Dynamic Responses to Immigration[*]

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Abstract

This paper analyzes the dynamic effects of immigration by estimating an equilibrium model of local labor markets in the United States. The model includes firms in multiple cities and sectors which combine capital, skilled and unskilled labor in production, and forward-looking workers who choose their optimal sector and location each period as a dynamic discrete choice. Counterfactuals show that a sudden unskilled immigration inflow leads to an initial wage drop for unskilled workers and a wage increase for skilled workers. These effects dissipate as unskilled workers migrate away from heavily affected cities and workers shift towards unskilled intensive industries.

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. 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 sectors 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.[1]

One of the primary benefits of my framework is the transparency with which the key parameters are identified. To estimate labor demand, I identify exoge-

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[1]Several important margins of adjustment are not included in this paper and are left for future work: choice of production technology (as in Lewis (2011)), education level choice (as in Llull (2017)) and occupation choice (as in Peri and Sparber (2009) or Llull (2017)).

nous shifts in immigrant labor supply across sectors and local labor markets by modifying the "ethnic enclave" instruments employed by Card (2001); 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.[2] 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 over 700,000 individuals from 20 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 equal to 10% of the unskilled population. Immediately following the shock unskilled agents experience roughly a 2% decrease in their wages while skilled wages increase by 1%. Cities with larger inflows experience wage decreases of over 3.5% for unskilled workers while less affected cities see wage declines of less than 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 ten years, as a result of these adjustments, the effect of immigration on wages decrease by over one half.

Next I compare the costs and benefits of the immigration inflow by calculating the effects of the immigration flow on the lifetime utility of workers. I find that the average unskilled worker experiences a decrease in lifetime utility equivalent

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[2] Calculations of average log wages from 1980 census and 2010 aggregated ACS.

to \$1,600 in present value, while skilled workers see a lifetime utility increase of \$1,300. Conditional on education, I find substantial heterogeneity based on a worker's unemployment status and sector before the inflow. Overall, I find a lifetime utility cost on unskilled workers for *each* unskilled immigrant who enters as part of the inflow of roughly \$16,000. This per immigrant cost is slightly larger than the costs paid to human smugglers to illegally cross the border into the United States and small in magnitude compared to the wage gains immigrants from poor countries experience after coming to the United States.[3] Overall these results suggest that a "immigration tariff" policy, in which immigrants pay a fee to migrate to the US, could allow the US to increase immigration while offsetting the costs on native workers and bringing gains for skilled workers.[4]

Methodologically, this paper is related to a series of papers which estimate dynamic equilibrium models of occupation or industry choice (Lee (2005), Lee and Wolpin (2006), Johnson and Keane (2013), Dix-Carneiro (2014), Ashournia (2017), Llull (2017) and Traiberman (2017)). Within this literature, this paper is closest to Llull (2017) in terms of focus. Llull (2017) uses a dynamic labor market equilibrium model to estimate the effects of immigration on wages and welfare. Workers dynamically choose their occupation, education and labor force participation. He finds that immigration from 1967–2007 led to significant changes in the occupation and education choices of native workers. These changes in occupation and education choices helped to mitigate the effects of immigration on native wages.

My paper differs from Llull (2017) and this literature in general in several important ways. First, rather than considering one national labor market, this paper models many labor markets in the United States. The results reveal substantial heterogeneity in the effects of immigration across local labor markets, in both the short and long run. Additionally, local labor market variation helps to to identify the key parameters of the model. I utilize variation in labor supply and labor demand across local labor markets to to separately identify workers' responsiveness to wages from the wage determination process. To my knowl-

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[3]In 2017, The Department of Homeland Security (2017) found that the fees for human smugglers reached \$8,000 in some regions. The fees charged coming from Central America or Asia are considerably higher (Johnson, 2011). Schoellman and Hendricks (2017) find that the average immigrant from a poor countries increases their wages by 200 to 300 percent upon migration.

[4]The program suggested here shares the spirit of the "radical solution" suggested by Becker (2011).

edge this is the first paper to utilize a local labor market approach to identify a dynamic labor market equilibrium model.

Second, my paper differs from Llull (2017) and this literature in that I model migration in addition to industry or occupation choice. My results show that migration responses play an important role of mitigating the effects of immigration on wages over time.[5] Finally, the focus of the counterfacutals in Llull (2017) is measuring the role of labor supply adjustments in determining the wage effects of immigration over the past 40 years. Counterfactuals in this paper highlight the differences between the short and long run effects of immigration and measuring the lifetime utility costs of immigration inflows.

This paper also is related to a large empirical literature on the effects of immigration on receiving country wages (e.g. LaLonde and Topel (1991), Card (2001), Borjas (2003), Lewis (2003), Ottaviano and Peri (2012), Piyapromdee (2017)). This 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. A smaller literature utilizes "natural experiments" to measure the effects of immigration immediately after a sudden immigration inflow (e.g. Card (1990), Cohen-Goldner and Paserman (2011), Monras (2015), Borjas (2017), Edo (2017)). 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.[6]

In the next section I describe the model. Section 3 introduces the data I use in estimation while Section 4 describes the estimation procedure. I present the estimation results in Section 5 and the counterfactual simulations in Section 6. Section 7 concludes.

2 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

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[5]Borjas (2006), Borjas, Freeman and Katz (1997), Monras (2015) and others have also emphasized that migration across local labor markets is important margin of adjustment for workers living in cities with high levels of immigration.

[6]Card (1990), however, finds no significant impact of the Mariel boatlift on the wages and employment rates of native workers.

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, perfectly competitive 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.[7] 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

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[7]I model sector and location choice as sequential choices rather than simultaneous choices largely because of data limitations. The main dataset I use for sector transitions, the CPS MORG, does include follow agents who migrate. The ACS does not include information on an agent's lagged industry choice. I therefore do not observe sector transitions for agents who migrate in either of these data sets.

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.

2.1 Labor Demand

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

$$Y_{njt} = A_{njt} K_{njt}^{(1-\alpha_n)} \mathcal{L}_{njt}^{\alpha_n}, \tag{1}$$

where A_{njt} is city-sector productivity, K_{njt} is capital, $\mathcal{L}_{njt}$ is a CES aggregate combining unskilled and skilled labor, and α_n is a parameter.[8]

The CES aggregator $\mathcal{L}_{njt}$ is given by

$$\mathcal{L}_{njt} = \left(\theta_{njt} L_{njtS}^{\zeta} + (1 - \theta_{njt}) L_{njtU}^{\zeta} \right)^{1/\zeta}. \tag{2}$$

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. θ_{njt} is the relative productivity of skilled labor, and $\varsigma = \frac{1}{1-\zeta}$ is the elasticity of substitution between skill levels in each sector.[9] Notice that the factor intensity parameters (the θs) and productivity (the As) are allowed to vary by time, sector, location and city, while the elasticity of substitution is fixed across sectors.[10]

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[8]Krusell et al. (2000) and Baum-Snow, Freedman and Pavan (2014) have emphasized the importance of capital-skill complementarity in explaining changes in the skill wage premium over time. As a do not have access to data on capital levels at the local labor market level, I instead assume a Cobb-Douglas production function. As I describe in this section, the production function I use here can be estimated without data capital levels across local labor markets.

[9]Lewis (2011) argues that firms may change their production technology in response to immigrant inflows while Peri (2012) argues that immigration inflows may increase productivity. By assuming that A_{njt} and θ_{njt} are parameters and thus exogenous to immigrant inflows, I am abstracting away from endogenous technology choice and productivity which is endogenous to immigrant inflows.

[10]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

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 (θ'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 sectors which intensively use unskilled labor (sectors with low θ) 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 immigrants 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, sector 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.[11]

As the market is perfectly competitive, the firms choose labor quantities such that the marginal productivity of each labor inputs is equal to the human capital prices. Let r_{njte} represent the price of one unit of human capital supplied by

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intensive sectors 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.

[11]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. Ultimately I find that the costs of immigration for unskilled native workers are small, allowing for complementarity between immigrants and natives would make them even smaller.

workers of skill group $e \in \{S, U\}$. Then we can write:

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\begin{aligned}
r_{njtS} &= \frac{P_{nt}Y_{njt}\alpha_n}{\mathcal{L}_{njt}}\mathcal{L}_{njt}^{1-\zeta}\theta_{njt}L_{njtS}^{\zeta-1} \\
r_{njtU} &= \frac{P_{nt}Y_{njt}\alpha_n}{\mathcal{L}_{njt}}\mathcal{L}_{njt}^{1-\zeta}\left(1-\theta_{njt}\right)L_{njtU}^{\zeta-1},
\end{aligned}
\tag{3}
$$

where P_{nt} is the price of the output good.

Crucially, I assume that each local labor market is a small open economy and the output produced in each sector is tradeable—or equivalently, that demand for all goods is perfectly elastic. As shown by Burstein et al. (2017), immigrant inflows have a much larger effect on wages and employment in nontradeable industries compared to those in tradeable industries because an increase in the supply of a nontradeable good leads to a drop in the price. As I do not have access to goods prices at a local labor market level, I leave an investigation of the role of nontradeable goods in this setting for future work.[12]

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 an infinitely elastic supply of capital with rental rate $\bar{r}_{tK}$.[13] Taking the first order condition of the production function with respect to capital and solving for the capital labor ratio yields:

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\frac{\mathcal{L}_{njt}}{K_{njt}} = \left(\frac{\bar{r}_{tK}}{P_{nt}A_{njt}\left(1-\alpha_n\right)}\right)^{1/\alpha_n},
$$

which implicitly defines demand for capital K_{njt} as a function of the labor supply aggregate $\mathcal{L}_{njt}$, the price of capital $\bar{r}_{tK}$, the goods price P_{nt}, TFP A_{njt}, and the parameter α_n. Note that the capital labor ratio is not a function of capital or labor quantities.

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

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[12]One option would be to assume that agents spend a constant fraction of their earnings on each nontradeable sector and assume the market for nontradeable goods must clear in each local labor market. For example, if I calibrate that agents spend 10% of their earnings on goods produced in nontradeable sector n, I can calculate the total expenditure on good n in each local labor market. I can then find the price of good n which clears the market.

[13]I test the robustness of my counterfactuals to the assumption of infinitely elastic capital supply in section B.2.

$$r_{njtS} = \tilde{A}_{njt} \mathcal{L}_{njt}^{1-\zeta} \theta_{njt} L_{njtS}^{\zeta-1}$$
$$r_{njtU} = \tilde{A}_{njt} \mathcal{L}_{njt}^{1-\zeta} (1 - \theta_{njt}) L_{njtU}^{\zeta-1}, \tag{4}$$

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.

2.2 Labor Supply

I model sector 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 earnings 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 the decision to immigrate from abroad or choice of education level.[14] All agents are assumed to retire at age 65.

At the beginning of each period, agents receive a vector of sector preference shocks and choose between working in one of the productive sectors 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.

In what follows, I describe each portion of the labor supply model in chronological order: 2.2.1 describes the flow utility associated with each sector choice, 2.2.2 describes the human capital accumulation process, 2.2.3 describes the flow

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[14]Modeling the decision to immigrate is difficult for both computational and data reasons. Hunt (2012) and McHenry (2015) find that natives may increase schooling attainment in response to immigrant inflows while Llull (2017) finds that some native workers increase their education in response to counterfactual immigration inflows while others obtain less education. I leave modeling endogenous education choice in this setting for future work.

utility associated with each location choice and 2.2.4 connects the three steps into a dynamic programming problem.

2.2.1 Sector Choice Flow Utility

At the beginning of each year, agents can either work in one of the sectors in the set N, or engage in home production. Let $v_n^{Sec}(\cdot)$ 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 a sector amenity, $\gamma_{n,e,m}$, a location amenity $\gamma_{j,e}$, a switching cost $\phi_e(n, n_{t-1})$, and an idiosyncratic preference shock ε_{int}. We can therefore write the flow utility function as:

$$v_n^{Sec}(\cdot) = \beta_{e,m}^w W_{int} + \gamma_{n,e,m} + \gamma_{j,e} + \phi_e^{Sec}(n, n_{t-1}) + \varepsilon_{int}.$$

$\beta_{e,m}^w$ is a parameter which measures the weight agents place on consumption relative to the idiosyncratic preference shock, whose variance is normalized across agents. $\beta_{e,m}^w$ plays a crucial role in determining how quickly an economy will respond to immigrant inflows. A high value of this parameter implies workers will be more responsive to the wage effects of immigration and therefore quickly leave sectors and cities which are negatively affected; a low value implies workers will not respond strongly to the effects of immigration and thus the wage effects of immigration will be long-lasting. The value of $\beta_{e,m}^w$ 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.

$\gamma_{n,e,m}$ 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. Sector amenity terms are allowed to vary by an agent's skill level and immigrant status while city amenity terms vary by skill level.[15][16]

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[15]Another option would be to allow immigrants to value cities with large enclaves of immigrants from their home country, as in Piyapromdee (2017).

[16]Crucially, I abstract away from the effects of immigration on local goods prices. Cortes (2008) shows that immigrant inflows lower the prices of immigrant intensive services while Saiz (2007) shows that immigration increases housing prices and rents. As I do not have access to goods prices at the local labor market level it would be difficult to estimate the effect of immigration on local goods prices. The ACS and Census contain data on housing values and

The agent pays the sector switching cost, $\phi_e^{Sec}(n, n_{t-1})$, if she chooses a sector 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, ε, allows for idiosyncratic differences in agents' preferences over sectors and cities. I assume the ε's are jointly distributed extreme value type I.

2.2.2 Earnings and Human Capital Accumulation

Agents' earnings are given by the product of their human capital, the price of human capital in their sector of choice and an idiosyncratic productivity shock. Earnings for agent i in sector n can therefore be written as:

$$W_{int} = r_{njte} H_{it} \exp\left(\nu_{int}\right),\tag{5}$$

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, and ν_{int} is a mean zero productivity shock that is uncorrelated with everything in the model and is observed after agents make their sector choice.[17] The productivity follows a normal distribution with standard deviation σ_{ne}^ν. This shock accounts for idiosyncratic differences in productivity and wages that are not accounted for by an agent's observable characteristics.

I assume one-dimensional human capital that is imperfectly transferred when an agent switches sectors. Conceptually, each period an agent is engaged in the same sector, her 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.[18]

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rents, however, modeling the housing market would significantly complicate the model.

[17]Another option would be to assume that agents observe a vector of productivity or 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.

[18]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. The one dimensional human capital specification is especially problematic if "return switching" is common—that

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. Letting t_0 represent the first year in which the agent works, I write the initial level of human capital as:

$$h_{it_0} = \beta_{ne}^{new} \mathbf{X}_{it_0}^{new}, \tag{6}$$

where n is the sector chosen by the agent, $\mathbf{X}_{it_0}^{new}$ is a vector of the agent's characteristics and β_{ne}^{new} is a vector of parameters.

After entering the labor market, human capital accumulates as follows. 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 process:

$$h_{it} = \delta_e h_{it-1} + \alpha_e^{n,n_L} + \beta_{ne} \mathbf{X}_{it}, \tag{7}$$

where δ_e measures serial correlation in worker productivity. α_e^{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 α to be large for agents whose chosen sector is the same as their most recent 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.[19] $\mathbf{X}_{it}$ is a vector of worker characteristics.

If an agent is engaged in home production, her human capital depreciates according to:

$$h_{it} = \delta_e^{Home} h_{it-1}. \tag{8}$$

is, that agents switch into sectors into which they have accumulated human capital. In the extreme case in which there is no return movement, all workers switching into a sector will have exactly 0 sector specific human capital so the one-dimensional human capital assumption in this setting would be innocuous. Using data from the PSID Retrospective Occupation-Industry Supplemental 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.

[19]To limit the number of parameters to be estimated, I restrict the α parameters for agents who switch sectors ($n \neq n_L$) to be the same across all combinations of sectors. I therefore estimate $N + 1$ of these parameters—one for each of the N sectors and one for agents who switch sectors. Without this restriction I would need to estimate N^2 of these parameters.

2.2.3 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 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 that is a function of the distance between the two labor markets. Let $v_{j'}^{Loc}$ denote an agent's location flow utility conditional on choosing location j':

$$v_{j'}^{Loc} = \phi_e^{Loc}\mathbb{I}\left(j' \neq j\right) + \phi_e^{Dist}d\left(j',j\right) + \sigma_e^\iota \iota_{ij't}. \tag{9}$$

ϕ_e^{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. We can think of this as capturing the utility cost of leaving a city and finding a home in a new city as well as the monetary cost of moving to a new location. The function d gives the straight line distance between location j' and j, and ϕ_e^{Dist} is a parameter which dictates how moving costs increase with distance. We expect $\phi_e^{Dist} < 0$ as both the utility and monetary costs of moving should increase with distance. $\iota_{ij't}$ is a location preference shock which is assumed to be distributed extreme value type I, and σ_e^ι is a scale parameter.

2.2.4 Dynamic Programming and Equilibrium Outline

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.[20]

Let V_n represent the value function at the beginning of the period conditional on choosing $n \in \{N \cup \{Home\}\}$. The state 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 ε.[21] Let

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[20]Another option would be to assume that workers use a forecasting role to predict future human capital prices, as in Lee and Wolpin (2006), Dix-Carneiro (2014), Llull (2017), and many others. Dix-Carneiro (2014) argues that qualitative conclusions of a similar model are not sensitive to the choice of perfect foresight or a forecasting rule in estimation.

[21]The sector most recently employed in will differ from the choice in the previous period if

$\Omega = (j, t, e, m, age, n_{t-1}, n_L, h_{t-1})$ 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:

$$V_n(\Omega, \varepsilon) = \mathbb{E}_\nu \left[v_n^{Sec}(\Omega, \varepsilon) + \mathbb{E}_\iota \left(v_{j^\star}^{Loc}(\Omega, \iota) + \beta \mathbb{E}_{\varepsilon'} \left[V(\Omega', \varepsilon') | n, j^\star \right] \right) \right], \quad (10)$$

where the first expectation is the over current year's productivity shock, the second expectation is over location preference shocks, and the final expectation is over next year's sectoral preference shocks. $j^\star$ 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 therefore write an agent's decision, $n^\star$ as:

$$n^\star = \arg\max_{n \in \{N \cup \{Home\}\}} V_n(\Omega, \varepsilon).$$

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

$$V(\Omega, \varepsilon) = V_{n^\star}(\Omega, \varepsilon).$$

At the end of the period, the agent chooses their next location $j^\star$ after receiving the vector of location preference shocks ι. The state at the time of location choice consists of the agent's observables, Ω, and the vector of location preference shocks, ι. The agent chooses $j^\star$ by solving the discrete choice problem:

$$j^\star = \arg\max_{j' \in \{J \cup \{Outside\}\}} v_{j'}^{Loc}(\Omega, \iota) + \beta \mathbb{E}_{\varepsilon'} \left[V(\Omega', \varepsilon') | n, j' \right].$$

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

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

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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.

	Service	Manufacturing	Professional
Age	38.3	42.3	41.4
	(12.8)	(11.1)	(11.5)
Hourly Wage	19.3	26.1	27.1
	(12.9)	(16.7)	(17.3)
Agent Types			
High Skill Imm	10.3	11.3	13.3
High Skill Native	38.4	46.4	63.7
Low Skill Native	31.9	24.3	17.3
Low Skill Imm	19.4	18.1	5.8

Table 1: Summary statistics across the three sectors. 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 sector who belong to each immigration status-skill level type.

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. To simulate the perfect foresight equilibrium, I follow an algorithm described in Lee (2005). The details of this algorithm and the formal definition of the equilibrium are provided in appendix section A.1.

3   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. I therefore use these fourth and eighth month interviews to construct a panel of two yearly wage, employment status and sector observations for each household.[22]

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[22]See the Data Appendix for additional details on linking respondents across surveys and

I use CPS MORG data from 1994–2014, as data on immigration status are not available before 1994. I define the set of cities, J, as the 20 Core Based Statistical Areas (CBSAs) with the most observations in the CPS.[23] This leaves me with 720,060 observations from the CPS MORG, each which consists of two consecutive years of wages and sector choices for agents who do not move.[24]

I aggregate into three sectors: manufacturing, service, and professional.[25] Table 1 shows summary statistics for the three sectors. The professional sector 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 sector employs the fewest skilled workers; less than 49% of its workers have attended college.

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 sector 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.[26]

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.

4 Estimation

The set of parameters to be estimated include the labor demand, worker preferences and human capital accumulation parameters. Theoretically, I could esti-

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cleaning the CPS MORG data.

[23]To make CBSAs comparable over time, I combine any CBSAs that are combined later in the data.

[24]This constitutes 45% of the national sample.

[25]Appendix section A.3 gives details on this aggregation.

[26]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.

mate 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 across all 20 local labor markets at each guess of the parameter vector.

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.

4.1 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 $w = \log W$ and again let t_0 denote the first year in which an agent works. The estimating equation for agents entering the labor market is:

$$w_{int_0} = \log(r_{njt_0e}) + \beta_{ne}^{new} \mathbf{X}_{it_0}^{new} + \nu_{int}.$$

Log wages, w_{int_0}, and worker characteristics, $\mathbf{X}_{it_0}^{new}$, are observed by the econometrician. Given the assumptions made on the distribution of ν_{int} and the assumption that ν_{int} is realized after agents make their sector decision, ν_{int} is uncorrelated with all the right hand side variables. Therefore, the full set of human capital

prices, the parameter vector β_{ne}^{new}, and the variance of the human capital shock for entrants, $\sigma_{n,e}^{\nu,new}$ are identified.

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

$$w_{int} = \log(r_{njte}) + \delta_e \left(w_{in_L t_L} - \log(r_{n_L j_L t_L e}) \right) + \alpha_e^{n,n_L} + \beta_{ne}\mathbf{X}_{it} + \nu_{int}.$$

As ν_{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_{njte}'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, α_e^{n,n_L} 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, δ_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, δ_e^{home}.

4.2 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 productivity shocks. 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:

$$\log \left(\frac{r_{njtS}}{r_{njtU}} \right) = -\frac{1}{\varsigma} \log \left(\frac{L_{njtS}}{L_{njtU}} \right) + \log \left(\frac{\theta_{njt}}{1 - \theta_{njt}} \right). \tag{11}$$

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

$$\Delta \log \left(\frac{r_{njtS}}{r_{njtU}} \right) = -\frac{1}{\varsigma} \Delta \log \left(\frac{L_{njtS}}{L_{njtU}} \right) + \varphi_j + \varphi_n + \varphi_t + \eta_{njt}, \qquad (12)$$

where φ_j, φ_n and φ_t are parameters and η_{njt} is a mean-zero productivity shock.

Ideally, I could use exogenous changes in labor supply to estimate φ_j, φ_n, φ_t and ς. However, changes in relative labor supply, $\Delta \log \left(\frac{L_{njtS}}{L_{njtU}} \right)$, will in general be correlated with productivity shocks, η_{njt}. To see this, consider a city and sector with a high value of η_{njt}. Mechanically, this leads to a higher value of skilled wages relative to unskilled wages. As a result, more skilled agents will choose this sector and city relative to unskilled agents, leading to an increase in $\frac{L_{njtS}}{L_{njtU}}$. Therefore, I cannot directly use variation in labor supply to estimate equation 12.[27]

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. Specifically, I modify the instrumental variables strategy developed by Altonji and Card (1991) and Card (2001) to predict *sector-specific* immigrant inflows. These papers utilize the insight that current migrants from a given country tend to settle in similar locations as previous migrants from that country. They therefore use the lagged geographic distribution of immigrants to predict current inflows of immigrants. I extend this instrument by first noting that immigrants from different countries vary considerably in their distributions across sectors.[28] Additionally, these differences are persistent over time.[29] Therefore to predict the number of immigrants entering a given sector, I can use lagged sectoral structure in addition to lagged geographic distribution of immigrants.[30]

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[27]Generally, papers in the dynamic labor market equilibrium literature (Heckman, Lochner and Taber (1998), Lee and Wolpin (2006) or Dix-Carneiro (2014), for example) have dealt with this issue by placing additional structure on the relative productivity parameters (θ_{njt} here).

[28] 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.

[29] Appendix section A.2 provides evidence on the persistence of immigration location and sector choices over time.

[30]In motivating his instrument, Card (2001) emphasizes the importance of *ethnic enclaves* in determining the location choices of new immigrants—immigrants tend to settle in cities which already have a large number of immigrants from their home country.

The model in this paper is agnostic on how immigrants chose their initial local labor market

Specifically, I write predicted sector-specific immigration inflows of skill level e into sector n, city j as:

$$\tilde{M}_{njte} = \sum_g M_{g(-j)te}\omega_{gne}^{1980}\omega_{gj}^{1980},\qquad(13)$$

where g indexes countries, ω_{gne}^{1980} is the proportion of total immigrants from country g and skill level e employed in sector n in 1980, ω_{gj}^{1980} is the proportion of total immigrants from country g living in location j in 1980, and $M_{g(-j)te}$ 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 sector 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 $\text{corr}\left(\tilde{M}_{njte}, \eta_{njt}\right) = 0$. 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.

4.3   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 $\mathcal{M}^{data}$. Then, for a given guess of choice parameters, Λ, I simulate the choices

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and sector and thus allows for the possibility that ethnic enclaves influence these choices. However, as ethnic enclaves do not enter the flow utility in the model, I assume that ethnic enclaves do not influence immigrants' sector or location choices after their initial location and sector choice. Piyapromdee (2017) formulates a static model in which immigrants take into account the existence of ethnic enclaves when choosing where to live.

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 $\mathcal{M}^{sim}(\Lambda)$. 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:

$$\Psi(\Lambda) = \left(\mathcal{M}^{data} - \mathcal{M}^{sim}(\Lambda)\right)' \Gamma \left(\mathcal{M}^{data} - \mathcal{M}^{sim}(\Lambda)\right), \qquad (14)$$

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

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 in the distance function to be minimized. From the CPS MORG, I include the choice probabilities of sector and home production conditional on education level, immigrant status, age, city, year and previous sector. 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, I include the number of agents who migrate to each of the J labor markets conditional on skill level and on their labor market in the previous year.

One main challenge of estimating the choice parameters is separately estimating the sector amenities and switching costs from the value of consumption, β^w. Separate identification is facilitated by the use of multiple local labor markets in estimation. β^w is largely identified by the correlation of average wages and choices across cities and over time. For example, a higher β^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 sector than people in Chicago. The switching costs are identified by the number of agents who switch sectors each year after accounting for switches in response to wage differences. Holding β^w constant, a larger switching cost implies less agents will switch sectors each year. 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, γ_j's, moving cost, ϕ^{Loc}, and the standard deviation of the location preference shock, σ^ι: σ^ι is identified by the responsiveness of migration flows to across city wage changes, the γ_j's are identified by the location choice probabilities that are not explained by wage differences and ϕ^{Loc} is identified by the total amount of migration after accounting for differences in expected utility across locations.
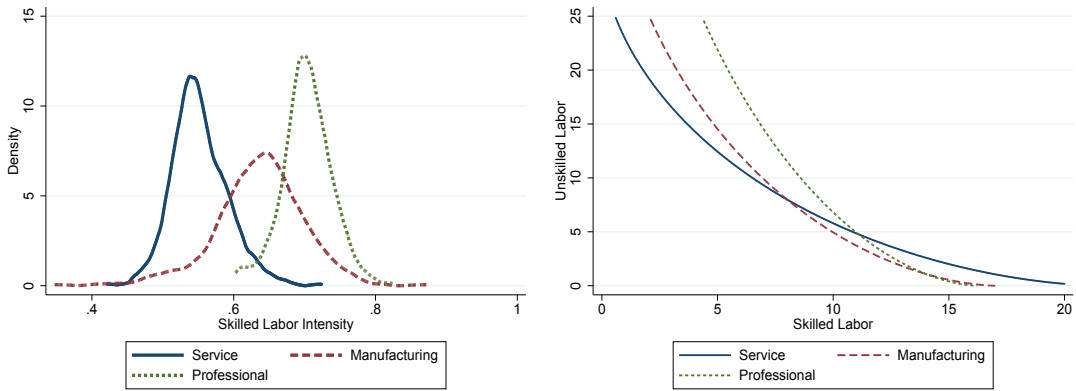
5 Results

5.1 Labor Demand

Table (2) summarizes the labor demand estimates. The elasticity of substitution between high and low skilled labor is 2.48. I am not aware of any studies that estimate sector 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 (θs) in each sector across all cities and years. The first panel of figure 1 shows the distributions of the estimated skilled labor intensities in the three sectors. The average factor intensity of skilled labor is highest in the professional sector, followed by the manufacturing sector. We can also see that the standard deviations of the three relative productivity parameters are relatively small.

The second panel of 1 displays isoquants for an arbitrary level of production in the three sectors given the average estimated skilled labor intensities. As expected, we can see that the service sector is the most unskilled intensive sector, professional is the most skilled intensive sector, and manufacturing sits between the two.

ς: Elasticity of Sub.	2.48		
	(0.92)		
	Service	Manu.	Professional
θ: Average Skilled Labor Intensity	0.54	0.64	0.71
	(0.033)	(0.050)	(0.028)

Table 2: Labor Demand Parameters. 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.

(a) Previous Sector: Service   (b) Isoquants

Figure 1: Visualisation of labor demand estimates. The first panel shows the density of estimated skillled labor intensity in the three sectors over time and across cities. The mean and standard deviation of the estimated skilled labor intensities are displayed in Table 2. The second panel shows isoquants for an arbitrary level of production for each of the three sectors. The isoquants are constructed according to the estimated elasticity of subsitution and the average skilled labor intensity in each of the three sectors.

5.2 Human Capital Accumulation

I assume the vector of worker characteristics for workers already in the market, $\mathbf{X}_{it}$, consists of the worker's potential experience, the worker's potential experience squared squared and a dummy for immigrants. Table 3 shows the estimated human capital accumulation parameters. The estimates show that, in each sector, human capital is an increasing, concave function in age.

The α 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. α's for skilled and unskilled agents who remain in the professional of manufacturing sector are large, while α's agents who switch sectors or for agents who remain the service sector are smaller. The term measuring serial correlation in worker productivity, δ, is close to 0.5 unskilled and skilled agents, implying that agents with low levels of human capital accumulate human capital faster than agents with high human capital.

5.3 Choice Parameters

I set the discount rate, β, to .95. The parameters estimates are displayed in table (4). I do not report amenity values of the cities (γ_j's).

The first row displays the estimates of the coefficient on wages in the sectoral choice flow utility function. 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 Ω chooses sector n. Given that the preference shock vector ε is distributed as extreme value, we can write:

	Unsk.	Skilled		Unsk.	Skilled
I. Worker Characteristics			II. Lagged Human Capital		
$\beta_{Serv,Exp}(\times 100)$	2.06	2.91	$\alpha^{Serv,Serv}$	0.04	-0.02
	(0.06)	(0.04)		(0.006)	(0.005)
$\beta_{Manu,Exp}(\times 100)$	0.84	1.63	$\alpha^{Manu,Manu}$	0.11	0.09
	(0.13)	(0.05)		(0.008)	(0.008)
$\beta_{Pro,Exp}(\times 100)$	1.29	1.75	$\alpha^{Pro,Pro}$	0.07	0.07
	(0.10)	(0.04)		(0.008)	(0.004)
$\beta_{Serv,Exp^2}(\times 1000)$	-3.66	-5.75	$\alpha^{n,n_L}, n \neq n_L$	0.06	0.03
	(0.12)	(0.12)		(0.007)	(0.004)
$\beta_{Manu,Exp^2}(\times 1000)$	-1.18	-3.06	III. Serial Correlation		
	(0.27)	(0.09)	δ	0.48	0.55
$\beta_{Pro,Exp^2}(\times 1000)$	-2.17	-3.24		(0.003)	(0.003)
	(0.18)	(0.07)			
β_{Immig}	-0.15	-0.05			
	(0.004)	(0.002)			

Table 3: Human Capital Parameters for Agents with Work Experience: The human capital equation agents with work experience is given by: $h_{it} = \delta_e h_{it-1} + \alpha_e^{n,n_L} + \beta_{ne} \mathbf{X}_{it}$. To limit the number of parameters to be estimated, I restrict the α parameters for agents who switch sectors ($n \neq n_L$) to be the same across all combinations of sectors. $\mathbf{X}_{it}$ is a vector of worker characteristics. I parameterize $\beta_{ne}\mathbf{X}_{it} = \beta_{immig,e}Immig_i + \sum_{n \in N} \beta_{n,Exp}Exp_{it} + \sum_{n \in N} \beta_{n,Exp^2}Exp_{it}^2$ where $Immig_i$ is a dummy variable indicating an agent in an immigrant and Exp is an agent's potential experience. Bootstrap standard errors shown in parentheses.

		Unskilled		Skilled	
		Natives	Imm.	Natives	Imm.
I. Wages					
	β^w	0.09	0.11	0.10	0.12
		(0.011)	(0.006)	(0.008)	(0.022)
II. Amenities					
	γ_{Serv}	-0.23	-0.13	0.01	-0.44
		(0.001)	(0.002)	(0.002)	(0.003)
	γ_{Man}	-0.81	-0.53	-1.22	-1.33
		(0.001)	(0.004)	(0.001)	(0.005)
	γ_{Pro}	-0.16	-0.31	-0.17	-0.33
		(0.002)	(0.003)	(0.001)	(0.002)
III. Switching Costs					
	ϕ^{Sec}	-3.30		-3.71	
		(0.011)		(0.007)	
	ϕ^{Loc}	-5.31	-5.34	-4.92	-6.20
		(0.086)	(0.161)	(0.064)	(0.142)
	ϕ^{Dist}	-0.35		-0.15	
		(0.094)		(0.064)	
IV. Location Shock					
	σ^{Move}	1.33	1.16	1.14	1.37
		(0.008)	(0.011)	(0.003)	(0.006)

Table 4: Choice Parameters: Standard errors are calculated by a boostrapping procedure in which I re-sample the preference and human capital shocks at each draw. The sectoral choice flow utility is given by: $\upsilon_n^{Sec}(\cdot) = \beta_{e,m}^w W_{int} + \gamma_{n,e,m} + \gamma_{j,e} + \phi_e^{Sec}(n, n_{t-1}) + \varepsilon_{int}$.
The location choice flow utility is given by: $\upsilon_{j'}^{Loc} = \phi_e^{Loc}\mathbb{I}(j' \neq j) + \phi_e^{Dist} d(j', j) + \sigma_e^\iota \iota_{ij't}$.

$$\Pi_n\left(\Omega\right) = \frac{e^{\tilde{V}_n(\Omega)}}{\sum_{n'\in\{N\cup\{Home\}\}} e^{\tilde{V}_{n'}(\Omega)}},$$

where $\tilde{V}_n\left(\Omega\right) = V_n\left(\Omega, \varepsilon\right) - \varepsilon_{int}$ is the choice specific value function minus the sectoral preference shock. By taking the derivative of Π with respect to wages W_{int} and rearranging, we obtain the following expression for β^w:

$$\beta^w = \left(\frac{\partial\Pi_n\left(\Omega\right)}{\partial W_{int}}\right)\frac{1}{\Pi_n\left(\Omega\right) - \Pi_n^2\left(\Omega\right)}.$$

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 $.09 \times (.07 - .07^2) = 0.6$ percentage point increase in unskilled natives in that city choosing the service sector and a $.11 \times (.07 - .07^2) = 0.7$ percentage point increase in unskilled immigrants, conditional on working in the manufacturing sector last year.[31]

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

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 3.30. An unskilled native who was chosen at random and forced to switch sectors would therefore need to see a one year wage increase of \$37 dollars an hour, equal to 2 times average

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[31] An average unskilled worker in the service sector makes about \$17 an hour. As a comparison, Traiberman (2017), using data from Denmark, finds that a 1% decrease in an occupational skill price leads to a 1.2% increase in occupation switching.

wages, in order to be compensated for the switching cost. For skilled natives, the sector switching cost is estimated to be 3.7, equal to roughly a 41$ increase in hourly wages, or a 130% increase in wages. The migration costs are of a larger magnitude, at 5.3 for unskilled and skilled natives, and 4.9 and 6.2 for unskilled and skilled immigrants, respectively.

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 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.

5.4   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 the first four graphs of figure 2. 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 sectors. The last four graphs of figure 2 shows the distribution of agents across sectors conditional on their immigrant status and education level. The model does reasonably well at replicating these moments.

6   The Dynamic Effects of Unskilled Immigration

In this section I use the estimated model to simulate the effects of an an immigration inflow which increases the immigrant share as a fraction of total unskilled

(a) Previous Sector: Service

(b) Previous Sector: Manufacturing

(c) Previous Sector: Professional

(d) Previous Sector: Home

(e) Unskilled Natives

(f) Skilled Natives

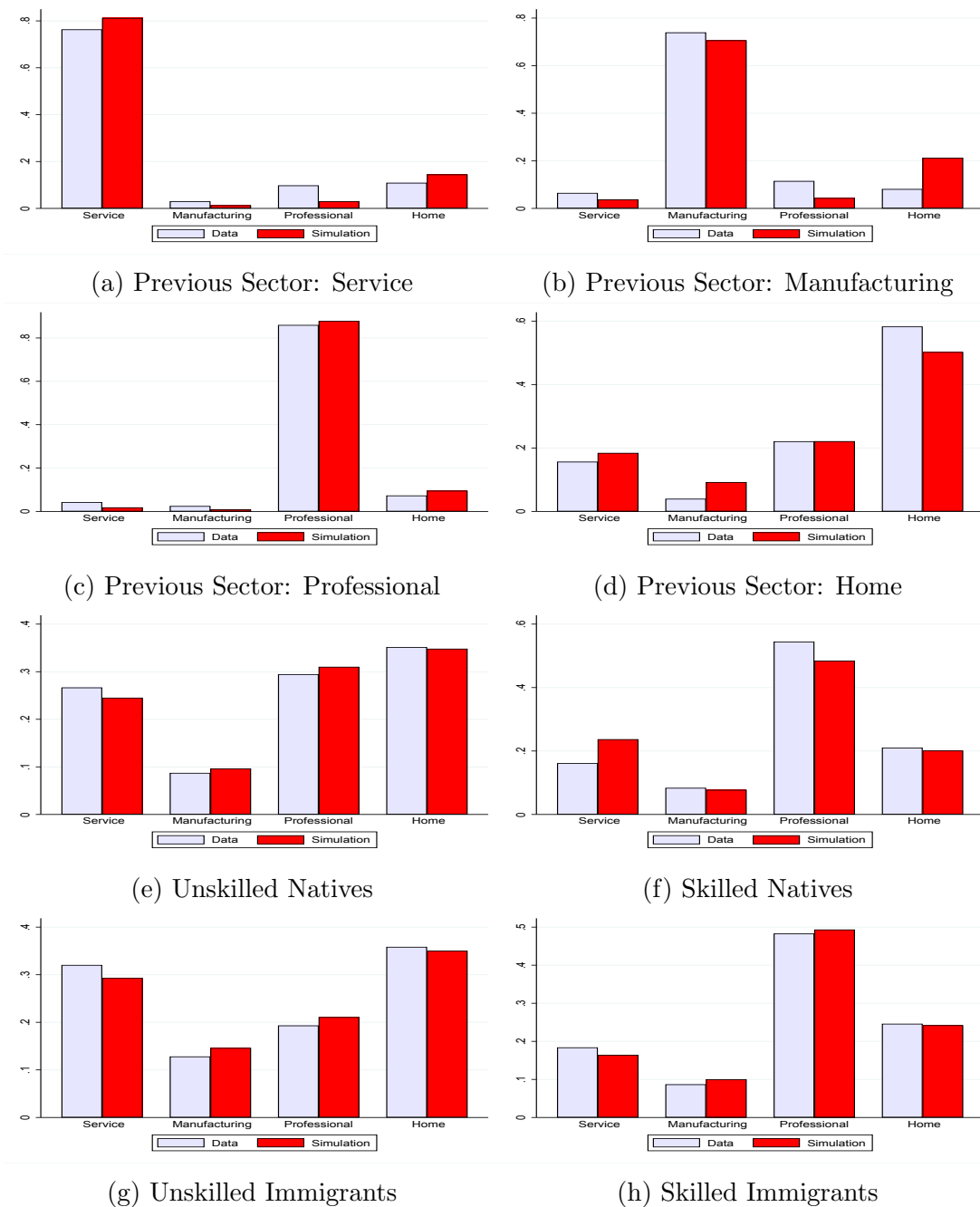(g) Unskilled Immigrants

(h) Skilled Immigrants

Figure 2: Model Fit: Transition Rates and Choice Probabilities. Each graph shows the proportion of workers choosing each sector conditional on their previous secto or 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.

workers by 10%.[32] 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. By choosing an immigration inflow of this magnitude I can easily compare my results with those found in a large "reduced form" literature on the wage affects of immigration.[33]

In the baseline calculations, I assume that capital is supplied perfectly elastically and is perfectly mobile across sectors and cities. I show that the counterfactual results are robust to alternative assumptions on capital mobility in section B.2. I also calculate the effects of an anticipated inflow in section B.1. The model does not include the initial migration decision of immigrants and is not able to determine the initial location, age, and the remainder of the state variables for the counterfactual immigrants. Instead, I assume that the counterfactual immigrants share the same distribution of state variables as recent immigrants in the data—immigrants who immigrated from 2005–2014. In practice, to generate the counterfactual immigrants, I randomly select from recent immigrants in the data and copy the state variables from these selected immigrants.

First I examine the effects on wages and flow utility across all cities and sectors in figure 3.[34] The first panel 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 skilled workers. Immediately following the shock, unskilled native wages decrease by 2.0%, unskilled immigrant wages decrease by 2.5% while skilled native wages increase by 0.8% and skilled immigrant wages increase by 0.9%.[35] Wages gradually converge to their baseline

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[32]In reality, immigrant inflows will contain both skilled and unskilled immigrant. In the model, immigration affects wages by changing the ratio of skilled to unskilled workers. Therefore, including more skilled immigrants in the immigration shock would decrease the impact of immigration on wages.

[33]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."

[34]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.

[35]One interesting result is that the wage effects for previous immigrants are slightly larger

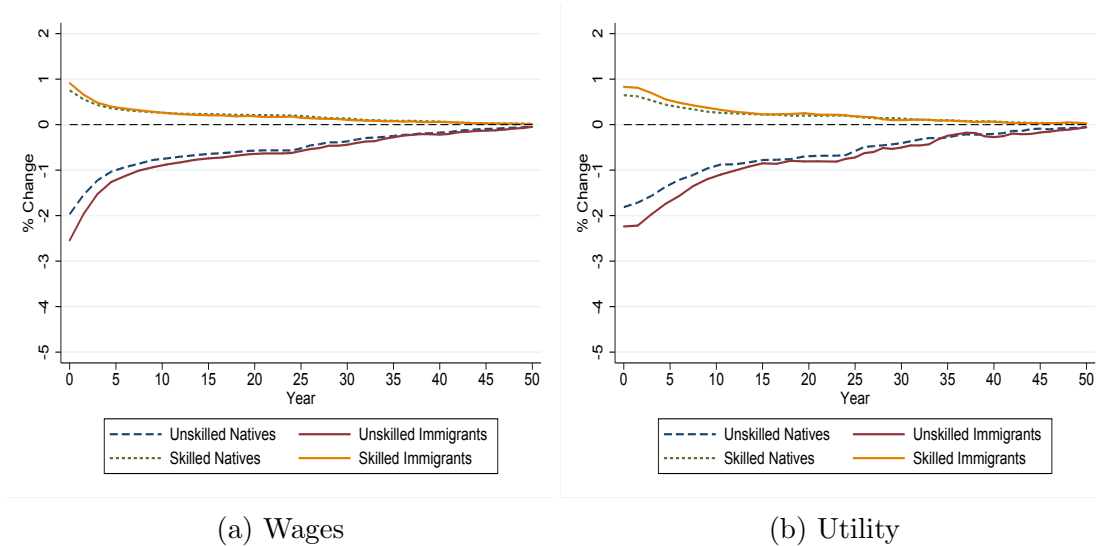<div align="center">(a) Wages   (b) Utility</div>

Figure 3: Sudden Immigration: Change in average wages and flow utility. This figure shows effect of a sudden immigration inflow on wages and utility. The results are displayed in percent differences from the baseline simulation.

trajectory over the sample period. Ten years after the inflow the wage effects are roughly half the size as immediately after the shock.

The second panel of figure 3 shows the change in flow utility, expressed as a wage change equivalent. Each agent's flow utility is the sum of the sector choice flow utility and the location choice flow utility : $\tilde{u}\left(\cdot\right) = \frac{1}{\beta_{e,m}^{w}}\left(\upsilon_{n}^{Sec}(\cdot) + \upsilon_{j}^{Loc}(\cdot)\right)$. The flow utility is multiplied by $\frac{1}{\beta_{e,m}^{w}}$ so that it can be interpreted as a change in utility measured in wage equivalents. The change in flow utility is very similar to the changes in wages, despite the estimated large switching costs parameters.[36] 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.

Next I explore heterogeneity in the wage effects across cities. Panel 1 of figure 4 shows the effects on unskilled wages across local labor markets. The 20 local labor markets are listed across the horizontal axis and are ordered by

than those for natives. Ottaviano and Peri (2012) come to a similar conclusion in their estimation of a national level production function. In this model, previous immigrants experience a larger wage cut because they are more heavily concentrated in local labor markets which receive large immigrant inflows.

[36]One important caveat is that average wages only include workers who are employed, but I calculate changes in utility for all workers, including unemployed workers.

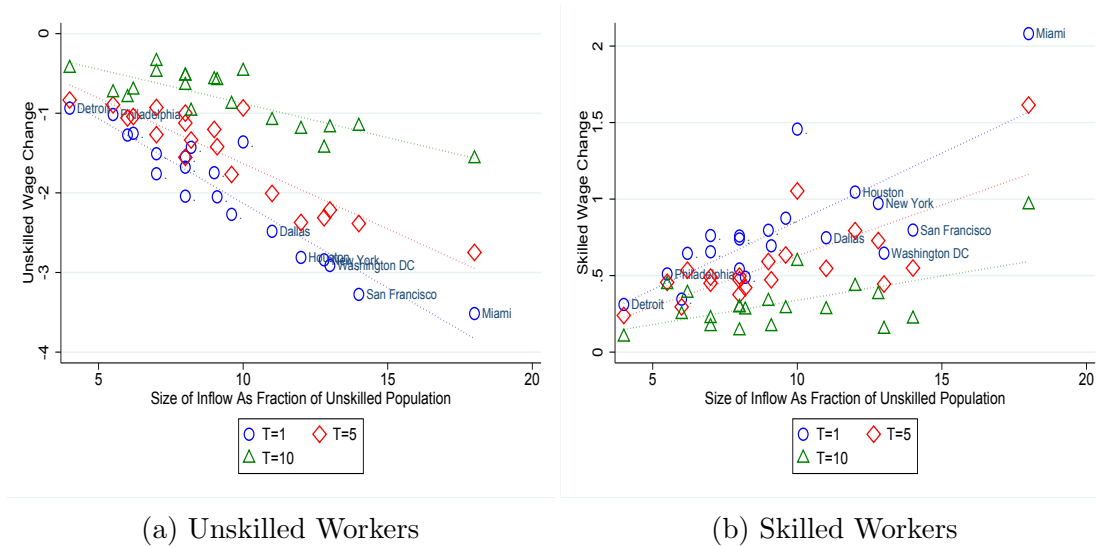(a) Unskilled Workers   (b) Skilled Workers

Figure 4: Sudden Immigration: Change in the wages of skilled and unskilled workers across cities. The results are displayed in percentage point differences of the total working population in each sector.

the size of the immigrant inflow as a fraction of the unskilled worker population. The blue circles show the percent change in wages for unskilled workers in the year of the immigration inflow, the red diamonds show the effects five years after the inflow, and the green triangles show the effect on wages 10 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 later. The cities with the largest immigrant inflows as a fraction of unskilled workers, Miami, San Francisco, Washington DC, New York and Houston, with immigrant inflows over 12% percent of their unskilled population, see their unskilled wages decrease by over 2.8%, while Detroit, Philadelphia and Boston, with immigrant inflows less than 7% of their unskilled population, experience unskilled wage decreases less than 1.3%. 10 years later, the differences are smaller, but still present. The five most affected cities still have over 1% lower wages than in the case in which the immigrant inflow did not occur while Philadelphia, Detroit and Boston still have less than a 0.9% decrease in unskilled wages.

The second panel shows the effect of the wages of skilled workers. The wage effects for skilled workers generally mirror the wage effects for unskilled workers. Cities with large immigrant inflows generally have larger wage increases for skilled workers in the short and long run.

To better understand how workers are responding to immigrant inflows, I next

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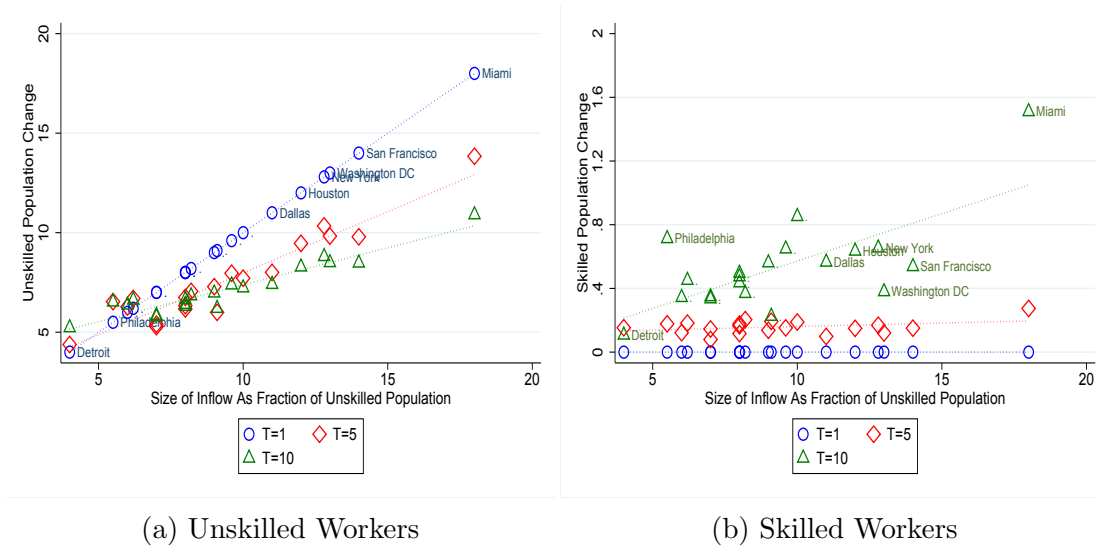(a) Unskilled Workers (b) Skilled Workers

Figure 5: Sudden Immigration: Change in the 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.

examine how the distributions of workers across sectors and labor markets change over time. Figure 5 shows the distribution of unskilled and skilled workers across cities immediately after the immigration shock, five years after the shock and 10 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. 10 years later, the change in unskilled population in cities which received large immigrant inflows has decreased as unskilled workers migrate away from these cities.

The right panel of 5 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— 10 years after the shock, the skilled worker population in the most affected cities has increased by less than 1.6%.

Figure 6 shows the change in distribution of skilled and unskilled workers across sectors. Immediately after the immigrant inflow, the proportion of both unskilled and skilled workers in the unskilled intensive service and manufactur-
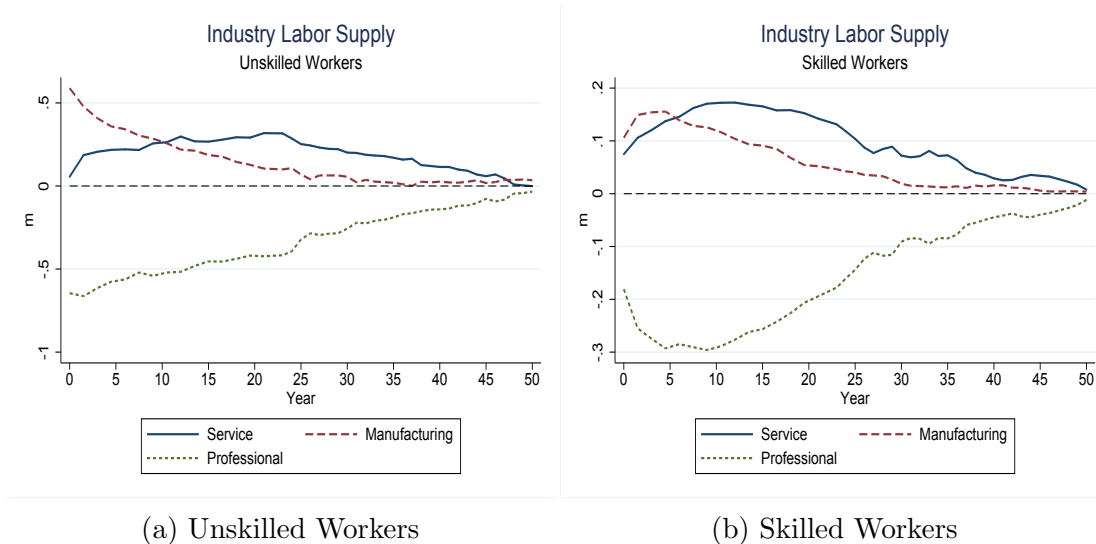
Figure 6: Sudden Immigration: Distribution of unskilled and skilled workers by city. The cities are arranged on the horizontal axis by the number of immigrants they receive as a fraction of their unskilled population. The left panel shows the change in unskilled workers while the right panel shows the change in skilled workers. The results are displayed in percent differences from the baseline simulation.

ing sector increases while the proportion in the skilled intensive professional decreases.

6.1 The Lifetime Costs and Benefits of Immigration

Several papers have shown that the potential wage and productivity gains of increases in immigration are massive.[37] However, as I have shown in the previous section, some workers suffer losses as a result of immigration, especially in the short run. To get a better sense of the magnitude of the costs and benefits of immigration, I calculate the compensating variation of the immigration inflow for workers in the US.

Formally, consider an immigrant inflow occurring in year $\hat{t}$. Let $E\left[V^{NoInflow}\left(\Omega_i, \varepsilon\right)\right]$ represent agent i's expected lifetime utility evaluated at the beginning of year $\hat{t}$ if the immigrant inflow does not occur and let $E\left[V^{Inflow}\left(\Omega_i, \varepsilon\right)\right]$ represent agent i's expected lifetime utility if the immigration inflow occurs. The effect of the immigrant inflow to agent i's lifetime utility is simply the difference in the two expected lifetime utilities. Lifetime utility is measured in utility units; dividing by

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[37]See Clemens (2011), Schoellman and Hendricks (2017), or Kennan (2013), for example.

	Unskilled	Skilled
I. Per Original Worker		
All	-1.6	1.3
By Original Sector:		
Service	-1.9	2.1
Manufacturing	-2.3	2.6
Professional	-2.3	1.1
Unemployed	-0.9	0.7
II. Per Immigrant		
All	-16.1	15.3

Table 5: Lifetime utility costs of a sudden immigrant inflow measured in thousands of dollars. The first panel shows the average cost of the sudden immigrant inflow for workers already in the country at the time of the inflow. The second panel shows the total cost of the immigrant flow divided by the number of immigrants who entered the country as part of the sudden inflow.

$\beta_{e,m}^w$ converts this to hourly wage units and multiplying by yearly hours working while employed, $\mathbb{H}_i$, converts to a dollar amount. Then we can write the change in lifetime utility for the immigrant inflow for agent i, measured in dollars, as:

$$CV_i = \frac{E\left[V^{Inflow}\left(\Omega_i, \varepsilon\right)\right] - E\left[V^{NoInflow}\left(\Omega_i, \varepsilon\right)\right]}{\beta_{e,m}^w}\mathbb{H}_i \tag{15}$$

where I set $\mathbb{H}_i = 2000$ for all workers.

The first panel of table 5 shows the average change in lifetime utility of various groups of workers, measured in thousands of dollars. The average unskilled worker experiences a lifetime utility decrease equal to $1600 dollars while the average unskilled worker experiences a lifetime utility increase equal to $1300 dollars. Next I explore heterogeneity based on a worker's sector the year before the immigration inflow. Not surprisingly, we see that unskilled workers who are initially employed experience much larger decreases in lifetime utility than unskilled workers who are unemployed before the immigrant inflow. Unskilled workers in the unskilled intensive service sector experience smaller utility decreases than workers originally employed in the more skilled intensive sectors. The effects for skilled workers largely mirror those of unskilled workers. Employed workers see much larger utility increases than workers who are initially not working. Furthermore, workers in the more unskilled intensive service and manufacturing sectors experience larger utility increases compared to workers originally in the professional sector.

The final row the table 5 gives the sum of lifetime utility changes divided by the total number of immigrants who enter as part of the immigration inflow. The total cost of an unskilled immigration on unskilled workers in the US amounts to $16,000 per immigrant. As a comparison, the Department of Homeland Security reported that the cost of hiring a human smuggler, or coyote, to cross the US Mexican border can reach up to $8,000 (The Department of Homeland Security, 2017). Workers from Central American and Asia pay considerably more; immigrants from Asia may pay up to $30,000 (Johnson, 2011). Furthermore, a line of research has shown that the wage gains for immigrants admitted into the United States are 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. Schoellman and Hendricks (2017) find wage gains of a similar magnitude.[38] These results suggest that the costs of immigration are much smaller than the gains for potential immigrants. Along these lines, Clarke (1994), Chang (1997) and Becker (2011) have suggested that increases in immigration combined with programs in which immigrants are charged a fee upon entering the country and the revenue is transferred to native workers, could be Pareto improving.

7 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

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[38]The utility gains, however, are more difficult to quantify. A series of studies (Diamond (2016), Kennan (2013) or Kennan and Walker (2011), for example) 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. As such, the utility gains of moving to the US are likely to be smaller than the wage gains.

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 roughly twice as large as the effects 10 years after the inflow. I also calculated the effects of an immigrant inflow on the lifetime utility of workers already in the country. In particular, I found that the costs of immigration on native workers are very small when compared to the potential gains of immigration for immigrants.

This paper has made several key simplifying assumptions due to data limitations. Because 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 affected by changes in local output quantity. Assuming that some sectors produce non-tradeable goods that must be consumed locally would limit the extent to which changes in the distribution of agents across sectors could mitigate the effect of immigration on wages. Also, I have abstracted away from the role of sector-specific experience in determining wages. In a model with sector-specific human capital, there would be much greater heterogeneity in wage costs to sector switching. For example, older workers would 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 sector choice and migration margins. Peri and Sparber (2009), Llull (2017) and Foged and Peri (2016), among others, have shown that workers may switch occupations in response to immigrant inflows. It would be interesting to extend the model here to incorporate dynamic occupation choice.

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A Data and Simulation Appendix: FOR ON-LINE PUBLICATION ONLY

A.1 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.

A.1.1 Labor Market Clearing

Quantities demanded of labor inputs L_{njtU}^D and L_{njtS}^D are implicitly defined as functions of human capital prices by the first order conditions of the firm's profit function:

$$
\begin{aligned}
r_{njtS} &= \frac{P_{nt}Y_{njt}\alpha_n}{\mathcal{L}_{njt}}\mathcal{L}_{njt}^{1-\zeta}\theta_{njt}(L_{njtS}^D)^{\zeta-1} \\
r_{njtU} &= \frac{P_{nt}Y_{njt}\alpha_n}{\mathcal{L}_{njt}}\mathcal{L}_{njt}^{1-\zeta}\left(1-\theta_{njt}\right)(L_{njtU}^D)^{\zeta-1}
\end{aligned}.
$$

In 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 sectors. Abusing notation, write $n_{it}^\star$ as agent i's optimal choice in period t given current prices r_{njte} and expectation $\tilde{r}$:

$$
n_{it}^\star\left(r_{njte},\tilde{r}\right) = \underset{n\in\{N\cup\{Home\}\}}{\arg\max}\; V_{i,n}\left(r_{njte},\tilde{r}\right). \tag{16}
$$

Labor supply is the sum of total human capital provided by agents who opti-

mally choose a sector in each labor market and year:

$$L_{njte}^{\mathcal{S}}\left(r_{njte}, \tilde{r}\right) = \sum_{i \in I_{jte}} \mathbb{I}\left(n_{it}^{\star}\left(r_{njte}, \tilde{r}\right) = n\right) H_{it} \exp\left(\nu_{int}\right), \qquad (17)$$

where I_{jte} is the set of agents of a given skill level in city j in time t. Labor market clearing for a given vector of expectations $\tilde{r}$ implies $L_{njte}^{\mathcal{S}}\left(r_{njte}, \tilde{r}\right) = L_{njte}^{D}\left(r_{njte}\right)$ for all sectors n, cities j, years t and skill levels e.

A.1.2 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 $r^{\star}\left(\tilde{r}\right)$.
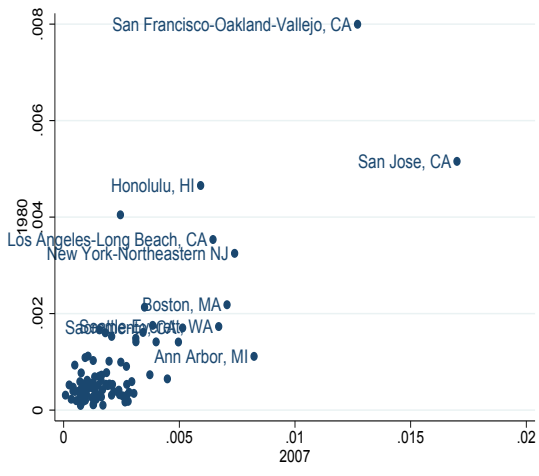
Under the perfect foresight assumption, equilibrium prices are equal to expectations of prices. Perfect foresight equilibrium prices $r^{\star\star}$ are therefore a vector of prices such that

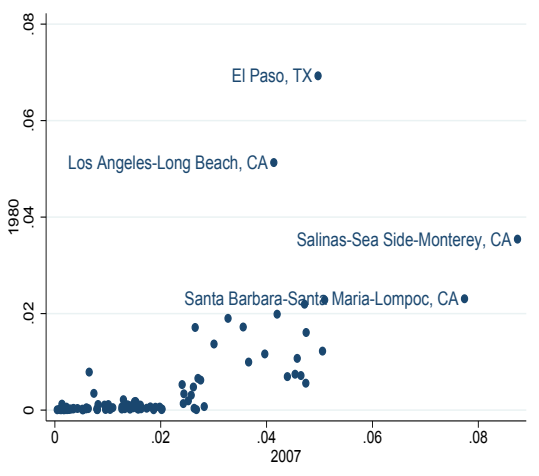$$r^{\star}\left(r^{\star\star}\right) = r^{\star\star} \qquad (18)$$

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 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.

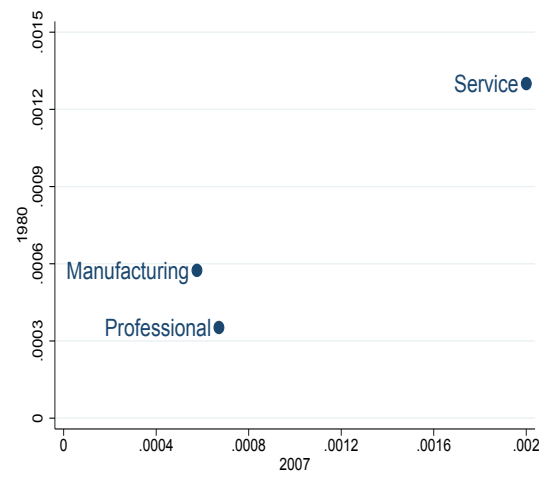## A.2 Distribution of Immigrants Over Time

Figure 7 shows that the sectoral distribution of new unskilled immigrants from Mexico and China are very persistent between the 1980 census and the 2007 ACS.
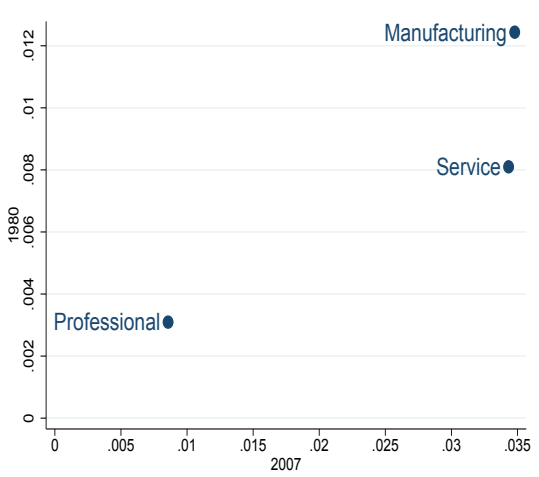
(a) Geographic: Chinese

(b) Geographic: Mexican

(c) Sector: Chinese

(d) Sector: Mexican

Figure 7: 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.

Service		Manufacturing		Professional	
Retail Trade	54.1%	Electrical Machinery	10.9%	Educational	17.8%
Construction	19.2%	Printing/Publishing	9.8%	Oth. Professional	11.7%
Transportation	13.8%	Oth. Machinery	9.6%	Health Services	10.1%
Personal Services	7.9%	Motor Vehicles	8.6%	Business	9.8%
Repair Services	3.4%	Food	7.7%	Public Admin.	9.5%
Private Household	1.6%	Fabricated metal	7.4%	Hospitals	8.2%
. . .		. . .		. . .	

Table 6: This table shows the six largest individual industries which make up the sectors used in structural estimation.

A.3 Construction of Aggregate Sectors

Table 6 shows the largest industries which make up each sector. To construct the sectors, I first aggregate all the manufacturing industries into the "manufacturing" sector. I divide the remaining industries into the "service" and "manufacturing" based on the proportion of workers in each sector who are skilled. If over 50% of the workers are skilled, the industry is aggregated into the professional sector. The remaining industries are aggregated into the "service" sector.

A.4 CPS MORG Data

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 her 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.[39] 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 resident is replaced by a new resident. 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 resident moves in, she is occasionally

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[39]See Madrian and Lefgren (2000) for a discussion of the pros and cons of various algorithms for matching individuals in the CPS

assigned the same identifiers as the old resident. 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 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.

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.

A.5   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.

A.6 Initial Conditions

I use data from 1995 to construct the simulation sample and use data from 1994 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 up to the productivity shock ν_{int}. However, if an agent is not employed in both of these periods, I cannot infer the agent's most recent sector or level of human capital.[40] 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 sector for these agents depends on the agent's education level, immigrant status, age and the distribution across sectors of all agents in the agent's labor market. For a given agent the probability of having n_L as their most recent sector is given by:

$$\Pr\left(n_L == n | j, m, e, a\right) = \frac{\pi_{n,e,m}^1 + \pi^2 \lambda_{j,m,e,n} + \pi_n^3 age}{\sum_{n' \in N} \left(\pi_{n',e,m}^1 + \pi^2 \lambda_{j,m,e,n'} + \pi_{n'}^3 age\right)} \quad (19)$$

where j is agent i's city, m is immigrant status, e is skill level and $\lambda_{j,m,e,n}$ 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 sector, 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.

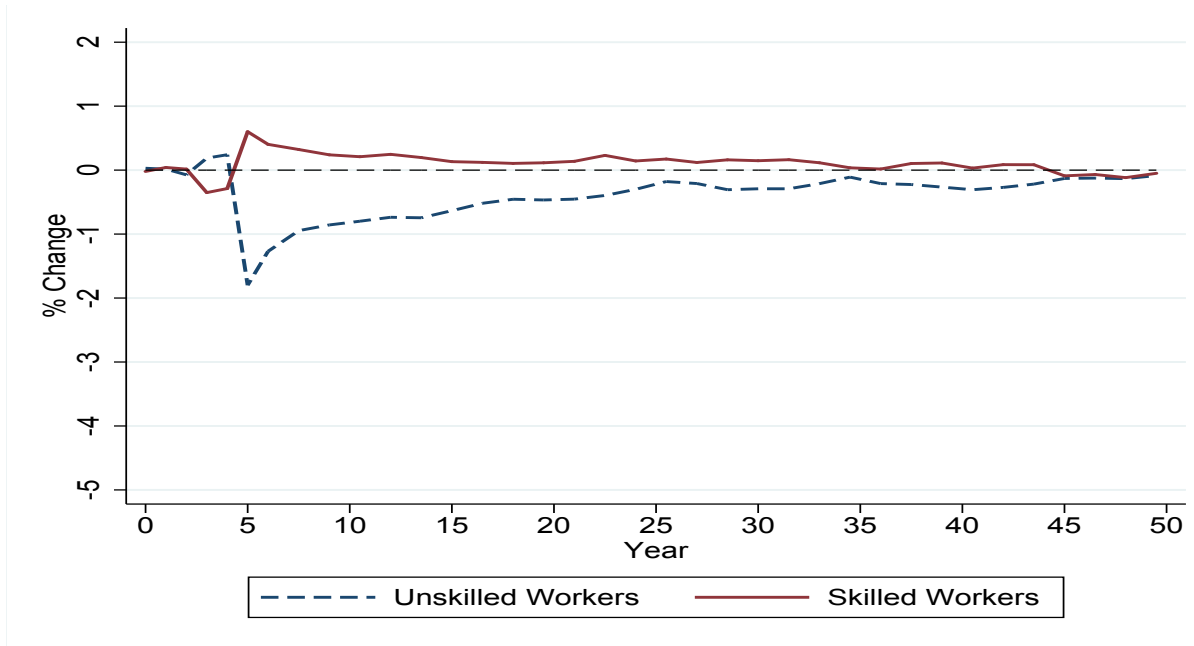[40]Agents who are not working in both years constitute 14% of my sample.

Figure 8: 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.

B   Additional Counterfactuals: FOR ONLINE PUBLICATION ONLY

B.1   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 five 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 8. We can see that the immigration inflow leads to smaller wage effects than the case in which the inflow is not anticipated.

B.2   Robustness: 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.[41]

From section 2.1, we know that the firms optimal choice of physical capital when the capital building constraint is not binding is given by the equation:

$$\frac{\mathcal{L}_{njt}}{K_{njt}^{eff}} = \left(\frac{\bar{r}_{tK}}{P_{nt}A_{njt}\left(1 - \alpha_n\right)}\right)^{1/\alpha_n}$$

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:

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

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, $\bar{r}_{tK}$, is fixed over time and normalize units of capital such that $\bar{r}_{tK} = (1 - \alpha_n)$. Then we can rewrite the unconstrained optimal level of capital as: $K_{njt}^{eff} = (P_{nt}A_{njt})^{1/\alpha_n}\mathcal{L}_{njt}$. I can estimate the ζs and θs 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 9. 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%. Skilled workers see slighter smaller wage gains compared to the case

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[41]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.
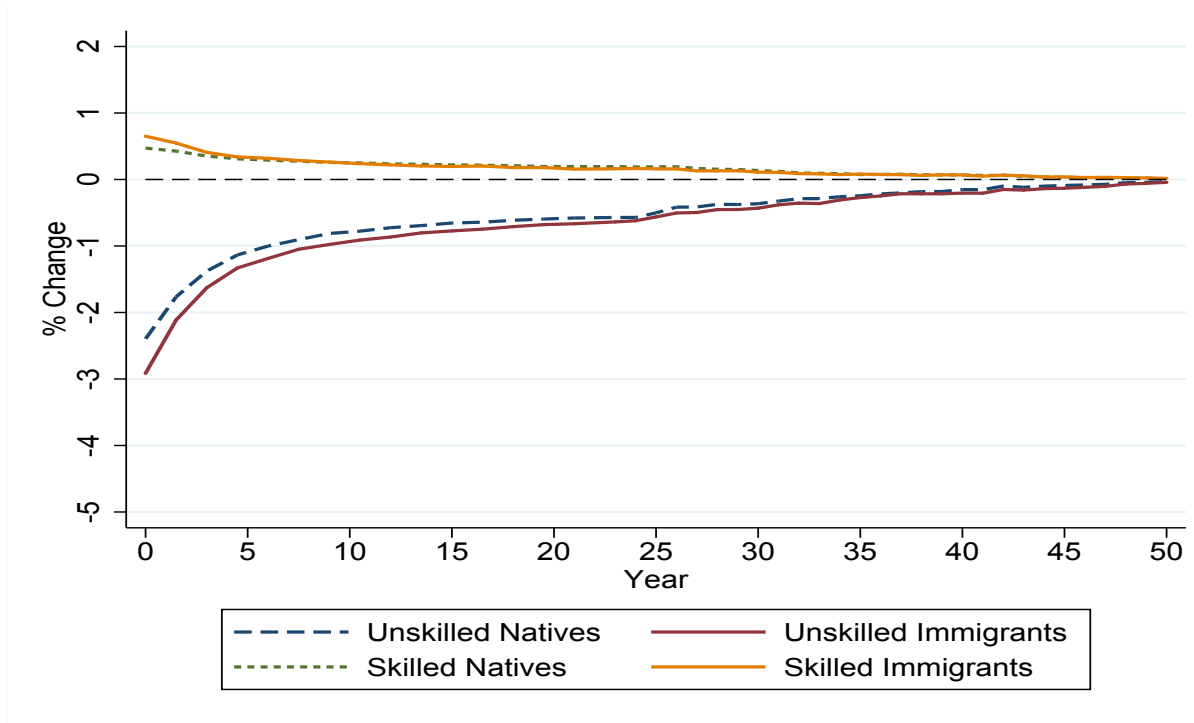
Figure 9: Imperfect Capital Mobility: Average Wages. This figure shows effect of a sudden immigration shock on wages. The results are displayed in percent differences from the baseline simulation.

with perfectly mobile capital. By the end of the sample period, the effects on wages are similar to those under the assumption 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.

B.3 Sudden Immigration: Decomposition of Adjustments

In the baseline model simulated in the previous section, which allows for workers to respond to immigrant inflows via migration and sectoral switching, the sudden immigrant inflow led to a 2.1% decrease in average wages for unskilled workers immediately after the immigration, a 1.6% decrease 1 year after the shock, a 0.8% decrease 10 years after the shock, and a 0.6% decrease 20 years after the inflow. 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 specifica-

tion 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 table 7.

In the first specification, I turn off the migration response by setting the moving cost, ϕ^{Loc}, to negative infinity. In this environment, workers can only adjust to migration inflows through their sector choices. In particular, if workers switch into sectors which more intensively use unskilled workers, within sector 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: 20 years after the shock, unskilled native wages are 1.6% below the case without the immigration shock, compared to 0.6% lower in the case with both migration and sector 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:

$$\tilde{v}_n^{Sec}(\cdot) = \beta_{e,m}^w \tilde{W}_{int} + \gamma_{n,e,m} + \gamma_{j,e} + \phi_e^{Sec}(n, n_{t-1}) + \varepsilon_{int}$$

where

$$\tilde{W}_{int} = r_{njte}^{base} H_{it} \exp(\nu_{int})$$

and r_{njte}^{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. One year after the shock, unskilled native wages decrease by 2.0%, compared to 1.6% in the full adjustment case. Twenty years after the shock, unskilled native wages are 1.0% lower, compared to 0.6% lower in the full adjustment case.

Finally, I turn off both the migration and sector switching adjustments by

	No Adj.	No Ind. Choice	No Mig.	Both Adj.
1 Year After	-2.1	-2.0	-1.8	-1.6
10 Years After	-1.9	-1.2	-1.7	-0.8
20 Years After	-1.8	-1.0	-1.6	-0.6

Table 7: Decomposition of Adjustments: Change in average unskilled wages. This table shows effect of a sudden immigration inflow on unskilled wages under the four environments described in the text. The results are displayed in percent differences from the baseline simulation.

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 sector 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 2.1% decrease in unskilled native wages one year after the shock, and a 1.8% decrease in wages twenty years after the shock.

These counterfactuals show that both migration and sector 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 considerably larger as in the case when agents can respond.