Workers' Age and the Impact of Trade Shocks

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Abstract

Do trade shocks affect workers differently because of their age? This paper examines the issue by estimating the lifetime mobility of workers based on the sectors in which they work. Using U.S. data, the paper shows that mobility costs rise with a worker's age and years of experience, but stay the same regardless of his or her education level. In addition, using a general-equilibrium

simulation of counterfactual trade-liberalization policies in the metal manufacturing sector, the paper shows that trade shocks affect workers with higher mobility costs more, for both winners and losers of the policy shocks. But the effects taper off over a worker's lifetime, especially when they are close to retirement.

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1 Introduction

One of the key policy questions in the international trade literature is the distributional effects of trade shocks. Policy makers need to know who are the winners and losers from trade liberalization in order to develop effective compensation programs and address inefficiencies. Recently, economists have started to use structural models to study trade policy, with a special emphasis on labor market dynamics and general equilibrium effects, to focus on issues that cannot be addressed with reduced form methods. The main motivation for structural estimation is running counterfactual policy simulations, such as trade liberalization, using estimated theoretical parameters.

Most of the frontier research on structural estimation of labor market parameters requires solution of agents' optimization problem, naturally from the agents' perspective. In order to solve workers' optimization problem, the econometrician has to know the exact distribution of expected aggregate shocks as perceived by agents, a popular special case being the perfect foresight assumption². This is a fundamental challenge for international trade research because trade policy, by its nature, is a shock that changes agents' expectations about the future dynamically.

The trade barriers have been changed very frequently by policy-makers, in most cases being reduced and in some cases being increased. Sometimes, a new trade policy is announced in advance, but in many other cases it appears as a shock-therapy. As new information arrives regarding the trade policy, agents update their expectations about future wage and employment outcomes in different sectors.

For example, when the Multi Fibre Agreement ended in 2005 after the establishment of the World Trade Organization, the original plan was to abolish textile quotas. This important change in the global trade policy had already been public information for many years. After the arrival of this new information, probably prior to the establishment of the WTO, agents updated their expectations about wages and employment prospects in the

²Some prominent examples are Keane and Wolpin (1997), Lee and Wolpin (2006) from the labor literature, Dix-Carneiro (2011) from the trade literature.

textile industry. It is safe to assume that both physical and human capital investments in textiles had declined significantly before 2005 in many countries, excluding China. Later on, however, the EU announced that they were imposing new quotas, causing an increase in trade barriers once more. Possibly, agents had updated their expectations several times as they learned more about the planned policy change. It is not possible to know when workers and employers changed their expectations and how much they changed them, since we do not have survey data on expected future wages.

Another sector that was subject to trade shocks is the metal manufacturing sector, in particular the steel industry. In 2002, the US administration announced that they would impose a 3 year temporary safeguard to protect the domestic steel industry, under Section 201 of the US Trade Act of 1974. According to news, this announcement raised hopes in the textile industry to receive a similar protection. Meanwhile, there were discussions about the US automotive industry and whether it was hurt due to the increase in steel prices, a major input for car production. Shortly after, WTO ruled against this decision asking the US to lift the temporary protection. Although initially the US was expected to appeal this ruling, in 2003 the temporary barrier was lifted voluntarily, 2 years before the scheduled time. Because of high uncertainty in metal tariffs, it is practically impossible to parameterize workers' and manufacturers' expectations about labor market outcomes in the metal sector: new information arrives frequently and changes expectations dynamically.

Identification of workers' expectations is a challenge for any research that relies on structural estimation of labor market parameters, such as migration, education choice, occupational mobility, sectoral mobility, etc. Just like trade shocks, other policy and macroeconomic shocks can also affect workers' expectations. Our contribution is studying distributional effects of trade liberalization, one of the key questions in the international trade research that is usually addressed via reduced form regressions, in a setting that allows unspecified fluctuations in workers' expectations due to policy and macroeconomic shocks. Different from the previous research, our main focus is the effect of trade shocks on different age groups.

Although reduced form econometrics provides useful insights on the distributional effects of trade shocks, structural estimation is the only known method to address certain important issues, such as adjustment dynamics, general equilibrium effects, and counterfactual policy simulations, despite the challenges we mentioned earlier.

In this paper, we study the impact of trade liberalization along the life cycle of workers from different skill and experience groups without imposing any strong restrictions on workers' expectations in the estimation stage. Therefore our estimation strategy, which is described fully in Artuc (2012), is applicable to environments that are subject to aggregate uncertainties. The econometrician does not need to know the distribution of aggregate shocks due to changes in trade policies, labor market policies, financial crises, technological progress, etc. We investigate how age interacted with education and experience affects the mobility of workers, and report the increase in mobility costs as workers get older. Then, we show that workers' mobility determines loss and gain from trade shocks, and provide a general picture of welfare changes across different worker subgroups.

To illustrate the connection between mobility and diffusion of gains from trade, imagine that all workers were perfectly mobile across sectors. Then, all workers would be unanimously better off or worse off after a policy shock thanks to factor price equalization. If workers were immobile and attached to their original sectors, then there would be distinct winners and losers from free trade. In that case, workers' sectors would determine their gain and loss. In reality, mobility costs probably lie between these two extremes and vary across groups. A major source of variation in mobility has to do with the age of affected workers, causing differences in their position towards free trade. For example, the Pew Global Attitudes survey, conducted in 2002, shows that young people are more enthusiastic about free trade compared to older people.

After the empirical exercise we conduct using the Current Population Survey and the 1979 cohort of the National Longitudinal Survey of Youth (henceforth CPS and NLSY respectively), we calibrate production, input demand and consumption demand functions to

set a general equilibrium framework with the estimated sectoral choice parameters. Finally, we simulate a hypothetical trade liberalization in the metal manufacturing sector (which has been especially vulnerable to trade shocks in the past) to analyze gradual adjustment of labor, wages and prices in all sectors in response to the trade shock. The counterfactual trade shock is a surprise reduction in protective trade barriers in the metal manufacturing sector, reducing metal prices. Wages, labor allocations, service sector price, gross flows of workers and sectoral outputs adjust endogenously during a transitional period, following the policy shock.

One important question is why old workers are less mobile than young workers. Following the previous literature we can give several different answers to this question: For example, Borjas and Rosen (1980) attribute decreases in mobility with age to the increase in wages with tenure. The decrease in mobility with age can be attributed to specific human capital as in Topel (1991), better job match as in Jovanovic (1979) or implicit contracts as in Lazear (1979). Groot and Verberne (1997) suggest that the decrease in mobility with age can be partially attributed to non-financial reasons. Possible non-pecuniary reasons are the likelihood of owning a house, having a spouse working in the same location, old workers' relatively lower education levels or shorter time horizon. Other examples are Davidson et al (1994) and Falvey et al (2010), who model employment prospective and training costs in relation to age of workers respectively. Since it is impossible to model all these important factors explicitly, we allow sectoral mobility costs of workers to change over their life-cycle with age, experience and education.

The most closely related work to ours is Artuc, Chaudhuri and McLaren (2010), (henceforth ACM). They introduce an empirical dynamic discrete choice model, a new direction for trade research, to study trade shocks without imposing restrictions on workers' expectations. However, their estimation strategy fails when there are more than a few worker types or small sectors. They can identify only a limited number of theoretical parameters. As it is incredibly difficult to fit such a compact model to data, they report imprecise and possibly

overestimated values for the structural moving cost parameters.

In this project, unlike ACM, we focus on distributional effects of trade shocks on disaggregated worker groups and provide a much sharper picture. We utilize a different estimation strategy which allows small sectors (such as metal), detailed worker heterogeneity and a large number of structural parameters without imposing distributional assumptions on workers' expectations. This new estimation strategy can successfully pin down a much richer set of theoretical parameters with more precision, without adding any computational burden. In fact, we show that workers' optimization problem can conveniently be collapsed to two linear equations, which are easy to estimate, without sacrificing from worker heterogeneity³.

It is possible to consider two main lines of quantitative research on labor market effects of trade liberalization: First, research that is conducted via reduced form estimation. Research based on reduced form estimation utilizes natural experiments to identify effects of free trade on import competing sector workers. This type of research usually contains rich worker heterogeneity and focuses on distributional effects⁴. The second type is general equilibrium models that are inspired from macroeconomics or structural labor economics (which requires calibration or estimation of theoretical parameters). General equilibrium models allow counterfactual policy simulations and focus on labor market interactions based on theory. Different from reduced form regressions, they require strong assumptions on workers' expectations and the distribution of aggregate shocks⁵.

Our paper is an intuitive combination of reduced form analysis and general equilibrium models. The model we present here is a general equilibrium model, and we estimate theoretical parameters; from this perspective it is structural. On the other hand, we employ linear regressions (Poisson and IV) to estimate structural parameters which are almost exclusively

³The main econometric analysis here can be conducted using standard statistical software, and can be applied to many other discrete choice problems, such as migration, occupational mobility, education choice, etc.

⁴Two well-known examples are, Pavcnik, Attanasio and Goldberg (2004) and Ravenga (1992); Slaughter (1998) provides a survey of this literature.

⁵Among others, some prominent examples are Cosar (2011), Cosar et al (2011), Dix-Carneiro (2011), Kambourov (2009) and Ritter (2009).

used in reduced form analysis. The linear regressions we employ allow us to be agnostic about aggregate policy and macroeconomic shocks in the estimation stage, but at the same time we run counterfactual simulations as we recover theoretical parameters.

In the next section, we specify the theoretical model, followed by an introduction of the estimation strategy. Then, we discuss data issues and present empirical results. Finally, we conclude after discussing the counterfactual trade simulations.

2 Model

Consider an economy with N industries, where workers choose a sector to work *dynamically* in each period to maximize their present discounted expected utility. The industries are indexed with $i \in \{1, 2, \dots, N\}$. We divide workers in each sector into economically relevant subgroups; a worker's subgroup is defined by the state vector $s \in S$. The state vector s includes workers' age, education, endogenous sectoral experience status and unobserved type. The state variable *age* can take six values, $age \in \{26, 33, 40, 47, 54, 61\}$. Since our main focus is age, we consider binary variables for the other elements of state space. The education variable is denoted as $edu \in \{noc, col\}$, standing for non-college and college educated respectively, while the sectoral experience variable is denoted as $exp \in \{in, ex\}$, inexperienced and experienced respectively. Finally, we consider two unobserved types denoted as $\tau \in \{I, II\}$. The state of a worker is his current industry i and the vector

$$s = [age, edu, exp, \tau]'. \quad (1)$$

At period t , a worker with state vector s receives an instantaneous utility in sector i , denoted as

$$u_t^{i,s} = w_t^{i,s} + \eta_t^{i,s}, \quad (2)$$

where $w_t^{i,s}$ is the wage and $\eta_t^{i,s}$ is a non-pecuniary utility common to all type s workers in sector i . The wage for a type s worker in sector i , $w_t^{i,s}$, is a function of the aggregate state

of the economy, denoted as ξ_t , where

$$w_t^{i,s} = W^{i,s}(\xi_t).$$

The aggregate state variable, ξ_t , captures all industry, macroeconomic and policy shocks. The workers are rational, hence any new information that updates expectations for this aggregate state variable is a surprise. More formally, $\varepsilon_w = E_{t+1}W^{i,s}(\xi_{t+n}) - E_tW^{i,s}(\xi_{t+n})$ is a mean zero iid shock for $n \geq 1$. This assumption applies to all random variables in our model. For the estimation purposes, we do not need to specify a functional form for $W^{i,s}(\xi_t)$, so we define this function in the next subsection when we focus on general equilibrium aspects of the model.

The non-pecuniary utility component, $\eta_t^{i,s}$ is distributed iid with mean $\bar{\eta}^{i,s}$. A rational worker chooses his sector after taking instantaneous utility, $u_t^{i,s}$, and the stream of expected future utilities into consideration. Workers can expect changes, trends and fluctuations in wages due to policy, sectoral and macroeconomic shocks. Hence expected future values of the aggregate state variable, ξ_{t+n} , can fluctuate over time. The econometrician does not need to know or quantify the expectations of workers.

We establish that a worker pays a moving cost, $C^{ij,s} + \epsilon_t^j$, if he decides to switch from sector i to sector j . This moving cost has two components, a fixed component C^{ij} , and an individual specific random component ϵ_t^j . Note that, ϵ_t^j is different for every worker as it is individual specific (but we omit the agent index). The fixed component C^{ij} is equal to zero for stayers, so $C_t^{ij,s} = 0$ if $i = j$, otherwise it is expressed as

$$C^{ij,s} = C^{1,age,edu} + \mathbf{1}_{exp}C^2 + \mathbf{1}_\tau C^3, \quad (3)$$

where $C^{1,age,edu}$ is the component changing with age and education of workers. $\mathbf{1}_{exp}$ is the indicator function which is equal to one when sectoral experience status is 'ex', i.e. when the worker has sectoral experience, zero otherwise. Hence, the workers with sectoral experience

pay an additional moving cost, C^2 , when they move. $\mathbf{1}_\tau$ is an indicator function which is equal to one when $\tau = II$ and zero otherwise, resulting in an additional C^3 units of moving cost for the unobserved type II workers.

The idiosyncratic individual specific moving costs shock ϵ_t^j is drawn from extreme value type I distribution with scale parameter ν and location parameter $-\nu\gamma$, where γ is the Euler's constant.

We define exogenous transition probabilities between states. Following Artuc (2006), a similar methodology was also used by ACM to introduce limited heterogeneity. We assume that the probability of moving from one age group to the next group is $1/k$, where k is the difference between two age groups. In our case $k=7$, since we consider age clusters of seven years such as 26, 33, 40, etc. We assume that workers gain sectoral experience if they stay in their sector as they move up to the next age group⁶. Experience is lost if a worker changes sectors. Workers' education and unobserved type do not change over time. Let us denote the probability of switching from state s to state s' as $\pi^{ij}(s, s')$ for a worker moving from i to j . Artuc (2006) shows that this approach provides a reasonable approximation of continuous state space.

Timing of the events is as follows: 1. Agents learn values of $w_t^{i,s}$ at time t when they learn ξ_t . They also update their expectations about future shocks, $E_t\xi_{t+n}$ for $n \in \{1, 2, 3, \dots\}$ when they receive new information. 2. Then, at the end of period t , they learn the random component of their "moving cost," ϵ_t^j , for every $j = 1, \dots, N$, and choose the next period sector (based on expected stream of future wages and moving costs). 3. Agents pay the moving cost, $C^{ij,s} + \epsilon_t^j$, where j is the chosen sector. 4. Period $t + 1$ starts, and the cycle repeats itself.

Workers' objective is to maximize their present discounted utility flows following the Bellman equation

⁶This is a binary variable, therefore only workers do not already have experience can gain additional experience.

$$V_t^s = \max_i (V_t^{i,s}), \quad (4)$$

alternative-specific values are defined as

$$V_t^{i,s} = w_t^{i,s} + \eta_t^{i,s} + E_t \max_j \left\{ \beta \sum_{s' \in S} \pi^{ij}(s, s') V_{t+1}^{j,s'} - C^{ij,s} - \epsilon_t^j \right\}, \quad (5)$$

where the expectation is taken with respect to all random variables including ξ_{t+n} for $n \geq 1$ (which can change with anticipated or realized policy shocks).

For the estimation purposes, we consider that expectations of agents are unknown to the econometrician, i.e. we do not know $E_t w_{t+1}$. For example, if there is a future shock, such as a trade shock, we do not need to assume whether the agents know it or not, when they learn about it, or how it affects wages. We only impose a certain distribution for the individual shock, ϵ_t^i . The distribution of other random variables is only needed for the simulations, not for the estimation. We are agnostic about the distribution of random shocks and workers' expectations, and unlike most of the other structural discrete choice models, we do not attempt to calculate values by backwards solution or iteration (for estimation purposes). We explain how we estimate the model without distributional assumptions in the next section.

The value function, then, can be re-arranged as

$$V_t^{i,s} = w_t^{i,s} + \eta_t^{i,s} + \beta \tilde{V}_{t+1}^{i,s} + \Omega_t^{i,s}, \quad (6)$$

where

$$\tilde{V}_{t+1}^{i,s} = \sum_{s' \in S} \pi^{ij}(s, s') E_t V_{t+1}^{i,s'}, \quad (7)$$

and

$$\Omega_t^{i,s} = -\nu \log \sum_{k=1}^N \exp \left(\left(\beta \tilde{V}_{t+1}^{k,s} - \beta \tilde{V}_{t+1}^{i,s} - C^{ik,s} \right) \frac{1}{\nu} \right). \quad (8)$$

See Artuc (2012) for the derivation of the equations above. Using the value functions, we can easily derive gross flows of workers (thanks to McFadden (1973)). The probability of a type s worker to move from sector i to sector j is equal to

$$m_t^{ij,s} = \frac{\exp \left(\left(\beta \tilde{V}_{t+1}^{j,s} - \beta \tilde{V}_{t+1}^{i,s} - C^{ij,s} \right) \frac{1}{\nu} \right)}{\sum_{k=1}^N \exp \left(\left(\beta \tilde{V}_{t+1}^{k,s} - \beta \tilde{V}_{t+1}^{i,s} - C^{ik,s} \right) \frac{1}{\nu} \right)}. \quad (9)$$

The equations (9) and (6) are pivotal for our estimation strategy.

Aggregate Economy

To be able to simulate workers' response to trade shocks, we need to define labor demand equations, more specifically $w_t^{i,s} = W^{i,s}(\xi_t)$. In this section, we define production functions and derive wage equations from them. Note that the equations we derive in this section are only required for simulations, and they do not play any role in the main estimation strategy.

The number of type s workers in sector i at time t is defined as $L_t^{i,s}$. Then, the distribution of workers at time $t + 1$ can be expressed as

$$L_t^{j,s'} = \sum_{i=1}^N \sum_{s \in S} L_t^{i,s} m_t^{ij,s} \pi(s, s') \quad (10)$$

We assume that any 61 years old worker moving up to the next age group is retired, he receives a lump-sum payment and exits the labor force, and is replaced by a 26 years old worker.

The production functions are Cobb-Douglass and they require skilled labor, unskilled labor, capital and intermediate inputs from all sectors. Some of the output is consumed by workers and some of it is used as input for production. In each sector, there is a large number of competitive employers offering workers their marginal product. We assume that

units of human capital possessed by type s worker for production of i sector output is equal to $h^{i,s}$.

We define production functions for i sector output y_t^i as

$$y_t^i = B^i \left(\sum_{s \in S^{noc}} L_t^{i,s} h^{i,s} \right)^{b_{noc}^i} \left(\sum_{s \in S^{col}} L_t^{i,s} h^{i,s} \right)^{b_{col}^i} (K^i)^{b_K^i} \prod_{j=1}^N (q_t^{ji})^{b_j^i}, \quad (11)$$

where S^{col} is the subset of S that includes only college educated workers (henceforth skilled), and S^{noc} is the subset that includes only non-college educated workers (henceforth unskilled), b_{noc}^i , b_{col}^i , b_K^i , and b_j^i are the Cobb-Douglass shares of unskilled labor, skilled labor, capital and sector j input to produce sector i output respectively. q_t^{ji} denotes the j -sector input used in i -sector output. We assume that capital, K^i , is fixed.

The consumer price index is defined as

$$\psi_t = \prod_{i=1}^N (p_t^i)^{\theta_i}, \quad (12)$$

where p_t^i is the price and θ_i is the consumption share of the sector i output (with an underlying Cobb-Douglas utility function).

Then the real wage equations are

$$w_t^{i,s'} = h^{i,s'} \frac{p_t^i}{\psi_t} \frac{b_{noc}^i y_t^i}{\sum_{s \in S^{noc}} L_t^{i,s} h^{i,s}}, \quad (13)$$

and

$$w_t^{i,s''} = h^{i,s''} \frac{p_t^i}{\psi_t} \frac{b_{col}^i y_t^i}{\sum_{s \in S^{col}} L_t^{i,s} h^{i,s}}, \quad (14)$$

for unskilled and skilled labor respectively, where $s' \in S^{noc}$ and $s'' \in S^{col}$. Note that the wage, $w_t^{i,s}$, is a function of labor allocation matrix, $L_t^{i,s}$, and the price vector, p_t^i . Therefore, the aggregate state variable, ξ_t , consists of labor allocations and prices for simulation purposes.

Thanks to the Cobb-Douglass nature of production and utility functions, we can define the expenditure functions as

$$\mu_t^i = \sum_{j=1}^N [b_i^j + \theta_i (b_{noc}^j + b_{col}^j + b_K^j)] y_t^j p_t^j, \quad (15)$$

where μ_t^i is the expenditure on sector i product.

Finally, we close the model by deriving an equilibrium price equation over the transition for non-traded goods,

$$p_t^i = p_{t-1}^i \frac{\mu_t^i}{\mu_{t-1}^i} \frac{y_{t-1}^i}{y_t^i}. \quad (16)$$

Note that the equations we derive in this subsection, *Aggregate Economy*, are not relevant for the estimation strategy, but they are used for simulations. In the next section we describe the basic estimation strategy.

3 Estimation Strategy for the Workers' Problem

Artuc (2012) explains the estimation strategy in detail. The optimization problem of workers can be expressed with two linear equations, which can be estimated easily with standard statistical software.

Step 1: Flow Equation

We denote number of type s workers in sector i at time t as $L_t^{i,s}$. Then, the number of type s workers moving from sector i to sector j , denoted with $z_t^{ij,s}$, is equal to $z_t^{ij,s} = L_t^{i,s} m_t^{ij,s}$. After multiplying (9) with L_t^i , we get

$$\begin{aligned} z_t^{ij,s} = \exp & \left[\frac{\beta}{\nu} \tilde{V}_{t+1}^{j,s} - \frac{1}{\nu} C_t^{ij,s} - \frac{\beta}{\nu} \tilde{V}_{t+1}^{i,s} + \log(L_t^{i,s}) \right. \\ & \left. - \log \left\{ \sum_{k=1}^N \exp \left(\left(\beta \tilde{V}_{t+1}^{k,s} - \beta \tilde{V}_{t+1}^{i,s} - C_t^{ik,s} \right) \frac{1}{\nu} \right) \right\} \right]. \end{aligned} \quad (17)$$

This equation can be considered as a Poisson pseudo maximum likelihood regression with a destination dummy for sector j , origin dummy for sector i , and a bilateral resistance dummy for the moving cost⁷. This log-linear regression can be expressed as

$$z_t^{ij,s} = \exp [\alpha_t^{i,s} + \lambda_t^{j,s} + \delta_t^{ij,s} \mathbf{1}_{(i \neq j)}] + e_t^{ij,s}, \quad (18)$$

where $\alpha_t^{i,s}$ is the coefficient of origin dummy, $\lambda_t^{j,s}$ is the coefficient of destination dummy, $\mathbf{1}_{(i \neq j)}$ is an indicator function equal to one when $i \neq j$ and zero otherwise, $\delta_t^{ij,s}$ is the moving cost coefficient, and $e_t^{ij,s}$ is the regression residual.

The regression coefficients can be interpreted as:

$$\begin{aligned} \lambda_t^{j,s} &= \frac{\beta}{\nu} \tilde{V}_{t+1}^{j,s} + \Lambda_t, \\ \delta_t^{ij,s} &= -\frac{C^{ij,s}}{\nu}, \end{aligned}$$

and

$$\alpha_t^{i,s} = -\frac{\beta}{\nu} \tilde{V}_{t+1}^{i,s} - \log \left\{ \sum_{k=1}^N \exp \left(\left(\beta \tilde{V}_{t+1}^{k,s} - \beta \tilde{V}_{t+1}^{i,s} - C^{ik,s} \right) \frac{1}{\nu} \right) \right\} + \log(L_t^{i,s}) - \Lambda_t,$$

where Λ_t is an unidentified constant common to all $j = 1, \dots, N$.

Note that at this step we estimate $\lambda_t^{i,s}$, which is simply equivalent to the expected value of type s workers in sector i at time t . Unlike most of the dynamic structural estimation methods, we do not calculate values by backwards solution, but we estimate them from data. Therefore, all expectations of agents, however they affect estimated values, are fully taken into consideration. If new information arrives about a future event, the workers simply update $\tilde{V}_{t+1}^{i,s}$, which is an estimated parameter. This gives us the convenience of being agnostic

⁷Gourieroux et al (1984) introduced Poisson pseudo-maximum likelihood regression, Cameron and Trivedi (1998) is an excellent source on its applications and Santos Silva and Tenreyro (2006) is an influential paper that popularized this approach in trade research.

about workers' expectations and distributions of aggregate shocks.

After recovering the moving cost parameters and expected values in this step, we recover distributional and fixed utility parameters in the second step, as discussed in the following subsection.

Step 2: Bellman Equation

In this section, we re-write the Bellman equation that characterizes the optimization problem of workers using the estimated parameters from Step 1. After multiplying (6) with β/ν , and aggregating it over possible states and moving all terms to the left hand side, we get

$$E_t \left[\frac{\beta}{\nu} \tilde{V}_{t+1}^{i,s} - \frac{\beta}{\nu} \sum_{s \in S} \pi^{ij}(s, s') \left(w_{t+1}^{i,s'} + \eta_{t+1}^{i,s'} \right) - \frac{\beta}{\nu} \sum_{s \in S} \pi^{ij}(s, s') \left(\beta \tilde{V}_{t+2}^{i,s'} + \Omega_{t+1}^{i,s'} \right) \right] = 0. \quad (19)$$

We plug in the estimated coefficients from Step 1 to construct the second step regression equation. Note that λ_t^j corresponds to the expected value expression, δ_t^{ij} corresponds to the moving cost expression. One important missing parameter is the option value, Ω_t^i . Let $\omega_t^{i,s} = \Omega_t^{i,s}/\nu$, thus

$$\omega_t^{i,s} = -\lambda_t^{i,s} - \alpha_t^{i,s} + \log(L_t^{i,s}).$$

Finally, we replace the expressions in (19) with ω_t^i and λ_t^j , and take its difference between sectors, thus

$$\begin{aligned} E_t [& (\lambda_t^{i,s} - \lambda_t^{j,s}) - \frac{\beta}{\nu} \sum_{s \in S} \pi^{ij}(s, s') \left(w_{t+1}^{i,s'} + \eta_{t+1}^{i,s'} - w_{t+1}^{j,s'} - \eta_{t+1}^{j,s'} \right) \\ & - \beta \sum_{s \in S} \pi^{ij}(s, s') \left(\lambda_{t+1}^{i,s'} + \omega_t^{j,s'} - \lambda_{t+1}^{j,s'} - \omega_t^{i,s'} \right)] = 0. \end{aligned} \quad (20)$$

The equation (20) can be interpreted as a linear regression equation and no assumptions are needed on agents' expectations for it to hold, except rationality. This is due to the fact

that agents do not make any systematic mistakes. Naturally, residuals of the regression may be correlated across observations within the same time period, this creates bias in the estimated standard errors. Clustering, as described in Artuc (2012), solves this problem. Another potential problem is the correlation between the residuals and other variables. Since residuals capture arrival of new information, lagged variables can be used as instruments because past variables should be uncorrelated with surprise shocks.

We take values of λ_t^i and ω_t^i from the first step regression and the transition matrix π is already defined exogenously. The remaining parameters β , ν , and $\bar{\eta}^{i,s}$ can be estimated using the Instrumental Variables method.

Our estimation strategy is related to ACM, Hotz and Miller (1993) and Arcidiacono and Miller (2011). The method herein is significantly more efficient compared to ACM, both econometrically and computationally. Unlike ACM, it can handle rich heterogeneity, small sectors, and a large number of structural parameters. Arcidiacono and Miller (2011) is based on the conditional choice probability (henceforth CCP) method introduced by Hotz and Miller (2011) and an expectation maximization algorithm (henceforth EM). Unlike theirs, our method does not use maximum likelihood, it is based on orthogonality conditions. Therefore it does not require parameterization of aggregate shocks, which is a non-trivial convenience when the economy is subject to shocks that are difficult to model (such as the trade shocks in the metal and textile sectors). See Artuc (2012) for a detailed comparison.

4 Data

For estimation of the workers' problem, we use the 1979 cohort of the NLSY and CPS.

The CPS sample is from 1983 to 2001 and constructed in a way similar to ACM: We use white males, who are between 23 and 64, and who worked at least 26 weeks in a given year. We have a minimum of 11,857 and a maximum of 20,211 individuals in our final sample between the years 1984 and 2001 (sample size changes every year). In CPS, the reported mobility rates are 5 months' mobility rather than annual mobility, we correct the transition probabilities. CPS is a repeated cross section, so agents are not followed over years. This

prevents us from being able to construct work history, thus the sectoral experience parameter can not be estimated. The work history is also required to identify unobserved heterogeneity.

NLSY is widely used for estimation of occupational choice models, since it follows individuals over years and provides detailed information on work history. The sectoral experience variable can be easily constructed from NLSY. Initially, NLSY has 12,686 individuals in the sample, consisting of 6,403 males and 6,283 females. The individuals in our sample are between 14 and 21 years old as of 1979.

Following the previous research, we only use white males. We also take individuals with missing observations out, since their sectoral experience can not be calculated correctly. After this data cleaning procedure, we end up with 1,190 individuals in the sample.

Neal (1999) reports that there are coding errors in NLSY79 regarding occupations. A similar error is also present for industry codings. In order to minimize this problem, we use the following method of Neal (1999): Whenever a sector change is reported, we require the worker to change his employer as well, otherwise it is considered as a coding error and the original sector is kept.

NLSY follows individuals annually until about age 40, so we can not identify parameters for older individuals in the model. Only years 1991-1993 have sufficient number of observations to include both experienced and inexperienced workers at the same time, as most of the individuals in our sample are too young to have sufficient sectoral experience before 1991. We do not have enough observations for college graduates, as the metal sector is a quite small and unskilled labor intensive sector. Because of these data problems, we only estimate the first step equation for non-college graduates with NLSY.

First, using CPS, we estimate a special case of the model without sectoral experience and unobserved heterogeneity. Then, using NLSY, we estimate parameters of the general model for only unskilled workers who are less than 37 years old. Fortunately, we are able to see the complete picture when we combine estimates from both datasets, as the changes in worker mobility across different subgroups are fully identified.

The industries are aggregated into 4 main sectors: 1. “Manuf”: Manufacturing and Agriculture (tradable sector), 2. “Metal”: Metal Manufacturing (sector subject to policy change), 3. “Service”: Service except Trade (non-tradable sector), and 4. “Trade”: Wholesale and retail trade (another non-tradable sector). The industries are aggregated mainly in two groups, tradable and non-tradable. Since “wholesale and retail trade” is a relatively large industry, we consider it as a separate sector apart from service.

Table 1 summarizes the distribution of workers across sectors, age, sectoral experience and education groups in both NLSY and CPS samples. Note that the sectoral experience variable is not available for the CPS sample and the NLSY sample includes individuals only up to age 40. Manufacturing and agriculture workers (henceforth manuf.) are approximately 27%, metal workers are about 4%, service workers except trade workers (henceforth service) are about 49% and finally wholesale and retail trade workers (henceforth trade) are close to 20% of the total sample (see Panel A). Panel B shows age distribution and Panel C shows sectoral experience distribution in the sample. As illustrated in Panel D, about 40% of workers have college education in the sample.

Table 2 shows example transition probabilities from different age groups, education groups and sectors. Panel A presents probabilities of sector change for workers with no college education while Panel B shows it for those with at least one year of college education. The effect of education on probability of sector change is ambiguous. However, it is clear that the probability of sector change is decreasing with age for both education groups. Panel C shows transition probability from one sector to another. As one would expect, the probability of moving out of a larger sector is lower than the probability of moving out of a smaller sector, and the probability of moving into a larger sector is higher than the probability of moving into a smaller sector.

5 Regression Results

We have two data sets, CPS and NLSY, for the estimation. CPS is missing the sectoral experience and work history variables, while NLSY has enough observations for only limited

number of types and a short time-series. Therefore, we consider two separate regressions for the two data-sets we have in hand. In the next section, when we run counterfactual simulations, we demonstrate how we use results from both regressions in the same simulation.

Estimation with CPS

Since we do not observe sectoral history, neither unobserved heterogeneity nor sectoral experience is included. This means that we have to impose two restrictions in order to make the model identifiable with the CPS data: $C^2 = 0$ and $C^3 = 0$. Henceforth, we call this version of the model the “constrained model.”

The restrictions imply that workers’ sectoral experience and unobserved type have no affect on mobility costs. For the first step regression (the flow equation), we correct the mobility rates reported in CPS to annual rates. Then, we run Poisson pseudo maximum likelihood regression using (18). For the second step (the Bellman equation), we use time lagged variables as instruments and run IV regression using (20). We normalize the average wage in the economy to one. Since we can not identify the discount parameter, β , we assume that $\beta = 0.95$. The estimation procedure is explained in detail in Artuc (2012).

The regression results are reported in Table 3. We find that the moving cost parameter, $C^{1,s}/\nu$, is increasing with age and is between 2.62 and 4.5, significant at the 99% level for all types. The moving cost does not seem to vary much across education groups. The variance parameter, $1/\nu$, is about 1.67 and also significant at the 99% level. We find that the mean of the fixed utility parameter for the metal sector, $\bar{\eta}^{i,s}$, is negative and significant at the 99% level for unskilled workers. Also, the mean fixed utility parameter for the trade sector, $\bar{\eta}^{i,s}$, is positive and significant at the 95% level for skilled workers.

ACM report that the common moving cost parameter for all types, $C^{1,s}$, is equal to 6.56 when $\beta = 0.97$ and 4.7 when $\beta = 0.90$, relative to the annual average wages normalized to one. They find that the variance parameter, ν , is equal to 1.88 and 1.22 respectively. Differently, we use $\beta = 0.95$ and report parameters divided by the scale parameter v . If we convert our results to make them consistent with ACM, the estimated moving cost is

between 1.57 and 2.69. Note that these are implied mean moving costs faced by agents, not moving costs paid by those agents who actually move. Because of the random components of the moving cost, the actual moving cost paid may be small or negative for movers. Thanks to the new estimation strategy, we are able to estimate a model with much richer worker heterogeneity, with a larger number of structural parameters and with a higher efficiency compared to ACM.

As we discussed in the introduction, it is difficult to pin down the moving cost parameter precisely following ACM's estimation strategy due to the sparsity in workers' choice probability matrices, especially when there is heterogeneity. In addition to loss of precision due to the sparsity problem, omission of the fixed utility parameter, $\eta_t^{i,s}$, also causes the moving cost parameter to be overestimated. We find that workers receive a disutility from working in the metal sector due to a negative $\bar{\eta}^{i,s}$, therefore flows out of the metal sector are much larger than what its relatively high wages would imply. If the fixed utility parameter is not included in the model, then the model can only be made to fit to the data by imposing high variance, ν , for the individual shock, ϵ^i and high moving costs, $C^{1,s}$, simultaneously. When both ν and $C^{1,s}$ are large simultaneously, correlation between outflows and wage differences becomes weaker, as the data imply (i.e. workers' decisions are random). With the inclusion of $\eta^{i,s}$, however, the wages and outflows are not required to be highly correlated. Even if the wages are high in a sector, workers still may not choose it if the fixed utility for that sector is negative. Thus, ACM report much higher moving costs compared to us, possibly due to their omission of the fixed utility parameters.

Estimation with NLSY

With NLSY, we estimate the model for workers with no college education and who are less than 37 years old. The age restriction is due to the nature of the data as its name implies, also since the metal sector is small and unskilled labor intensive, we do not have enough observations to include workers with college education in our sample. Our main goal is to estimate the moving cost parameter that captures sectoral experience, C^2 , and the

extra moving cost paid by the unobserved type II workers, C^3 .

First, we run the regression without types, hence imposing that $C^3 = 0$. The results are reported in the first row of Table 4. We find that $C^{1,s}/\nu$ is equal to 2.68 for young workers who are less than 30 years old, similar to what we find with CPS data. We find that $C^{1,s}/\nu$ is equal to 3.09 for the workers between 30 and 36, and with less than seven years of sectoral experience. We find that $(C^{1,s} + C^2)/\nu$ is equal to 4.38 for the workers who are older than 30 years and with more than 7 years experience. All estimates are significant at the 99% level.

The workers are divided into two unobserved types. In reality, if there is a continuum of types with different moving costs, then allowing two types of workers is equivalent to discretizing a continuous distribution into two pieces. Ideally, we would like to discretize into finer grids but it is not possible given the available data. Therefore, we consider two types, and impose the restriction that $C^3/\nu = 1$, then estimate $C^{1,s}/\nu$ and C^2/ν , while we calculate the mass of each type with an EM loop. Although it is theoretically possible with very detailed data, we can not estimate $C^{1,s}/\nu$ and C^3/ν separately without a restriction, since we do not have enough observations of workers with different work histories. It is possible to try different values for C^3/ν and change the distance between the centers of mass of the grids; we find that the weighted average of moving costs $C^{1,s}/\nu$ and C^2/ν is robust to different specifications.

The EM loop converges to a distribution with 50% type I and 50% type II. We report the estimated moving costs for type I workers in the second row of Table 4. Since we impose $C^3/\nu = 1$, the moving costs for type II workers are exactly one unit larger than type I workers, which are reported in the third row.

6 Simulations

In the previous section, we estimated parameters of the workers' optimization problem. In order to simulate the model, we need to parametrize wage equations, or in other words the labor demand functions. Thanks to the Cobb-Douglass nature of the production functions, it

is straightforward to calculate its parameters using input-output tables. Also, consumption shares give the consumer price index weights, θ^i . We use Bureau of Economic Analysis input-output and consumption share tables to calculate the parameters of the labor demand equations⁸. The calculated parameters are reported in Table 5.

Unlike the estimation step, we need to define all aggregate shocks for the simulations. We assume that there is an unexpected shock-therapy trade liberalization in the metal manufacturing sector which decreases the metal output price 50%⁹. As we discussed previously, it is practically impossible to model the exact liberalization process in the metal sector as the trade policy has been changing dynamically. Our simulation exercise is an illustrative counterfactual. We normalize initial prices to one. After the metal sector trade shock, prices in the tradable sectors adjust endogenously over the transition, while non-tradable sectors' output prices stay constant. Thanks to uniqueness of the equilibrium, and the concavity of relevant equations, the simulations are straightforward: After we guess initial values for $V_t^{i,s}$ and $L_t^{i,s}$ for $t = 1, 2, \dots, T$, we calculate $w^{i,s}$, then implied $V_t^{i,s}$ and $L_t^{i,s}$ by the wage flows using equations presented in the *Model* section. Using an arbitrarily weighted average of the initial and implied values and labor allocations, we update the guessed values. We repeat this procedure recursively until we reach a fixed point and make sure that the economy reaches free trade steady state before time T . We omit the details because the simulations are easy to replicate.

We consider two different specifications. Simulation I uses the restrictions we imposed to estimate the model with CPS (i.e. the constrained model). Hence, we assume that $C^2 = 0$ and $C^3 = 0$. Therefore, we directly use the estimated parameters from CPS for Simulation I. However, Simulation II uses estimates from both NLSY and CPS simultaneously.

First, note that the model with $C^2 = 0$ and $C^3 = 0$ imposed as a constraint is called

⁸The fixed capital, K^i , is normalized to unity.

⁹This 50% price decrease is approximately equal to the change in steel price in the US between 1980 and 1998. Since the US uses about 10% of world metal output, a metal sector liberalization would not affect world price significantly. We experimented with an alternative specification where world price is determined endogenously and found that the qualitative implications are unchanged.

the “constrained model.” The estimation procedure outlined in the econometric section of the paper for the CPS can estimate only the constrained model. However, for any set of parameters for the “unconstrained” model, one can generate simulated data and estimate the parameters of the constrained model on the simulated data. A reasonable way of calibrating the model is to find parameters for the unconstrained model that generate simulated data that generate estimated parameters for the constrained model that are close to the parameters for the constrained model estimated from the “actual” data. That is the approach taken for Simulation II.

The parameters for Simulation II, that give the same estimates as the actual data, are reported in Table 6. We find that the second step (the Bellman equation step) regression results are almost unchanged. Therefore, we understand that the restrictions we impose on the moving costs in the first step do not bias the second step results. Note that the restrictions we impose for the CPS estimation essentially aggregate types, i.e. unobserved type I, type II, experienced and inexperienced workers are clustered into a single type. In panel D of Table 6, we present weighted averages of moving costs based on age and education level, which are directly comparable to the numbers presented in Panel A of Table 3. We show that aggregation is not a significant source of bias, causing only 6 % to 14% difference between estimates of the aggregated and the disaggregated models.

In Table 7, we present steady state labor allocations and wages for CPS, Simulations I and II. Although we do not attempt to match them in the simulations, the implied distributions are close to the actual data.

In Figures 1 to 5, we present the results for Simulation I. For the sake of clarity, we only illustrate the sector averages because there are 12 types of workers in Simulation I and 48 types of workers for Simulation II. Since the results for Simulation II are almost identical to these, we omit them. In Figure 1, we show how workers react to the 50% drop in metal price. After the price drop, real wages decrease causing an increase in outflows from the metal sector. We find that 25% of the metal workers leave their sector within one year after

the shock, and this number reaches 45% in the long run.

When metal workers leave their sector, the output decreases as seen in Figure 2. Note that metal sector output is used as an input in the manufacturing sector, so the manufacturing sector grows significantly after this trade shock. In Figures 3 and 4, we show the change in unskilled and skilled workers' wages respectively. We find that the metal sector wage drops significantly as expected, while the manufacturing sector wage increases due to the decrease of the metal price as an important input. After this initial change, the metal sector wage increases as workers leave their sector, but can not catch up with the original wage.

In Figure 6, we report the change in workers' present discounted value based on their age and skill level. Since metal is an unskilled labor intensive sector, workers without college education are more hurt in the metal sector compared to workers with college education. Skilled workers benefit more in the manufacturing sector. The unskilled workers, especially young workers, are almost unaffected. We find that young workers in the metal sector are not as hurt as the middle aged workers. Initially, the impact of trade shocks increases with age, but since the time horizon gets shorter this effect is diminished for workers who are older than 50 years. We find that workers are split based on their sectors, and other factors are not important as workers' sectors. All metal workers are worse off, while all manufacturing workers are better off regardless of their education and experience level.

In Figures 7 to 9, we report welfare results for Simulation II. In Figure 7, worker types are aggregated and the weighted averages of welfare changes for workers from different age and education groups are reported. Surprisingly, Figures 6 and 7 are almost identical. So we find that aggregating workers (as in Simulation I) does not affect the welfare implications of the model. Since studying welfare changes after the policy shock is our main interest, we can conclude that Simulation I is less informative compared to Simulation II since it has fewer worker types, but it is not necessarily biased.

Figures 8 and 9 show that as the moving cost increases, either with sectoral experience or unobserved type, the impact of trade shocks on workers increases in both directions. Workers

with higher moving costs are hurt more in the metal sector, as they are less likely to leave their sector and suffer from the lower wages. Intriguingly, the workers with higher moving costs benefit more in the manufacturing sector. Because workers with higher moving costs are less likely to leave manufacturing, and more likely enjoy higher wages in the long run compared to others. The manufacturing workers with lower moving costs are more likely to end up in the metal sector; this decreases the change in their expected welfare relative to the workers with higher moving costs. This result can be generalized for age as well: As workers get older their moving costs increase and the impact of trade shocks increases. However, at the same time workers' time horizon gets shorter; this decreases the impact simultaneously. The second effect starts to dominate after workers reach age 50. Therefore, in general, large moving costs magnify the impact of trade shocks for both winners and losers (with an exception of workers who are close to retirement).

7 Conclusion

We estimate a dynamic model of labor mobility using US data, CPS and NLSY. We find that moving costs increase with age and experience, but are unchanged with workers' education level. Then, we simulate a counterfactual trade liberalization in the metal manufacturing sector using the estimated labor mobility model and calibrated production function parameters in a general equilibrium setting. We consider two alternatives with different levels of heterogeneity and find that aggregating worker types does not change the welfare implications of the model.

We show that trade shocks affect workers with higher mobility costs more, for both winners and losers of the policy shocks. In the metal sector, workers with higher moving costs are hurt more, while in the manufacturing they benefit more. But the effects are non-monotonic and they taper off over a worker's lifetime, especially when they are close to retirement. We also find that a worker's sector is the main determinant of how he is affected; this shows that moving costs are large enough to cause significant wage differentials across sectors, in contrast with models that have perfect labor mobility and factor price

equalization.

The estimation strategy herein is more efficient and easier to implement compared to ACM. It can handle rich heterogeneity and allows estimation of workers' expected values without solving their optimization problem explicitly. This feature of our method is especially important when it is difficult to parameterize workers' expectations due to policy shocks. This new method can be easily applied to other discrete choice problems, such as migration, occupational choice, education choice, and others.

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Table 1 - Distribution of Workers

Panel A: Sectors		
<i>Sector</i>	<i>NLSY</i>	<i>CPS</i>
Manuf	27.5%	27.2%
Metal	3.8%	3.3%
Service	50.1%	52.9%
Trade	18.6%	16.6%

Panel B: Age		
<i>Age</i>	<i>NLSY</i>	<i>CPS</i>
23 to 29	56.6%	17.1%
30 to 36	44.4%	23.3%
37 to 43	NA	21.5%
44 to 50	NA	17.0%
51 to 57	NA	13.1%
58 to 64	NA	7.9%

Panel C: Sectoral Experience		
<i>Experience</i>	<i>NLSY</i>	<i>CPS</i>
1 to 7	78.9%	NA
8 to 14	21.1%	NA

Panel D: Education		
<i>Education</i>	<i>NLSY</i>	<i>CPS</i>
No-college	59.9%	59.4%
College	40.1%	40.6%

Table 2 - CPS Transition Probabilities

Panel A: Non-College Graduates				
<i>Age</i>	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
23 to 29	0.067	0.076	0.055	0.090
30 to 36	0.041	0.050	0.032	0.061
37 to 43	0.030	0.035	0.021	0.041
44 to 50	0.022	0.035	0.017	0.036
51 to 57	0.018	0.016	0.014	0.026

Panel B: College Graduates				
<i>Age</i>	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
23 to 29	0.065	0.085	0.039	0.104
30 to 36	0.041	0.065	0.019	0.060
37 to 43	0.032	0.048	0.015	0.046
44 to 50	0.033	0.046	0.011	0.042
51 to 57	0.025	0.050	0.010	0.033

Panel C: Transition Matrix				
	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
<i>Manuf</i>	0.963	0.002	0.025	0.011
<i>Metal</i>	0.019	0.954	0.020	0.007
<i>Service</i>	0.011	0.001	0.977	0.011
<i>Trade</i>	0.017	0.002	0.039	0.943

Table 3: Regression Results with CPS

Panel A: First Step, Moving Cost (C^1/v)				
Age	No-college		College	
	Estim	SE	Estim	SE
23 to 29	2.62	(0.04)	2.66	(0.04)
30 to 36	3.19	(0.04)	3.34	(0.04)
37 to 43	3.57	(0.04)	3.64	(0.04)
44 to 50	3.84	(0.04)	3.78	(0.05)
51 to 57	4.14	(0.05)	4.10	(0.06)
58 to 64	4.50	(0.07)	4.19	(0.10)

Panel B: Second Step, Variance Parameter ($1/v$)		
	Estim	SE
	1.67	(0.51)

Panel C: Second Step, Average Fixed Utility (η/v)				
Sector	No-college		College	
	Estim	SE	Estim	SE
<i>Manuf</i>	0.00	NA	0.00	NA
<i>Metal</i>	-0.34	(0.07)	-0.17	(0.12)
<i>Service</i>	0.02	(0.07)	0.08	(0.11)
<i>Trade</i>	0.10	(0.09)	0.35	(0.16)

Table 4: Moving Cost Estimates with NLSY, Non-College (C/v)

Type	Age 23 to 29, Exp<7 C^1/v		Age 30 to 36, Exp<7 C^1/v		Age 30 to 36, Exp>7 $C^1/v+C^2/v$	
	Estim	SE	Estim	SE	Estim	SE
Both	2.68	(0.11)	3.09	(0.15)	4.38	(0.19)
I	2.21	(0.07)	2.96	(0.16)	3.88	(0.26)
II	3.21	NA	3.96	NA	4.88	NA

Table 5 - Calibration of Production and Utility Functions

Panel A: Cobb-Douglas Production Function Input Shares

	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
<i>Labor-Noc</i>	0.10	0.18	0.16	0.21
<i>Labor-Col</i>	0.08	0.07	0.21	0.16
<i>Capital</i>	0.13	0.13	0.29	0.27
<i>Manuf</i>	0.35	0.07	0.08	0.04
<i>Metal</i>	0.05	0.29	0.01	0
<i>Service</i>	0.24	0.19	0.23	0.3
<i>Trade</i>	0.05	0.07	0.02	0.02

Panel B: Cobb-Douglas Production Function Constant

	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
<i>B</i>	2.10	0.33	2.17	0.91

Panel C: Cobb-Douglas Utility Function Shares

	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
θ	0.4	0	0.6	0

Panel D: Units of Human Capital, Unskilled Labor Input (No-College)

<i>Age</i>	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
23 to 29	1.00	1.00	1.00	1.00
30 to 36	1.19	1.14	1.21	1.23
37 to 43	1.32	1.24	1.32	1.38
44 to 50	1.40	1.30	1.38	1.43
51 to 57	1.39	1.29	1.35	1.41
58 to 64	1.30	1.29	1.26	1.30

Panel E: Units of Human Capital, Skilled Labor Input (College)

<i>Age</i>	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
23 to 29	1.00	1.00	1.00	1.00
30 to 36	1.27	1.27	1.35	1.35
37 to 43	1.48	1.50	1.57	1.60
44 to 50	1.61	1.69	1.67	1.68
51 to 57	1.66	1.68	1.71	1.67
58 to 64	1.63	1.67	1.65	1.49

Table 6: Parameters for Simulation II

Panel A: Moving Cost (C^1/v)		
Age	No-college	College
23 to 29	2.29	2.37
30 to 36	2.60	2.75
37 to 43	2.89	2.98
44 to 50	3.10	3.07
51 to 57	3.33	3.34
58 to 64	3.60	3.37

Panel B: Average Fixed Utility (η/v)		
Sector	No-college	College
<i>Manuf</i>	0.00	0.00
<i>Metal</i>	-0.31	-0.11
<i>Service</i>	0.02	0.08
<i>Trade</i>	0.10	0.36

Panel C: Other Parameters	
($1/v$)	1.67
C^2/v	0.91

Panel D: Implied Average Moving Cost (C^1/v)		
Age	No-college	College
23 to 29	2.79	2.87
30 to 36	3.69	3.89
37 to 43	4.06	4.19
44 to 50	4.31	4.31
51 to 57	4.58	4.61
58 to 64	4.89	4.66

Table 7: Simulated Wages and Labor Allocations

	Labor Allocations			
	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
<i>Data</i>	27.26%	3.36%	52.73%	16.65%
<i>Simulation I</i>	27.88%	3.35%	51.27%	17.50%
<i>Simulation II</i>	27.80%	3.39%	51.38%	17.43%

	Average Wages			
	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
<i>Data</i>	1.02	0.97	1.05	0.89
<i>Simulation I</i>	1.00	0.97	1.07	0.87
<i>Simulation II</i>	1.00	0.96	1.06	0.87

Figure 1: Percent Change in Labor Allocation

Figure 2: Percent Change in Output

Figure 3: Average Wages (No-College)

Figure 4: Average Wages (College)

Figure 5: Average Values

Figure 6: Age, Education and Welfare Change (Simulation I)

Figure 7: Age, Education and Welfare Change (Simulation II)

Figure 8: Age, Experience and Welfare Change (Simulation II)

Figure 9: Age, Unobserved Types and Welfare Change (Simulation II)