Fit: Choice Probabilities. Each graph shows the proportion of workers choosing each industry conditional on their education level and immigration status. The light blue bars show the proportion in the data while the red bars show the proportion in the simulation.
a different set of amenities, $\gamma_{n,e}$ and $\gamma_{j,e}$. Finally she will receive different idiosyncratic preference shocks, $\varepsilon_{idt}$ and $\iota_{ijt}$. To capture these effects, I calculate each agent’s **non-wage utility** as the sum of the flow amenity utility, switching costs and idiosyncratic preference shock:

$$\tilde{u}_n(\cdot) = \frac{1}{\beta_{w,m}} \left( \upsilon_{n}^{Sec}(\cdot) + \upsilon_{j}^{Loc}(\cdot) - \beta_{w,m} W_{int} \right)$$

The non-wage utility is multiplied by the $\frac{1}{\beta_{w,m}}$ so that it can be interpreted as a change in utility measured in dollar equivalents. That is, workers would be indifferent between increasing their non-wage utility by some amount $X$ and by increasing their wages by $X$ dollars. For all wage and utility calculations, I only include previous immigrants in the calculations and do not include immigrants who entered as part of the counterfactual inflow. Thus the effects on wages and utility do not include the composition effect of unskilled immigrants forming a larger share of the population.

In the baseline calculations, I assume that capital is supplied perfectly elastically and is perfectly mobile across industries and cities. I show that the counterfactual results are robust to more restrictive assumptions on capital mobility in section 7.4. In all specifications in which I increase the number of immigrants I assume that new immigrants share the same state space as recent immigrants at the time of immigration.

### 7.1 Sudden Immigrant Inflow

In this section I simulate an immigration inflow which increases the immigrant share as a fraction of total unskilled workers by 10%. Choosing an immigration inflow of this magnitude is appealing for a number of reasons. First, I can easily compare my results with those found in a large “reduced form” literature on the wage affects of immigration.\(^{16}\) Second, the simulated inflow is of similar magnitude to the 14.4 million applicants for the United States Diversity Immigrant Visa in 2015.\(^{17}\)

First I examine the effects on wages and non-wage utility across all cities and industries. Figure 9 shows the average wage change by education level and immigration status. The immigration shock leads to an initial wage decrease for unskilled workers and increase for

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\(^{16}\)Card (2001) notes that “Typically, a 10-percentage point increase in the fraction of immigrants... is estimated to reduce native wages by no more than 1 percentage point.” while Friedberg and Hunt (1995) write that “Most empirical analysis of the United States and other countries finds that a 10 percent increase in the fraction of immigrants in the population reduces natives wages by at most 1 percent.”

\(^{17}\)The Diversity Immigrant Visa program gives out 50,000 green cards each year. Applicants must have at least a high school education and must be born in a country that has sent less than 50,000 immigrants to the United States in the last five years. Visa recipients are determined via lottery.
skilled workers. Immediately following the shock, unskilled native wages decrease by 2.5%, unskilled immigrant wages decrease by 4.0% while skilled native wages increase by 1.0% and skilled immigrant wages increase by 1.6%. Wages gradually converge to their baseline trajectory over the sample period. By the end of the sample period, the wage effects are less than half the size as immediately after the shock.

One interesting result is that the wage effects for previous immigrants are considerably larger than those for natives. Ottaviano and Peri (2012) come to a similar conclusion in their estimation of a national level production function. In their model, the differential effects of immigrant inflows on natives versus previous immigrants arise because they allow for natives and immigrants to be imperfect substitutes in production. In this model I assumed that natives and immigrants of the same skill level are perfect substitutes in production but assume multiple industries and local labor markets. Previous immigrants experience a larger wage cut because they are more heavily concentrated in local labor markets which receive large immigrant inflows.

Figure 10 shows the change in non-wage utility. The effects are remarkably small, despite the estimated large switching costs parameters. The presence of the idiosyncratic preference
shocks for sector switching and migration imply that some agents are close to the margin between two sectors or locations each period and therefore can switch sectors or migrate relatively painlessly. Given the small effect on non-wage utility, I focus on the effects of immigration on wages for the remainder of the section.

Next I explore heterogeneity in the wage effects felt by unskilled workers. Figure 12 shows the average wage change for unskilled workers by their sector in the year prior to the immigrant shock. Skilled intensive sectors, which unskilled immigrants are least likely to be employed in, experience the largest wage drop. To explain this result, from equation 4, first note that the derivative of log equilibrium unskilled human capital prices with respect to log unskilled labor when capital can adjust fully is:

$$\frac{\partial \ln r_{njtU}}{\partial \ln L_{njtU}} = -\frac{1}{\sigma} \left[ \frac{\theta_{njt}L_{njtS}}{\theta_{njt}L_{njtS} + (1 - \theta_{njt}) L_{njtU}} \right]$$

The term in brackets is the share of total labor income that is paid to skilled labor.\(^{18}\) There-

\(^{18}\)In the data, the income share of skilled labor in the professional, manufacturing and service sectors is .85, .70 and .55, respectively.
Figure 11: Sudden Immigration: Change in unskilled human capital prices. This figure shows the effect of immigration on human capital prices. The results are displayed in percent differences from the baseline simulation.

Therefore, for a given change in $\ln L_{njtU}$, sectors in which skilled labor has the largest income share will see the largest decrease in log human capital prices.\(^{19}\) As the distribution of new unskilled immigrants across sectors is not drastically different than that of all unskilled workers, the change $\ln L_{njtU}$ is similar across sectors and skilled intensive sectors experience the largest drops in log human capital prices. To illustrate this, figure 11 displays changes in unskilled human capital prices across sectors. We can see that the decrease in human capital prices is smallest for the service sector.

Figure 13 shows the effects on unskilled wages across local labor markets. The 12 local labor markets are listed across the horizontal axis and are ordered by the size of their immigrant inflow as a fraction of their unskilled population. The solid dots show the percent change in wages for unskilled workers in the year of the immigration inflow while the hollow dots show the effect on wages 20 years later. Intuitively, workers who work in cities which receive large inflows experience the largest wage decreases, both at the time of the inflow and

\(^{19}\)This is essentially a special case of the Hicks-Marshall formula. While the Hicks-Marshall laws of demand show that the labor demand elasticity for a given input in a CES production function with respect to its wage is increasing in its income share, the formula here shows that the elasticity of equilibrium wages with respect to input quantity is increasing in the income share of that input.
Figure 12: Sudden Immigration: Change in average wages of unskilled workers by original sector. This figure shows effect of immigration on wages. The results are displayed in percent differences from the baseline simulation.

20 years later. Miami Los Angeles and New York, with immigrant inflows over 9% percent of their population, see their unskilled wages decrease by over 3.9%, while Minneapolis, Detroit and Philadelphia, with immigrant inflows less than 3% of their population, experience unskilled wage decreases less than 1.2%. 20 years later, the differences are smaller, but still present. Miami, Los Angeles and New York still have 2% lower wages than in the case in which the immigrant inflow did not occur while Minneapolis, Detroit and Philadelphia still have less than a 1% decrease in unskilled wages.

To better understand how workers are responding to immigrant inflows, I next examine how the distributions of workers across industries and labor markets change over time. Figures 14 and 15 shows the change in distribution of skilled and unskilled workers across industries. Immediately after the immigrant inflow, the proportion the skilled workers in the unskilled intensive service industry increases by .2% while the proportion in the skilled intensive professional decreases by .4%. Consistent with the Rybczynski theorem, over time skilled workers continue to switch out of the skilled intensive sector and into the unskilled intensive sector.

Figure 15 shows that, as the immigrant share of unskilled workers increases and immi-
Figure 13: Sudden Immigration: Change in average wages of unskilled workers by city. The cities are arranged on the horizontal axis by the number of immigrants they receive as a fraction of their unskilled population. This figure shows effect of immigration on wages. The results are displayed in percent differences from the baseline simulation.

Figure 14: Sudden Immigration: Change in skilled industry distribution. This figure shows the change in the distribution of workers across industries in response to a sudden unskilled immigration. The results are displayed in percent differences from the baseline simulation.
Figure 15: Sudden Immigration: Unskilled Industry Distribution. This figure shows the change in the distribution of unskilled workers across industries in response to the unskilled immigration shock.

...immigrants are more likely to be employed in unskilled intensive industries, the proportion of total unskilled workers in the service sector increases and the proportion in the professional sector drops. These changes in the distribution of unskilled workers remain relatively constant over the 20-year period considered.

Figures 16 shows the distribution of unskilled and skilled workers across cities immediately after the immigration shock and 20 years after the shock. The left panel shows the change in the distribution of unskilled workers. Again, cities on the horizontal axis are ordered by the size of the immigrant inflow as a fraction of their unskilled population. As a result of the immigration inflow, all cities experience an increase in their unskilled population. The two most heavily affected cities, Miami and Los Angeles, both experience over a 20% increase in the size of their unskilled immigrant population. 20 years later, the change in unskilled population in cities which received large immigrant inflows has decreased by roughly half as unskilled workers migrate away from these cities.

The right panel of 16 shows the distribution of skilled immigrants across cities over time. The immigration shock increases the proportion of skilled workers in cities which receive the most immigrants. However, the magnitude is quite small—20 years after the shock, the skilled
Figure 16: Sudden Immigration: Distribution of unskilled and skilled workers by city. The cities are arranged on the horizontal axis by the number of immigrants they receive as a fraction of their unskilled population. The left panel shows the change in unskilled workers while the right panel shows the change in skilled workers. The results are displayed in percent differences from the baseline simulation.

worker population in the most affected cities has increased by less than .5%.

7.2 Decomposition of Adjustments

In the baseline model simulated in the previous section, which allow for workers to respond to immigrant inflows via migration and industry switching, the sudden immigrant inflow led to a 2.5% decrease in average wages for unskilled natives and .9% decrease 22 years after the shock. To better understand how worker migration and sector switching can mitigate the effect of immigration on wages, I simulate the sudden immigration inflow under three additional different model specifications. In the first alternative specification workers cannot migrate, in the second specification workers cannot adjust their sector choices to the immigrant shock and in the third specification agents cannot migrate or adjust their sector choices. The effect of the immigrant inflow on unskilled native wages in the full adjustment environment and in these three alternative environments are displayed in figure 17.

In the first specification, I turn off the migration response by setting the moving cost, $\phi^{Loc}$, to negative infinity. In this environment, workers can only adjust to migration inflows through their industry choices. In particular, if workers switch into industries which more intensively use unskilled workers, within industry factor ratios will approach their initial values and the
effect of immigration on unskilled wages will decrease. Because workers cannot respond to
immigrant inflows via migration, the effects of immigration on unskilled wages are longer-
lasting than in the baseline case: 22 years after the shock, unskilled native wages are 1.4%
below the case without the immigration shock, compared to .9% lower in the case with both
migration and industry choice adjustments.

In the next specification, I turn off the sector choice response to immigration by assuming
that agents make their sector choice without taking into account the effect of the immigrant
shock on wages. Specifically, I assume that when agents make their sector choices, their flow
utility from sector choices is given by:

\[ \tilde{\nu}_n^{\text{Sec}}(\cdot) = \beta w_{e,m} \tilde{W}_{\text{int}} + \gamma_{n,e} + \gamma_{j,e} + \phi_e^{\text{Sec}}(n, n_{t-1}) + \varepsilon_{\text{int}} \]

where

\[ \tilde{W}_{\text{int}} = r_{njte}^{\text{base}} H_{it} \]

and \( r_{njte}^{\text{base}} \) is the human capital price in the baseline case when there is no immigration shock.

Intuitively, under these assumptions workers make their sector choices as if human capital
prices had not been affected by the immigration shock.

Compared to the full adjustment case, the immigration shock in this specification leads
to both a larger short run and long run effect on unskilled native wages. In the year of the
shock, unskilled native wages decrease by 2.9%, compared to 2.5% in the full adjustment
case. Twenty years after the shock, unskilled native wages are 1.4% lower, compared to .9%
lower in the full adjustment case.

Finally, I turn off both the migration and industry switching adjustments by setting
the moving cost to negative infinity and assuming that agents make their sector choices as
described in the previous environment. In this environment, workers cannot change their
industry or migration decisions in response to immigrant inflows. However, as agents retire
and new workers enter the market, the effect of immigration on wages will shrink. In this
case, the effects of immigration on wages are considerably larger and longer-lasting than in
the full adjustment case: the immigrant shock leads to a 2.9% decrease in unskilled native
wages immediately after the shock, and a 1.9% decrease in wages 22 years after the shock.

These counterfactuals show that both migration and industry switching play important
roles in mitigating the effects of immigration on wages. If agents both cannot migrate and
cannot respond to the inflow with their sector choices, the long run effects of immigration
on wages are over twice as large as in the case when agents can respond. In the two cases in
which workers either cannot migrate or cannot switch sectors in response to the immigrant
shock, the long run effects of immigration on wages are 1.5 times as large as in the baseline case. Therefore we can conclude that both margins of adjustments are equally important in mitigating the long run effect of immigration on wages.

7.3 Gradual Inflow

In this section I simulate an immigrant inflow of the same magnitude as the previous counterfactual in which the inflow is smoothed over a 10 year period. In each of the 10 years, the immigrant inflow is equal to 1% of the original unskilled population—similar in magnitude to the roughly 1.5 million immigrants the United States receives each year. Intuitively, this will be less costly to unskilled workers as the economy can adjust simultaneously to the immigrant inflows. The results are displayed in figures 18 through 22.

Figure 19 compares the effects on unskilled wages of the sudden and the gradual inflows. The wage effects of the gradual immigration are considerably smaller than in the case of the sudden immigrant inflow. For the 10 years of immigration, wages for both unskilled natives and immigrants gradually decrease. By the tenth and final year of the immigration inflow, wages for unskilled immigrants are nearly 3% below their baseline level while wages
Figure 18: Gradual Immigration: Average wages. This figure shows effect of one year of immigration on wages. The results are displayed in percent differences from the baseline simulation.

for unskilled natives are 2% below their baseline level. Over the remaining 10 years, the economy recovers slightly. Also, as in the first counterfactual, the effects of immigration on non-wage utility are small.

Why are the wage effects of a gradual immigrant inflow so small compared to the sudden inflow? A sudden immigration inflow changes factor ratios and thus leads to wage decreases for unskilled workers. As workers migrate and switch sectors, the factor ratios gradually approach their baseline levels, which causes wages to approach their initial values. However, in the case of the smooth immigration inflow, as there is no large immigration shock in the first year, factor ratios do not dramatically change. As more immigrants enter the country over the following years, workers adjust to the immigration concurrently, and therefore do not allow factor ratios to be dramatically affected by the immigration.

Figures 21 and 22 show how the distributions of workers across sectors change over time. In the long run, the economy responds by decreasing the size of skilled intensive professional industry and increasing the size of the unskilled intensive service industry. However, compared to the sudden inflow counterfactual, the change in industry distribution happens more gradually.
Figure 19: Sudden vs. Gradual Immigration: Average wages. This figure shows effect of both a gradual and sudden immigrant inflow on unskilled wages. The results are displayed in percent differences from the baseline simulation.

Figure 20: Gradual Immigration: Average Non-Wage Utility. This figure shows effect of a gradual immigrant inflow on non-wage utility. Non-wage utility are measure in dollar equivalent as detailed in the section.
Figure 21: Gradual Immigration: Skilled Industry Distribution. This figure shows the change in the distribution of workers across industries in response one year of unskilled immigration. The results are displayed in percent differences from the baseline simulation.

Figure 22: Gradual Immigration: Unskilled Industry Distribution. This figure shows the change in the distribution of unskilled workers across industries in response to the immigration shock.
7.4 Imperfect Capital Mobility

In this section, I repeat the two previous counterfactuals under the assumption that the amount of physical capital in each sector can only increase by a maximum of 5% each year.\(^20\)

From section 3.1, we know that the firms optimal choice of physical capital when the capital building constraint is not binding is given by the equation:

\[
\frac{L_{njt}}{K_{njt}^{eff}} = \left( \frac{\tilde{r}_t K}{P_{nt} A_{njt} (1 - \alpha_n)} \right)^{1/\alpha_n}
\]

In the case in which capital is not perfectly mobile, the amount of capital is not necessarily equal to this efficient level of physical capital. Specifically, the amount of physical capital is given by:

\[
K_{njt} = \begin{cases} 
K_{njt}^{eff}, & \text{if } K_{njt}^{eff} \leq 1.05 K_{njt-1} \\
1.05 K_{njt-1}, & \text{if } K_{njt}^{eff} > 1.05 K_{njt-1}
\end{cases}
\]

As the capital labor ratio is not necessarily at its optimal level in which the capital labor ratio is strictly a function of exogenous prices and parameters, I need to make a few additional assumptions and calibrations. First, I assume the price of capital, $\tilde{r}_t K$, is fixed over time and normalize units of capital such that $\tilde{r}_t K = (1 - \alpha_n)$. Then we can rewrite the unconstrained optimal level of capital as: $K_{njt}^{eff} = (P_{nt} A_{njt})^{1/\alpha_n} L_{njt}$. I can estimate the $\zeta$s and $\theta$s as I estimated the parameters under the assumption of fully mobile capital and I calibrate $\alpha_n = .66$ for all sectors. I assume that capital is efficiently distributed in the data and can therefore solve for the product of the goods price and total factor productivity as: $P_{nt} A_{njt} = \left( \frac{\tilde{A}_{njt}}{\alpha_n} \right)^{\alpha_n}$. In simulations, I first then check if $K_{njt}^{eff} \leq K_{njt-1} \times 1.05$. If the inequality holds, then I set $K_{njt} = K_{njt}^{eff}$. If the inequality does not hold, then $K_{njt} = 1.05 \times K_{njt-1}$.

The wage changes as a result of a sudden immigration with imperfectly capital mobility are shown in figure 23. The short run wage of effects of the immigration are larger than under the assumption of perfectly mobile capital. Unskilled immigrant wages decrease by nearly 5% while unskilled native wages decrease by over 3%. While skilled workers experienced wage increases under the assumption of perfectly mobile capital, in this simulation both skilled natives and immigrants experience slight wage drops immediately after the immigration. By the end of the sample period, the effects on wages are similar to those under the assumption

\(^{20}\)I have simulated counterfactuals in which capital can adjust by 10% each period. However, the capital mobility constraint is not binding in any period and thus the results are exactly the same as in the counterfactual in which capital is perfectly mobile.
of perfectly mobile capital. The wage effects of a smooth immigration are not shown as they are exactly the same as in the case of perfectly mobile capital.

The results in this section show that the quantitative results of a sudden immigration are somewhat sensitive to assumptions on capital mobility. However, two of my main qualitative results—that the short run wage effects of immigration exceed the long run effects and that the wage effects of a smooth inflow are smaller than that of a sudden inflow—are even more pronounced under the assumption of imperfect capital mobility.

7.5 A Paid Visa Program

In this section I propose a simple visa program which allows in a large inflow of unskilled immigrants. However, unlike the previous counterfactuals, I show that the program can lead to income gains for unskilled natives. Immigrants admitted under the program pay an annual fee for each year they remain in the US and the revenue raised is transferred to unskilled natives.

Over a ten year period, the program allows unskilled immigrants equal to 1% of the total
unskilled worker population into the United States each year—the same inflow of immigrants as considered in the gradual inflow counterfactual. Immigrants admitted under the program pay 15% of their income each year they are in the United States. The revenue raised in the program is divided evenly between unskilled natives who work in the same city as the visa recipients.

The effect of immigration on average income under the visa program are shown in figure 24. The effects on average income for all groups are similar to the case without the visa program, except that unskilled natives experience a slight increase in their income as a result of the immigrant inflow. The income they receive from the transfer compensates them for the wage loss that results from the immigrant inflow.

These results show that the simple visa program would benefit both skilled and unskilled natives. But how large would the gain be for immigrants admitted under the program? The wage gain would likely be massive: Clemens, Montenegro and Pritchett (2008), for example, find that a Mexican immigrant in the United States earns 2.5 times higher wages than similar Mexican workers working in Mexico. The utility gains, however, are more difficult to quantify. A series of studies have highlighted the importance of a home premium in explaining migration flows—large proportions of workers in relatively low productivity areas may choose...
not to migrate to high productivity areas because they receive utility from remaining their home location.\textsuperscript{21} As such, the utility gains of moving to the US are likely to be smaller than the wage gains.

8 Discussion and Conclusion

Proposals for more lenient immigration policies in the United States are generally met with claims that immigration will hurt American workers. However, economists have generally found that immigration leads to minimal effects on natives wages and unemployment levels.

To better understand the costs workers face and analyze immigration-induced transitional dynamics, I have presented a dynamic equilibrium model of wage determination, sector choice and migration. I estimated the model using three datasets by leveraging differences in wages and labor supply quantities across local labor markets to identify the key parameters of the model. I then used the estimated model to simulate a large unskilled immigrant inflow.

My results highlight the importance of accounting for dynamic adjustment mechanisms when modeling the effects of immigration on an economy. I find that workers respond to immigrant inflows by both switching sectors and by migrating across cities. As a result of these dynamic adjustments the effects of immigration on wages decrease over time—I find that the effects of immigration on wages immediately after an immigration inflow are more than twice as large as the effects 20 years after the inflow.

Furthermore, my results shed light on how immigration policy should be conducted in a dynamic setting. I show that, holding the magnitude and skill mix of immigrants constant, a policy maker can drastically reduce the negative effects of immigration by allowing immigrants to enter the country gradually. As immigrants gradually enter an economy, simultaneous migration and sector switching allow within sector factor ratios to remain relatively stable and thus prevent large effects on wages.

Finally, I’ve shown that under a paid visa program a large influx of unskilled immigrants can lead to income gain for both skilled and unskilled natives. Immigrants admitted under the program pay 15\% of their income each year they remain in the country and the revenue from the program is transferred to unskilled natives. This result shows that, with carefully designed policy, the United States can dramatically increase the number of immigrants admitted each year without depressing wages of native workers.

This paper has made several key simplifying assumptions due to data limitations. Because

\textsuperscript{21} Diamond (2016), Kennan (2013) or Kennan and Walker (2011), for example.
I do not use data on local goods prices, I have assumed that all goods are tradeable and therefore that the price of the output good is not effected by changes in local output quantity. Assuming that some industries produce non-tradeable goods that must be consumed locally would limit the extent to which changes in the distribution of agents across industries could mitigate the effect of immigration on wages. Also, I have abstracted away from the role of sector-specific experience in determining wages. As such, I am not able to explain much of the heterogeneity in wage costs to sector switching. For example, in a model with sector-specific experience, older workers will generally face larger costs to switching sectors because they have more sector-specific experience in their original sector.

Finally, this paper has focused on the industry choice and migration margins. Peri and Sparber (2009), Foged and Peri (2016) and Llull (2016), among others, have shown that workers may switch occupations in response to immigrant inflows. It would be interesting extend the model here to incorporate dynamic occupation choice.
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Figure 25: Anticipated Immigration: Average wages. This figure shows effect of an anticipated immigration inflow on wages. The results are displayed in percent differences from the baseline simulation.

Appendix

Counterfactual: The Importance of Expectations

In this section I evaluate the role of expectation by considering an environment in which workers anticipate the change in immigration flows. Specifically, I assume that two years before the immigration change, workers are informed of the policy change and allowed to respond accordingly.

The results for average wages are displayed in figure 25. We can see that the immigration inflow leads to similar wage effects as in the case in which the inflow is not anticipated.

IV Regressions

In this section, I provide motivating evidence on natives’ responses to immigrant inflows. Specifically I analyze how the distribution of natives across industries changes in response to low skilled immigrant inflows. Let $j$ index MSAs, $n$ index industries and $t$ index 4-year
periods. I estimate the following equation for each industry:

$$\Delta \left( \frac{Natives^n_i}{Natives_j} \right)_{t,t-1} = \beta NewHSImmig^j_t + \Delta \gamma_{t,t-1} + \Delta \epsilon^j_{t,t-1}$$ (20)

where $\frac{Natives^n_i}{Natives_j}$ is the proportion of total natives in city $j$ who are employed in industry $n$ and $NewHSImmig^j$ is the total amount of low skilled new immigrants in city $j$ measured as a fraction of total population of $j$. I estimate equation 20 separately for skilled and unskilled natives, and for ten mutually exclusive industries: 1) Construction, 2) Personal Services 3) Retail Trade 4) Manufacturing 5) Wholesale Trade 6) Utilities (Transportation/Communications/Sanitary), 7) Health 8) Business/Professional 9) Public Administration and 10) Education. This set of industries correspond with the SIC 1 digit industry codes except for the following two differences: first, I do not include agriculture and mining, as I am using data from metropolitan areas. Second, the SIC industry “Services” includes industry ranging from the very low skilled intensive “Personal Household Services” to the very high skilled “Legal Services”. Therefore, I disaggregate into “Low Skilled Services”, “Health”, “education” and “Business/Professional” which also includes the SIC code “Finance, Insurance, And Real Estate”.

We might be concerned that immigrants are migrating into labor markets in response to local labor market conditions which may also affect native choices. To deal with this endogeneity concern, I instrument for number of immigrants using an “ethnic enclave” instrument as in Card (2001). Card notes that the distribution of immigrants from a given country across US cities is persistent over time. The researcher can therefore use the lagged geographic distribution of immigrants to predict the geographic distribution of current immigrants. Specifically, one can write predicted inflow of immigrants of education level $e$ into city $j$ as:

$$\tilde{I}_{jte} = \sum_g \omega_{gj}^{1980} I_{g(-j)te}$$ (21)

where $g$ indexes countries, $\omega_{gj}^{1980}$ is the proportion of total immigrants from country $g$ living in location $j$ in 1980, and $I_{g(-j)te}$ is the year $t$ national inflow of immigrants from country $g$ with education $e$ to all locations except for $j$.

The coefficient estimates of $\beta$ and standard errors for each industry are displayed in figure 26. The three industries are sorted by their level skill ratio along the horizontal axis. The first figure shows the results for all natives, regardless of their education levels.

These results suggest that unskilled immigrant inflows lead to changes in natives’ distri-
bution across sectors and can be rationalized by a Heckscher-Ohlin model in which skilled and unskilled labor are complementary in production (Rybczynski (1955)). If local labor markets are small open economies, an increase in the endowment of unskilled labor via immigration will lead to a contraction of skilled intensive industries and an expansion of unskilled intensive industries. Additionally, the factor price equalization theorem implies that the ratio of low skilled to high skilled workers in each industry will be unchanged in the new long-run equilibrium. Therefore, the theory implies that both skilled and unskilled natives will move from skilled intensive to unskilled intensive industries in response to an increase in low skilled workers.

Lewis (2003) analyzes the extent to which product mix and employment change in response to immigrant inflows. However, my analysis here differs from his in two important ways. First, as I am using the CPS, I can observe at changes in immigration and sector distribution over a much shorter time span than the census. My results here suggest that the industry switching patterns observed across censuses occur on a much shorter time span as well. Second, I run the regression for natives exclusively and separately for each industry while Lewis (2003) aggregates immigrant and native employment levels and analyzes the effect of immigration on the weighted sum of within sector employment levels. In this framework, it is not clear whether or not immigrant inflows lead to industry switching, as the changes in employment could simply by driven by the industry choices of new immigrants.

Calculating Expectation of Non-wage Utility

Non-wage utility is defined as follows:

\[ \tilde{u}_n(\cdot) = \frac{1}{\beta^w_{e,m}} \left( v^\text{Sec}_n(\cdot) + v^\text{Loc}_j(\cdot) - \beta^w_{e,m} W^\text{int} \right) \]

In this section, I describe how I calculate \( E \left[ v^\text{Sec}_n(\cdot) - \beta^w_{e,m} W^\text{int} \right] \). A similar argument applies for calculating \( E \left[ v^\text{Loc}_n(\cdot) \right] \).

Given that agents in the model choose \( n \) as the choice which maximizes lifetime utility, we can write:

\[ E \left[ v^\text{Sec}_n(\cdot) - \beta^w_{e,m} W^\text{int} \right] = \sum_{n' \in N} \Pr(n^* = n') E \left( v^\text{Sec}_{n'}(\cdot) - \beta^w_{e,m} W^\text{int} | n^* = n' \right) \]
Figure 26: Coefficient estimates and 95% confidence intervals for instrumental variables estimation of equation 20. The industries are sorted along the x-axis based on the proportion of workers in each sector with at least some college education. Standard errors are clustered by state.
From the extreme value assumption of $\varepsilon$, we can also write:

$$\mathbb{E} [V_n (\cdot)] = \sum_{n' \in \mathbb{N}} Pr(n^* = n') \mathbb{E} (V_{n'} (\cdot) | n^* = n') = \log \left( \sum e^{V_{n'} (\cdot)} \right)$$

Combining these two equations:

$$\mathbb{E} \left[ v_n^{Sec} (\cdot) - \beta_{e,m} W_{int} \right] =
\log \left( \sum_{d' \in D} e^{V_{n'} (\cdot)} \right) - \sum_{n' \in \mathbb{N}} Pr(n^* = n') \mathbb{E} \left( \beta_{e,m} W_{int} + \mathbb{E}_{c'} [V (\Omega', \varepsilon') | n, j^*] | n^* = n' \right)$$

Calculating the expectation of non-wage utility in this manner significantly reduces simulation noise compared to using the switching costs directly from the simulation.

**Construction of Simulation Sample**

The CPS data is not a true panel, so I need to construct a panel for simulations that is capable of matching the moments in the CPS MORG, NLSY and ACS. Therefore, I need a sample of agents across the cities with similar characteristics as agents in the CPS data at the beginning of the sample period. As new agents enter the labor market and in-migrate each year in the CPS MORG data, I also need to include labor market entrants and in-migrants in each year after the initial period. In the model, agents can endogenously migrate across the $J$ local labor markets. However, the number agents who enter a labor market when they finish their schooling, or via immigration from a foreign country or from a US location not included in $J$ are determined outside of the model.

Therefore, to construct the sample, I first use the cross-section of agents I observe in the first year of the data. To this sample I also add agents who finish their schooling or enter the labor market from a labor market outside of $J$ after the initial period. Specifically, from each year of data, I add all the agents who finished schooling or migrated from another labor market in the year of the survey. Finally, due to changes in survey methodology and the definitions of metropolitan areas over time, the total sample surveyed in each city may differ over time. To correct for this, I calculate the number of natives in each city born between 1954 and 1964 in each survey year to determine differences in total sample size over time and scale the number of entrants in a given year such that the number of natives born between 1954 and 1964 is constant over time.
Timing

\begin{align*}
\text{t} & \quad \text{Start Period} \\
\text{Sectoral Shocks} & \quad \text{Choose Sector} \\
& \quad n \in \{N \cup \{\text{Home}\}\} \\
& \quad n = n^* \\
\text{Accumulate Human Capital} & \\
\text{Location Shocks} & \quad \text{Choose Location} \\
& \quad j' \in \{J \cup \{\text{Outside}\}\} \\
& \quad j' = j^* \\
\text{t+1} & \quad \text{Start Period}
\end{align*}