

Intergenerational Effects of Trade Liberalization

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Abstract

2002 Pew Global Attitudes survey shows that workers' support for free trade decreases with age, which is a phenomenon previously unexplored by economists. We explore distributional effects of trade liberalization in particular age and gains from free trade, using a dynamic structural general equilibrium model. The model we develop here is in the same spirit as Artuc, Chaudhuri and McLaren (2007), but allows for a much richer treatment of both ex-ante and endogenous worker heterogeneity. This feature requires a completely different estimation strategy, which comes at a cost of more computation time and stronger assumptions on workers' expectations. After estimating the structural model with U.S. data sets NLSY and CPS, we simulate a hypothetical trade liberalization in metal manufacturing sector (which has been especially vulnerable to trade shocks in the past, the steel industry in particular). We show gradual adjustment of labor allocation, wages and prices in response to this trade shock. We find a "mirror effect" where very young workers are either moderately better off or moderately worse off, while older workers are either extremely better off or extremely worse off depending on their sectors.

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1 Introduction

Recently, trade economists have developed dynamic structural models to analyze effects of trade liberalization. Only a few of those structural models were designed to analyze welfare effects of free trade on workers, while many of them, especially those which generated a large body of research, focused on firms rather than workers.² Most of the research on distributional effects of trade liberalization on workers have been conducted via reduced form regressions.³ Although reduced form regressions helped economists to answer many questions about effects of trade policy shocks, there are certain very interesting questions that can not be answered by them, such as: How long will it take to reach the new steady state after a trade shock? What are the welfare effects on export-sector workers? How do workers adjust to free trade in case of delayed trade liberalization - if it is not implemented yet? What are the non-pecuniary welfare costs of trade liberalization? Artuc, Chaudhuri and McLaren (2007) developed a method to answer such questions (henceforth ACM), within a dynamic structural general-equilibrium framework.⁴ The theoretical foundation of ACM was introduced by Cameron, Chaudhuri and McLaren (2008). Although ACM's method was well suited to analyze welfare effects of trade liberalization, it was not designed to study distributional effects in detail. Studying distributional effects seriously requires extremely large data sets, when detailed worker heterogeneity is introduced to their model. This is because their estimation strategy relies on aggregate mobility matrices for each observed worker type. which could easily be contaminated with empty cells if the state-space is finely partitioned.

In this paper, we develop a different method, complementary to ACM, which can be used to study distributional effects of trade liberalization at a cost of longer computation time and stronger assumptions on workers' expectations. The model we introduce in this paper is also based on Cameron, Chaudhuri and McLaren (2008) similar to ACM, but the main difference is we do not use their (computationally cheap and compact) Euler-equation condition approach. Instead, we calculate expected values of workers similar to structural discrete choice models in the labor economics literature, which allows us to introduce a richer treatment

²Such as Bernard, Eaton, Jensen and Kortum (2003) and Melitz (2003).

³Among others, some prominent examples are Revenga (1992), Pavcnik, Goldberg and Attanasio (2004) and Kletzer (2002). See Slaughter (1998) for an overview.

⁴Among others, we can list Davidson and Matusz (2001) and Kambourov and Manovskii (2003) as examples of structural trade models with a special emphasis on labor.

of ex-ante and endogenous worker heterogeneity compared to ACM. With the introduction of ex-ante and endogenous worker heterogeneity (age, education and experience), we can analyze distributional effects of trade liberalization in more detail in addition to dynamics of the adjustment process. Another difference is, we use NLSY data set along with CPS, which provides detailed work history. Using work history of workers, we model human capital accumulation process joint with sectoral mobility. By doing so, we can calculate welfare loss of workers in import competing sector, who lose their sector specific human capital as their sector shrinks, and welfare gains of workers in exporting sectors at the same time. The final major difference is the sector opening to free trade, in contrast to their analysis on the manufacturing sector, we focus on liberalization in the metal manufacturing sector. Since metal manufacturing output is not directly consumed, it has no effect on consumer price index. Therefore, we have to allow outputs of sectors to be used as inputs in the production function (otherwise free trade of metal manufacturing product would not directly affect other sectors). Studying a very small sector, such as metal manufacturing, with ACM's method would require an unreasonably large data set even without worker heterogeneity.⁵

In this paper, we will particularly focus on effects of trade liberalization on different generations. Recent Pew Global Attitudes survey, conducted in 2002, showed that young people are more enthusiastic about free trade compared to older people. The negative correlation between age and support for free trade is previously unexplored by economists. Without considering any economic explanation, one could attribute this negative correlation (between age and supporting free trade), to older people's being more comfortable with status-quo compared to young. In other fields of social sciences, there are studies analyzing age and openness to change, among others Na and Duckitt (2003) report that young Koreans are more open to change compared to old. Taking those and other researchers seriously, one can claim that older people's being more conservative can potentially explain their attitude towards free trade. However, we show that there is indeed an economic explanation as well for this intriguing difference between young and old workers, although it was unnoticed so far by economists. We do not deny the possibility of existence of psychological factors, which are out of the scope of this paper.

Imagine that all workers were perfectly mobile across sectors, then all workers would be

⁵Needless to say that their method also has some other advantages over ours. For example, it requires shorter time series since their method does not rely on calculation of future values.

unanimously better off or worse off after trade liberalization, as in Heckscher-Ohlin model. If all workers were absolutely immobile and attached to certain sectors, then there would be clearly distinct winners and losers from free trade, as in Ricardo-Viner model; 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.

In order to explore the relation between worker mobility, age and welfare effects of free trade, we first estimate human capital accumulation process and mobility of workers jointly with a sectoral choice model, using NLSY and CPS data. Then, 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, the steel industry in particular) to analyze gradual adjustment of labor, wages and prices in all sectors in response to this trade shock. The trade shock can be considered simply as an exogenous reduction in the metal manufacturing product's price, as cheaper imports will be available with trade liberalization; everything else will be endogenous.

It should be noted that, although we put a special emphasis on human capital accumulation process, our ultimate goal is to simulate trade shocks, which will make our model different from similar research in labor literature such as Keane and Wolpin (1997) and Lee and Wolpin (2004). We are borrowing some insights from sectoral/occupational choice literature to analyze a topic which can not be explored with other international trade economics tools. We deviate from them by modeling sectoral choice rather than occupational and educational choice, since a trade shock first hits sectors, then possibly occupations in a less direct way. Analyzing effects of trade liberalization on occupations is out of the scope of this paper, and a very good example on that topic is Kambourov and Manskii (2003). In addition to this deviation, we reduced the state space by using a limited number of age, education and experience groups, so that the counterfactual simulations are computationally feasible. This simplification decreases the computational burden significantly by reducing the time needed to calculate value functions, which makes our model relatively easy to im-

plement compared to other longitudinal-structural models. Since we have endogenous wages and multiple sectors, models developed by labor economists would not be computationally feasible for our purpose. Finally, we have included idiosyncratic utility shocks in addition to wage shocks, similar to Sullivan (2004) and ACM. Inclusion of these shocks is necessary because deviations in wages can only explain a very small part of labor mobility, see two papers mentioned earlier for more discussion.

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), attributed decreases in mobility with age to increases 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) suggested that the decrease in mobility with age can be partially attributed to non-financial reasons as well. Unfortunately, we will not be able to incorporate all these features in our model at the same time: we assume that workers become less mobile as they get older because they become more likely to hold sector specific human capital and the other reasons will be captured by their implicit moving cost a la Groot and Verberne (1997). Although models of sector specific human capital is less common in the literature compared to firm specific human capital; Neal (1999) shows that it is a very important part of human capital.

Another related line of research to ours is the displaced workers literature, such as Jacobson, LaLonde and Sullivan (1993). Although they also analyze distributional effects of trade liberalization, their analysis is focused on import competing sector workers only. They study only import-competing sector workers with a natural experiment, therefore their results can be considered as more precise, however they can not explain what will happen in a hypothetical scenario and what will happen in other sectors, such as service.

In the next section we will present the model, followed by estimation results. After a section on counterfactual simulation of trade liberalization in metal sector, we will introduce unobserved heterogeneity to the model. Then we will conclude the paper.

2 Model

Consider an economy with I industries, where workers choose a sector to work in dynamically in each period. Aggregate production functions for each sector has Cobb-Douglas form,

where workers' wages are marginal product of labor derived from the production functions. Workers preferences are also expressed with Cobb-Douglas utility functions. Our goal is to simulate a hypothetical trade liberalization in one of the sectors (metal manufacturing) and see how labor allocations, prices and wages adjust after the trade shock. We will discuss welfare effects of this policy change on workers from different age, education and experience groups. The parameters of the workers' problem are estimated from NLSY79 and CPS, while the parameters of the production functions are calibrated from BEA data.

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) 4. "Trade": Wholesale and retail trade (another non-tradable sector). The industries are aggregated mainly in two groups, tradeable and non-tradeables. However, since wholesale and retail trade is a very large industry, we decided to take it as a separate sector apart from service.⁶

In the next sub-section we will describe workers' problem.

2.1 Workers

Assume that there are N workers and I sectors in the economy. Workers choose a sector in which to work in each period. If a worker indexed by n decides to work in sector i then $d_t^n = i$ where

$$d_t^n \in \{1, 2, 3, 4\}. \quad (1)$$

A worker, n , receives wage w_t^{ni} from working in sector i . Wage of worker n is defined as the price of sector specific human capital, r_t^i , times units of human capital hold by the individual, h_t^{ni} :

$$w_t^{ni} = r_t^i h_t^{ni},$$

where units of human capital is defined as

$$\log h_t^{ni} = \phi_0^i + \phi_1^i \text{Coll}^n + \phi_2^i \text{SecEx}_t^{ni} + \phi_3^i \text{MktEx}_t^n + \phi_4 \text{Coll}^n \text{SecEx}_t^{ni} + \phi_5 \text{Coll}^n \text{MktEx}_t^n + z_t^{ni}, \quad (2)$$

⁶A more favorable approach could be using two digit definitions to separate industries which have different characteristics than the others such as Agriculture, Professional, Government, etc. There are two reasons that prevent us from doing so: First, Increasing number of choices will make the problem computationally infeasible, second, the main dataset we use, NLSY79, has a fairly small sample size therefore estimates of important sector specific parameters would not be significant.

where $Coll^i$ is a dummy for college education, $SecEx_t^{ni}$ is years of sectoral experience in sector i , $MktEx_t^n$ is years of market experience and z_t^{ni} is an iid normal random shock. Since we are interested in fluctuations in r_t^i we will not derive the standard Mincer wage equation from this specification but rather move in a slightly different direction. For convenience, let us define $\log h_t^{ni} = \phi_0^i + X_t^{ni} \Phi^i + z_t^{ni}$, where X_t^{ni} is a vector of individual characteristics, Φ^i is a vector of sector specific human capital parameters except the intercept ϕ_0^i . We can write wages as a function of average wages:

$$\begin{aligned} w_t^{ni} &= \bar{w}_t^i \frac{h_t^{ni}}{\bar{h}_t^i}, \\ \log w_t^{ni} &= \log \bar{w}_t^i + \log h_t^{ni} - \log \bar{h}_t^i, \\ &= \log \bar{w}_t^i + (X_t^{ni} - \bar{X}_t^i) \Phi^i + z_t^{ni}. \end{aligned} \tag{3}$$

In order to reduce the size of state space we discretize variables Age_t^n , $SecEx_t^{ni}$ and, $MktEx_t^n$ in such a way that they can only take the following values:

$$\begin{aligned} Age_t^n &\in \{26, 33, 40, 47, 54\}, \\ SecEx_t^{ni} &\in \{4, 11, 18\}, \\ MktEx_t^n &\in \{4, 11, 18\}. \end{aligned} \tag{4}$$

Although estimation of the model without discretizing these variables can be possible, simulation is not feasible with endogenous wages. To accommodate for discretization, we assume that in each year a worker with age, A , moves to the next possible age, $A + k$, with a probability $1/k$, where $k = 7$ in this case⁷. When a worker reaches age 54 there is a $1/k$ probability that she will receive a lump-sum money and retire, to keep the population constant we assume that a new worker enters system for each retiree. When age increases market experience increases as well until 18 and does not increase further. Sectoral experience will evolve depending on workers decision to stay in their current sector, the maximum value for sectoral experience is also 18.⁸

⁷Figure 16 shows how value functions of manufacturing workers would look like with $k=1$ (actual) and $k=7$ (approximation) using estimates from the next section.

⁸Estimating the life-time wage-tenure profile is out of the scope of this paper. We were not able to identify tenure-wage profile for workers above 40 using NLSY79, and work history is not available in CPS.

All sectoral experience will be lost if a worker changes her sector:

$$\begin{aligned}
& \text{if } d_t^n \neq d_{t-1}^n \implies SecEx_t^{ni} = 4 \\
& \text{else if } d_t^n = d_{t-1}^n \text{ and } Age_t^n = Age_{t-1}^n \implies SecEx_t^{ni} = SecEx_{t-1}^{ni}, \\
& \text{else if } d_t^n = d_{t-1}^n \text{ and } Age_t^n = Age_{t-1}^n + 7 \implies SecEx_t^{ni} = SecEx_{t-1}^{ni} + 7,
\end{aligned} \tag{5}$$

In addition to the wage, each worker, n , receives an idiosyncratic random utility, u_t^{ni} , from working in sector i . Where u_t^{ni} is distributed mean zero extreme-value with variance $\frac{\pi^2}{6}\nu^2$, see Patel, Kapadia and Owen (1976) for properties of the extreme-value distribution. Hence the instantaneous utility of being in sector i at time t is

$$U_t^{ni} = w_t^i(s_t^n, z_t^n, \xi_t) + u_t^{ni}, \tag{6}$$

where wage, $w_t^i(s_t^n, z_t^n, \xi_t^i)$ is a function of the state variables, random shock and average wages as described above, and $\xi_t = [\bar{w}_t^1 \dots \bar{w}_t^I \ \bar{h}_t^1 \dots \bar{h}_t^I]'$ is a vector of relevant aggregate state variables. The non-random state vector s_t^n is consist of education, previous period's choice, sectoral and market experience:

$$s_t^n = \begin{bmatrix} d_{t-1}^n & Coll^n & SecEx_t^{nd_{t-1}^n} & MktEx_t^n \end{bmatrix}'. \tag{7}$$

The non-random state vector s_t^n can also be considered as type of a worker. Workers who move from sector i to j will incur a moving cost, C^{nij} , if they change their sectors, so $C^{nij} > 0$ if $i \neq j$ and $C^{nij} = 0$ if $i = j$. If a worker changes her sector, the moving cost will be a function of her age, education and the sector she is moving in

$$C_t^{nij} = C_1^{Age_t^n} + C_2^j + Coll^n C_3,$$

this moving cost should not be taken literally as "financial cost", it will account for all

Lee successfully estimated wage-tenure profile from CPS via MSM, however their method does not allow us to identify parameters of the idiosyncratic utility shock. We simply assume that for the last two age groups wage contribution of market and sectoral experience stay constant following the general shape of tenure-wage profile estimated in previous works, such as Mincer (1958).

unmodelled frictions and psychological costs as well.

For notational simplicity, consider a vector of all relevant state variables for an individual, which are s_t^n , ξ_t , $z_t^n = [z_t^{n1}..z_t^{nI}]'$ and $u_t^n = [u_t^{n1}..u_t^{nI}]'$, such that $\eta_t^n = [s_t^n \ \xi_t \ z_t^n \ u_t^n]'$. The objective of an individual for any time $t = 1, \dots, T$ is to maximize her present discounted total utility following a Bellman equation:

$$V_t(\eta_t^n) = \max_i (V_t^i(\eta_t^n)), \quad (8)$$

where sector (alternative) specific value functions are:

$$\begin{aligned} V_t^i(\eta_t^n) &= U_t^i(\eta_t^n) + E \max_j \beta \{V_{t+1}^j(\eta_{t+1}^n) - C^{i,j}(s_{t+1}^n)\}, \\ &= U_t^i(\eta_t^n) + \beta E_s \Omega_{t+1}^i(\eta_{t+1}^n) + \beta E_{u,z,s} V_{t+1}^i(\eta_{t+1}^n), \end{aligned} \quad (9)$$

for all periods where β is the discount factor. Thus, we can write the option value of moving as

$$\Omega_{t+1}^i(\eta_{t+1}^n) = E_{u,z} \left(\max_j \{V_{t+1}^j(\eta_{t+1}^n) - V_{t+1}^i(\eta_{t+1}^n) - C^{i,j}(s_{t+1}^n)\} \right), \quad (10)$$

and note that $\Omega_{t+1}^i(\eta_{t+1}^n)$ can be calculated analytically upto a certain level. {See Appendix B for details. }

Timing:

At any given time period t the order of events for a worker is as follows: 1. Pays the moving cost $C > 0$ if her previous sector is different. 2. Works and enjoys her utility: $w_t^{ni} + u_t^{ni}$, 3. Learns the next period's random shocks $\{z_{t+1}^{nj}, u_{t+1}^{nj}\}_{j=1}^6$. 4. Chooses her sector. 5. Enters the next period $t+1$ and repeats steps 1-5 for $t+1$. Note that there is no aggregate uncertainty in the model except for the shock therapy (e.g. $\xi_t, \xi_{t+1}, \xi_{t+2}, \dots, \xi_T, \dots$ are known at time t).

Estimation of workers' problem:

Using the equations above we can calculate probability of a worker's transition from state s to s' {see Appendix B for details.} let us denote this probability with $m^{ss'}$, which is a function of s_t^n and expected next period alternative-specific values for each state.

In addition to the transition probabilities $m^{ss'}$, it is also possible to calculate probability of observing wage w_t^n given n 's type s_t^n and average wage in her sector: $\bar{w}_t^i$. The estimation

strategy is to maximize the log-likelihood function

$$\Lambda = \sum_{n=1}^N \sum_{t=1}^T \log \int_z \int_u m^{s_{t-1}^n s_t^n} \Pr(w_t^n) du_t^n dz_t^n.$$

Note that it is possible to solve the integral over u_t^n analytically in a way similar to multinomial logit models, however, the integral over z_t^n has to be calculated numerically with a quadrature or simulation based method. Thus, we use "method of simulated maximum likelihood" to estimate the parameters of interest. { See Appendix B for details. }

2.2 Aggregate Economy:

Let $l(s)$ be the ratio of workers with a given state $s \in \{1, \dots, S\}$, where s is an index representing type of a worker, where total number of workers are normalized such that $1 = \sum_{s=1}^S l(s)$. There are 96 possible states thus $S=96$ types of workers. For any given type s we can calculate time t labor allocation given time $t-1$ labor allocation and transition probabilities

$$l(s_t) = \sum_{s_{t-1}=1}^S m^{s_{t-1} s_t} l(s_{t-1}). \quad (11)$$

Let L_t be a vector representing the distribution of workers such as $L_t = [l(1) \dots l(96)]'$. Then L_t can be expressed as a function of previous period's distribution L_{t-1} , average wages and expected next period alternative specific values:

$$L_t = M(L_{t-1}, \xi_t, \bar{V}_{t+1}^1(1), \dots, \bar{V}_{t+1}^I(S)), \quad (12)$$

where $\bar{V}_{t+1}^i$ is expected alternative specific value and ξ_t is a vector of average wage and human capital levels. Average wages are endogenous from the aggregate perspective. Let production functions be

$$y_t^i = B^i (L_t^i \bar{h}_t^i)^{b_L^i} (K^i)^{b_K^i} \prod_{j=1}^I (q_t^{ji})^{b_j^i}, \quad (13)$$

where L_t^i is the ratio of workers in sector i , where $L_t^i = \sum_{s \in S_i} l(s)$ and S_i is the set of types of worker where $d_t^m = i$ (types that are from sector i), $\bar{h}_t^i$ is average human capital, K^i is capital, and q_t^{ji} is amount of product from sector j used in production in sector i .

We assume that capital is specific to sectors similar to Ricardo-Viner models as in ACM. (We also experimented with perfect capital mobility simulations and found that qualitative implications of the model, in general, are unchanged).

Each worker will receive her real marginal product, given price level p_t^i and consumer price index φ_t :

$$w_t^{ni} = \frac{p_t^i}{\varphi_t} \frac{\partial y_t^i}{\partial L_t^i} \frac{h_t^{ni}}{\bar{h}_t^i}, \quad (14)$$

thus

$$\bar{w}_t^i = \frac{p_t^i}{\varphi_t} \frac{\partial y_t^i}{\partial L_t^i}. \quad (15)$$

Therefore the average wages can be written as a function of L_t^i and $\bar{h}_t^i$ (hence the distribution of workers L_t),

$$w_t^i = b_L^i (L_t^i \bar{h}_t^i)^{b_L^i - 1} \bar{h}_t^i \zeta_t^i \frac{p_t^i}{\varphi_t}, \quad (16)$$

where ζ_t^i is a part of the Cobb-Douglas production function, $\zeta_t^i = B^i (K^i)^{b_K^i} \prod_{j=1}^I (q_t^{ji})^{b_j^i}$. Finally consumption preferences are described by a simple utility function:

$$\Upsilon_t = \prod_{j=1}^I (q_t^{jc})^{\theta_j}, \quad (17)$$

where q_t^{jc} is quantity of j consumed at time t and θ_j 's are the weights. In the next section we discuss estimation results of workers' problem and calibration of production functions.

3 Estimation and Calibration of Parameters:

We are interested in estimation to find plausible parameters for the simulations, thus in contrast to papers from labor economics literature, our main focus will be counterfactual trade liberalization simulations. We estimate human capital accumulation and mobility parameters jointly, from each worker's simulated likelihood contribution. Then we calibrate production function parameters from Bureau of Economic Analysis data, assuming Cobb-Douglas forms.

Data

For estimation of the workers' problem, we use 1979 cohort of the National Longitudinal Survey of Youth (henceforth NLSY) as our main data set. NLSY is widely used in estimation of occupational choice models, since it follows individuals over years and provides

detailed information on work history. The sectoral experience variable, $SecEx_t^{ni}$, can be easily constructed from NLSY. One important restriction of NLSY is it follows individuals annually until about age 40, so we can not identify parameters for older individuals in the model. In order to identify moving cost parameter C^{nij} for individuals over 40 we include Current Population Survey March sample (henceforth CPS) in our estimation. Since sectoral experience is not observed in CPS, we can not use it to calculate likelihood contribution of observed wages. The average wages are also calculated using CPS because NLSY sample size is much smaller.

Initially, NLSY has 12,686 people in the sample, consisting of 6,403 males and 6,283 females. Like most of the other mobility models, we only pick males for our sample (such as Keane and Wolpin (1997) and ACM). Moreover, we take blacks and Hispanics out of our sample, who are over-sampled by the NLSY, again following the previous research. This reduces our sample size by approximately 40%, so we are left with 3,790 individuals. The individuals in our sample are between ages of 14 and 21 as of year 1979. We use observations, from years 1983 to 1994, of individuals who were at least 23 years old, worked at least 26 weeks in the observed year and who do not have any missing industry information from previous years. For example if a certain individual's data is missing for 1990, we do not use him after 1990 since we can not construct sectoral experience data for him after the missing observation. If a certain individual is observed less than 7 years between 1983 and 1994, we take him out from the sample. We do not use observations of individuals whose implied full time real annual wage income is less than \$5000, or more than \$300,000 (where the base year is 2000). We end up with 1190 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 as in Neal (1999); whenever a sector change is reported, we require that the worker has to change his employer as well, otherwise it is considered as a coding error and the original sector is kept. Tenure of workers with their current employer is reported in NLSY.

The CPS sample is from 1983 to 2001 and constructed in a similar way: We use white and male individuals, who are between 23 and 57, and who worked at least 26 weeks in a given year. We have a minimum of 11,857 and a maximum of 20,211 people in our final

sample between the years 1984 and 2001 (sample size changes every year). In CPS, reported mobility rates are 5 months' mobility rather than annual mobility, we follow a procedure similar to ACM to correct transition probabilities.

Table 1: Distribution of Workers.

Panel A: Sectors		
<i>Sector</i>	<i>NLSY</i>	<i>CPS</i>
<i>Manuf</i>	27.7%	27.2%
<i>Metal</i>	3.8%	3.3%
<i>Service</i>	49.5%	52.9%
<i>Trade</i>	19.0%	16.7%

Panel B: Age		
<i>Age</i>	<i>NLSY</i>	<i>CPS</i>
<i>23 to 29</i>	58.8%	18.6%
<i>30 to 36</i>	41.2%	25.4%
<i>37 to 43</i>	NA	23.4%
<i>44 to 50</i>	NA	18.5%
<i>51 to 57</i>	NA	14.3%

Panel C: Sectoral Experience		
<i>Experience</i>	<i>NLSY</i>	<i>CPS</i>
<i>1 to 7</i>	86.0%	NA
<i>8 to 14</i>	14.0%	NA
<i>14 to 18</i>	NA	NA

Panel D: Education		
<i>Education</i>	<i>NLSY</i>	<i>CPS</i>
<i>No-college</i>	60.3%	59.1%
<i>College</i>	39.7%	40.9%

Table 1 summarizes distribution of workers across sectors, age, sectoral experience and education groups in both NLSY and CPS samples. Note that sectoral experience is not available for CPS sample and NLSY sample includes people only up to age 40. Manufacturing and agriculture workers (henceforth manuf.) are approximately 28%, metal workers are about 3%, service workers except trade workers (henceforth service) are about 50% and finally

wholesale and retail trade workers (henceforth trade) are close to 20% of the total sample (see Panel A). Unlike ACM, our analysis does not rely on calculation of aggregate transition probabilities, which allows us to have a very small sector, such as metal. Calculation of aggregate transition probabilities requires observing some workers from each sector moving to every possible direction, which is impossible when one of the sectors is small or when there are many worker types. 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 at least one year of college education in the sample.

Table 2: Transition Probabilities (CPS).

Panel A: No College Education				
<i>Age</i>	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
<i>23 to 29</i>	0.067	0.076	0.055	0.090
<i>30 to 36</i>	0.041	0.050	0.032	0.061
<i>37 to 43</i>	0.030	0.035	0.021	0.041
<i>44 to 50</i>	0.022	0.035	0.017	0.036
<i>51 to 57</i>	0.018	0.016	0.014	0.026

Panel B: Some College Education				
<i>Age</i>	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
<i>23 to 29</i>	0.065	0.085	0.039	0.104
<i>30 to 36</i>	0.041	0.065	0.019	0.060
<i>37 to 43</i>	0.032	0.048	0.015	0.046
<i>44 to 50</i>	0.033	0.046	0.011	0.042
<i>51 to 57</i>	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 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 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 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, probability of moving out of a larger sector is lower than probability of moving out of a smaller sector, and probability of moving in a larger sector is higher than probability of moving in a smaller sector.

Estimation Results

Wages are deated by the CPI, and normalized so that over the whole sample the average annualized wage is equal to unity. Numbers reported in Table 3 are comparable to average annual wage, which is equal to unity. This is because the instantaneous utility including the moving cost can be expressed in a money metric form for workers who change sector: $U_t^{ni} = w_t^{ni} + u_t^{ni} - C^{ji}$ where j is last year's sector. However, the numbers in Table 4 are not comparable with the numbers in Table 3 because wage equation is expressed in a log form. The estimation results show that idiosyncratic shocks play a very important role in decision of workers. The parameter of the extreme value distribution ν is about 1.5 (reported in Table 3 - Panel A) which means that standard error of the idiosyncratic utility shock is approximately double of average annual wage. In the Table 4 - Panel A the standard error of wage shock. σ_z is reported as 0.41.

The estimated moving cost, reported in Table 3 - Panel B, starts from 4.5, increases with age, and end up being as large as 5.9 for the oldest type. These numbers are large but not surprising since similar projects with idiosyncratic utility shocks such as Sullivan (2006), Kennan and Walker (2003), and ACM also report such large mobility cost. For example ACM find a moving cost equal to 6.5 times of average annual wage. We present estimation results of an extended model with unobserved heterogeneity to shed some light on possible reasons of this unrealistically large moving costs in a later section. Panel C shows the sector specific component of the moving cost, which is how much more (or less) the moving cost would be depending on the sector a person chooses to work in. The moving costs reported in Panel B can be 3.2 more if a worker is moving to metal sector (which is the smallest sector) or -1.5 less if a person is moving to service sector (the largest sector). Panel D shows that people with some college education bear larger moving costs, this can be attributed to

Table 3: Estimation - Moving Cost.

Panel A: Idiosyncratic Shock Parameter			
		<i>Coefficient</i>	<i>t-stat</i>
	ν	1.53	11.85
Panel B: Age specific cost			
	<i>Age</i>	<i>Coefficient</i>	<i>t-stat</i>
C_1^1	<i>Age 26</i>	4.45	12.00
C_1^2	<i>Age 33</i>	4.89	11.38
C_1^3	<i>Age 40</i>	4.86	8.93
C_1^4	<i>Age 47</i>	5.12	8.76
C_1^5	<i>Age 54</i>	5.92	8.74
Panel C: Additional sector specific cost			
	<i>Sector</i>	<i>Coefficient</i>	<i>t-stat</i>
C_2^1	<i>Manuf</i>	0.00	N/A
C_2^2	<i>Metal</i>	3.24	10.04
C_2^3	<i>Service</i>	-1.46	-9.49
C_2^4	<i>Trade</i>	-0.51	-4.79
Panel D: Additional education specific cost			
	<i>Education</i>	<i>Coefficient</i>	<i>t-stat</i>
C_3	<i>College</i>	0.13	1.69

the fact that people with more education earn higher wages. Because of higher wages, their wage offers fluctuate more in levels (obviously not necessarily in logs), hence for a similar mobility rate, as reported in Table 2, people with more education should face larger moving costs.

Table 4 reports estimates of the wage equation related parameters. Panel B shows that return on education is the highest for service sector and the lowest for metal sector. This is an expected result since sectors like professional, finance, public are parts of service sector. Return on sectoral experience for different sectors and education levels is shown in Panel C. Finally, Panel D reports return market experience (which is almost the same as age in our model since we do not model labor force participation as an alternative choice).

Table 4: Estimation - Human Capital.

Panel A: Std. Dev. Of Wage Shock

	<i>Coefficient</i>	<i>t-stat</i>
σ_z	0.4114	319.52

Panel B: Education Parameters

	<i>Sectors</i>	<i>Coefficient</i>	<i>t-stat</i>
ϕ_1^1	<i>Manuf</i>	0.1262	8.73
ϕ_1^2	<i>Metal</i>	0.0581	2.29
ϕ_1^3	<i>Service</i>	0.1870	12.97
ϕ_1^4	<i>Trade</i>	0.1533	10.95

Panel C: Sectoral Experience Parameters

	<i>Sectors</i>	<i>Coefficient</i>	<i>t-stat</i>
ϕ_2^1	<i>Manuf</i>	0.0255	14.55
ϕ_2^2	<i>Metal</i>	0.0138	3.00
ϕ_2^3	<i>Service</i>	0.0360	25.35
ϕ_2^4	<i>Trade</i>	0.0363	18.22
	<i>Education</i>	<i>Coefficient</i>	<i>t-stat</i>
ϕ_4	<i>College</i>	-0.0064	-3.78

Panel D: Market Experience Parameters

	<i>Sectors</i>	<i>Coefficient</i>	<i>t-stat</i>
ϕ_3^1	<i>Manuf</i>	0.0088	6.41
ϕ_3^2	<i>Metal</i>	0.0125	3.89
ϕ_3^3	<i>Service</i>	0.0041	3.29
ϕ_3^4	<i>Trade</i>	0.0040	3.25
	<i>Education</i>	<i>Coefficient</i>	<i>t-stat</i>
ϕ_5	<i>College</i>	0.0118	5.76

Calibration

The parameters b_L^i , b_K^i , b_j^i and ζ_A^i are calibrated from the Bureau of Economic Analysis data, they are reported in Panel A and Panel B of Table 5. We simply assume that cost shares of labor and inputs are parameters of the Cobb-Douglas production functions. We pick ζ_A^i 's such that observed average wages are as close as possible to the implied wages, given the distribution of labor. The parameters of Cobb-Douglas utility function, θ_i 's are calibrated from Consumer Price Index data, which are reported in Panel C of Table 6. ACM also follow a similar calibration method and provide more detail. For the estimation and the simulations, we assume that discount factor β is equal to 0.96. We were not able to estimate β since it is poorly identified by our model.

Table 5: Calibration - Production and Utility Functions.

Panel A: Production Function Input Shares				
	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
<i>Labor</i>	0.18	0.25	0.37	0.37
<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: Production Function Constant				
	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
$\log \zeta_A^i$	10.8404	9.0984	10.6266	9.75

Panel C: Utility Function Shares				
	<i>Manuf</i>	<i>Metal</i>	<i>Service</i>	<i>Trade</i>
θ_i	0.4	0	0.6	0

4 Simulation:

4.1 Autarky Steady State:

As first step for the counterfactual exercise, we simulate autarky steady state to calculate the initial labor distribution, L_t , which will gradually converge to the free trade distribution after the trade shock. Here we use the subscript A instead of t to refer to any time period

before the shock. We use equations from previous sections to illustrate autarky steady state:

$$\begin{aligned}
\bar{w}_A^i &= b_L^i (\lambda_A^i \bar{h}_A^i)^{b_L^i - 1} \bar{h}_A^i \zeta_A^i \frac{p_A^i}{\varphi_A}, \\
L_A &= M(L_A, \xi_A, \bar{V}_A^1, \dots, \bar{V}_A^I), \\
\bar{V}_A^i(s, \xi_A) &= \tilde{w}_A^i(s, \xi_A) + \beta E_s \Omega_A^i(s', \xi_A) + \beta E_s \bar{V}_A^i(s', \xi_A), \\
\bar{h}_A^i &= \exp(\bar{X}_A^i \Phi^i),
\end{aligned} \tag{18}$$

where $\tilde{w}_A^i$ is the expected autarky wage for type s workers in sector i , and $\xi_A = [\bar{w}_A^1 \dots \bar{w}_A^I \bar{h}_A^1 \dots \bar{h}_A^I]'$ is the vector of autarky average wage and human capital levels, $\bar{X}_A^i$ is the average of human capital parameters used in wage equation (3). For simplicity we assume that $p_A^i = 1$ and $\varphi_A = 1$. Note that λ_A^i and $\bar{h}_A^i$ can be calculated from L_A , since they are ratio of workers and average human capital in sector i respectively, where L_A is distribution of types in the economy. Other relevant variables are output:

$$y_A^i = (\lambda_A^i \bar{h}_A^i)^{b_L^i} \zeta_A^i,$$

and income spent on i :

$$\mu_A^i = \sum_{j=1}^I [b_i^j + \theta_i (b_L^j + b_K^j)] y_A^j p_A^j.$$

Define $X_A = [w_A^1 \dots w_A^I \bar{V}_A^1 \dots \bar{V}_A^I l(1) \dots l(96)]'$, the simulation exercise can be defined as a problem of finding a fixed point $X_A = F(X_A)$ where $F(\cdot)$ is a function described by the set of equations (18). The fixed point is calculated numerically, similar to Artuc, Chaudhuri and McLaren (2008).

4.2 Transition:

We assume that with the abolishment of tariffs in the metal sector, the prices will decrease about 30%, thus $p^{Metal} = 0.7$ when $t > 0$. First, we have conditions for the transition, similar to the autarky steady state condition (18) :

$$\begin{aligned}
\bar{w}_t^i &= b_L^i (\lambda_t^i \bar{h}_t^i)^{b_L^i - 1} \bar{h}_t^i \zeta_t^i \frac{p_t^i}{\varphi_t}, \\
L_t &= M(L_{t-1}, \xi_t, \bar{V}_{t+1}^1, \dots, \bar{V}_{t+1}^I), \\
\bar{V}_t^i(s_t, \xi_t^n) &= \tilde{w}_t^i(s_t, \xi_t) + \beta E_s \Omega_{t+1}^i(s_{t+1}, \xi_{t+1}) + \beta E_s \bar{V}_{t+1}^i(s_{t+1}, \xi_{t+1}), \\
\bar{h}_t^i &= \exp(\bar{X}_t^i \Phi^i).
\end{aligned} \tag{19}$$

However this time we can no longer assume that $p_t^i = 1$ or $\varphi_A = 1$, since prices change during transition. In addition to prices the inputs used in production will also change, thus the parameter ζ_t^i will be different from the calibrated parameter ζ_A^i . We normalize these parameters with their autarky values, such that $\tilde{x}_t$ denotes x_t/x_A . The change in consumer price index can be calculated with the change in prices

$$\tilde{\varphi}_t = \prod_{i=1}^I (\tilde{p}_t^i)^{\theta_i} \tag{20}$$

The change in prices (for service and trade) can be calculated with the change in income spent on each product and quantities produced, simply by exploiting the Cobb-Douglas form of demand and production functions

$$\begin{aligned}
\mu_t^i &= \sum_{j=1}^I [b_i^j + \theta_i (b_L^j + b_K^j)] y_t^j p_t^j, \\
\tilde{p}_t^i &= \frac{\mu_t^i}{\mu_A^i} \frac{1}{\tilde{y}_t^i}.
\end{aligned} \tag{21}$$

The change in ζ_t^i can be calculated using the change in prices and output

$$\begin{aligned}
\tilde{q}_t^{ij} &= \frac{\tilde{p}_t^i}{\tilde{p}_t^j} \tilde{y}_t^i, \\
\tilde{\zeta}_t^i &= \prod_{j=1}^I (\tilde{q}_t^{ij})^{b_j^i}.
\end{aligned} \tag{22}$$

Finally, the change in output can be written as a function of change in total human capital

in sectors and the change in ζ_t^i

$$\tilde{y}_t^i = \left(\frac{\lambda_t^i \bar{h}_t^i}{\lambda_A^i \bar{h}_A^i} \right)^{b_L^i} \zeta_t^i. \quad (23)$$

Define vector $X_t = [w_t^1 \dots w_t^I \bar{V}_t^1 \dots \bar{V}_t^I \tilde{y}_t^1 \dots \tilde{y}_t^I \tilde{p}_t^1 \dots \tilde{p}_t^I]'$, and matrix $X = [X_1 \ X_2 \dots X_T]$. We assume that for $t > T$, $X_t = X_{t-1}$. Let $X = G(X, L_A)$ be a function defined by equations (19), (20), (21), (23) and (22). Finding the transition values is also equivalent to finding a fixed point given the autarky labor allocation, L_A . Similar to the autarky problem, this problem can also be solved numerically. We check if X_T is indeed the free trade steady state, if not we increase T and find another fixed point. See Artuc, Chaudhuri and McLaren (2008) for details.

4.3 Results

We first simulate the model for the autarky steady state, where all prices are normalized to unity. Then, we assume that a shock-therapy trade liberalization in the metal sector decreases its product's price by 30%, forcing it to be equal to the world price at $t = 1$. We assume that service and trade sector outputs are non-tradable, while manufacturing sector output is tradable, which makes manufacturing price constant over time. Given the initial autarky labor allocation, outputs and prices, we calculate transition of labor allocation, wages, values of workers, prices, output and demand of goods after the trade shock.

Figures 1-3 show gross flows of workers, that is percentage of workers leaving their sectors. Figure 1 is for workers with average 4 years of sectoral experience and who are about 26 years old. Initially, approximately 19% of "trade" workers leave their sector, and 14% of other workers leave their sector every year. After the trade shock, this percentage increases to 29% for "metal" workers, decreases to 13% for "manuf" workers and stays approximately the same for "trade" and "service" workers. Figure 2 presents gross flows of workers with average 4 years of sectoral experience and who are about 54 years old; while Figure 3 shows gross flows of 54 years old workers with at least 18 years of sectoral experience. The general trend of gross flows are the same in all three figures: Sectoral mobility decreases with age and experience.

Figure 4 shows the adjustment of wages after the trade shock: We find that gross flow of workers are negatively correlated with wages. The adjustment process of "metal" sector is very simple but interesting: Initially price of "metal" sector product decreases, causing

the wages in "metal" sector to decrease. Workers start leaving "metal" sector, causing large out-flows, which eventually increases wages in "metal" sector. The long run free trade wage in "metal" sector is, however, lower than the autarky wage. For the other sectors, the adjustment process is quite subtle: First, it should be noted that "metal" sector product is not consumed, but used as an input in "manuf" and "metal" sectors. Therefore, "metal" price has no direct effect on CPI or real wages. However, the decrease in "metal" price increases its use as input, and increases the marginal product of "manuf" workers, causing an increase in wages. Other sectors' wages are do not change much after the shock. Figure 5 displays change in output, showing a notable increase in the "manuf" output and a very large decrease in "metal" output. Like wages, the other sectors' outputs are not significantly affected from the trade shock.

Figure 6 shows the change in demand (from both consumers and producers) for each product. As expected, demand for "metal" increases significantly with the price cut. Demand for "manuf" also increases, even though there is no change in its price, because of the general increase in output after the shock. (Since there are no market failures or externalities in our model, it is safe to assume that GDP increases after the trade liberalization although we do not explicitly calculate it). The demand for "service" also increases, but the change is much smaller compared to "manuf" because "service" price increases with demand. Note that "manuf" price is constant as it takes the world price. Figure 7 shows change in prices. Going back to Figure 4, the changes in "service" and "trade" prices pull the "service" and "trade" wages up, while workers moving in from "metal" sector push wages down. These two opposite forces cause wages in "service" and "trade" change only slightly: a small increase for "service" and a small decrease for "trade".

Figures 8-11 show how low-skill workers' value change right after the trade shock.⁹ (The results for high-skill workers are very similar and shown in Figures 12-15). Since "metal" sector output is used intensively only in "manuf" and "metal" and not consumed, "service" and "trade" sector workers are less affected from the trade shock compared to others. Note that size of "metal" sector is fairly small and flows out of metal sector do not significantly change labor allocations in other sectors. (We can safely ignore tariff revenues from "metal"

⁹Although we originally have only 96 types of workers, as shown in (4), we can calculate values for more a precisely partitioned state space, e.g. $\text{Age} \in \{23, 24, 25, 26, 27, \dots, 57\}$, using the aggregate distribution of workers and wages from the simulations.

sector because of its small size).

Figure 8 shows that "manuf" workers, in general, benefit from the shock, consistent with the fact that output increases more compared to the increase in number of workers in "manuf". The gains increase with age and experience, reaching maximum level for middle aged people who have worked in the "manuf" sector for their entire life. The gains decrease with age after a certain age because expected time horizon to enjoy benefits of free trade decreases. When a worker is sufficiently close to retirement, she would only care about purchasing power of her retirement savings. We assume that when a worker retires, she receives a lump-sum money which is not a function of price levels, thus retired workers are worse off after the shock since prices of "services" increase after the shock. An equally plausible assumption would be assuming an inflation-protected retirement benefits scheme, then retired workers would be unaffected from the shock. Since the difference is trivial we do not show simulation results for the alternative approach. However, we believe that to shed more light on this issue, a more detailed retirement model is required, which is out of the scope of this paper.

Younger workers benefit less compared to middle aged, because option value of younger people decrease after the trade shock - which is a significant portion of their value as shown in (10). As a worker's moving cost increases, her option value decreases, so it becomes fairly small when a worker gets old. After the shock "metal" sector becomes an unattractive alternative for working in "manuf", causing a notable drop in young "manuf" workers' option value. It is very unlikely for a person, who has been working in "manuf" for many, years to move to other sectors, so developments in other sectors do not change older workers' option value much.

Figure 9 shows change in "metal" workers' value, which is almost the opposite of previous figure. Young workers are hurt less because of the increase in their option value, while older workers are hurt more. Older and middle aged workers' inability to move to other sector makes them lose more compared to young. The story for the workers, who are close to their retirement, is exactly the same as "manuf" sector.

Figure 10 displays change in values of "service" and Figure 11 shows changes in values of "trade" workers. These two sectors are only slightly affected from the trade shock as they are not using "metal" in their production. "Service" workers are slightly better off, while

"trade" workers are slightly worse off. The general shape of the value functions surface is similar to other sectors: Middle aged workers benefit more if they workers benefit in general, and hurt more if workers are hurt in general (compared to young). We would like to call it a "mirror effect". Trade shocks affect older people by a large scale both positively and negatively, while younger people are affected usually in the same direction as older people in their sector but by a much smaller scale. (Yet, it is theoretically possible that old people are worse off in import competing sector while young people are better off.)

Our results show that there is a relation between age and supporting free trade, but they do not explain why older people would be less supportive of free trade, as it is seen in the Pew Survey.¹⁰ The counterfactual exercise presented here is of a very small sector, so the distributional effects of a long term globalization can not be studied from our graphs. Analyzing globalization in detail and explaining results of the Pew Survey is out of the scope of this paper. But just to shed some light on this interesting issue, we simulated an hypothetical trade liberalization in "manuf" sector. We find that all workers except middle aged and older "manuf" workers benefit from trade liberalization, including young "manuf" workers. So a liberalization in "manuf" sector would be perfectly consistent with the Pew Survey. We also experimented with perfect capital mobility and found that qualitative implications of our base simulations are unchanged. (results available upon request).

5 Unobserved Heterogeneity: An Extended Model

As we discussed earlier, the moving cost we estimate should not be taken as a financial moving cost since there are many unmodelled frictions in the labor market which is captured by the moving cost we estimate. We assume there is unobserved heterogeneity, particularly two types of workers: type I - workers who can move after paying some moving cost, and type II - workers who can not move at all. Having these two unobserved types will allow us to capture some of the unmodelled frictions which would otherwise be captured by the moving cost. In the original model we had 96 types, with inclusion of a binary unobserved heterogeneity we end up with 192 types. We assume that unconditional probability of being type II is α , probability of transition from type I to type II is γ_1 and probability of transition from type II to type I is γ_2 .

Consider this special case: If one's type in the next period is independent of her current

¹⁰We provide a simple analysis of the Pew Global Attitudes Survey in Appendix C for descriptive purposes.

type then, $\gamma_1 = \alpha$ and $\gamma_2 = 1 - \alpha$. For this special case, we can think of type I workers as those who can get job offers this year, and type II workers as those who can not get job offers. Then any friction captured by inclusion of unobserved types for this special case can be considered as search frictions. Another underlying friction can be time persistence of utility or wage shocks. If a worker likes one sector better than others, because of financial or non-financial reasons, her preference this year is most likely correlated with her preference last year. For example, the worker might be a very talented sales-person resulting in higher wages for her in trade sector, or her spouse might also be a sales-person and she might want to work in the same company with him. Both of these shocks are time persistent, inconsistent with our *iid* assumptions. By introducing two unobserved types, we allow a simple persistence in the idiosyncratic moving cost.

Probability of being type II unconditional on history depends on observed state of an individual. Assume that probability of being type II given the observed characteristics is $\alpha(s_t)$, where s_t is the observed characteristics (or state) of the individual. This probability can easily be calculated from the aggregate distribution vector, L_t . Also assume that probability that a worker will stay in her sector is $\varphi(s_t)$.

If a worker has moved in last period, we are sure that she was type I in last period, so for her to be type I again this period is

$$\Pr(I|s_t, s_{t-1}) = 1 - \gamma_1.$$

Similarly if a worker has moved two periods before today, she was a type I then so her probability of being type I today is

$$\Pr(I|s_t, s_{t-1}, s_{t-2}) = \frac{p^{11}}{p^{11} + p^{12}},$$

where

$$\begin{aligned} p^{11} &= \gamma_1 \gamma_2 + (1 - \gamma_1)^2 \varphi(s_{t-1}), \\ p^{21} &= (1 - \gamma_2) \gamma_2 + \gamma_2 (1 - \gamma_1) \varphi(s_{t-1}), \\ p^{12} &= \gamma_1 (1 - \gamma_2) + (1 - \gamma_1) \gamma_1 \varphi(s_{t-1}), \\ p^{22} &= (1 - \gamma_2)^2 + \gamma_2 \gamma_1 \varphi(s_{t-1}). \end{aligned}$$

If a worker has not moved in the last two periods, the probability that she is a type I is

$$\Pr(I|s_t, s_{t-1}, s_{t-2}) = \frac{\{1 - \alpha(s_{t-2})\} \varphi(s_{t-2}) p^{11} + \alpha(s_{t-2}) p^{21}}{\{1 - \alpha(s_{t-2})\} \varphi(s_{t-2}) \{p^{11} + p^{12}\} + \alpha(s_{t-2}) \{p^{21} + p^{22}\}}.$$

Finally, if a worker's history is unknown then her probability of being type I is

$$\Pr(I|s_t) = 1 - \alpha(s_t).$$

We use these probabilities in maximum likelihood contributions of individuals. Ideally, we could go back more in history of workers, but we prefer to go back only two periods since it is sufficient to identify the parameters we are interested in. Going back more in history would require computing all possible paths, which is computationally (and analytically) infeasible.

Tables 6 shows that moving costs are much lower with the inclusion of unobserved heterogeneity. We now find that moving cost varies between 1.4 to 3.1, while it varies between 4.5 to 5.9 without unobserved heterogeneity. Other results, that are presented in Tables 6 and 7 are very similar to Tables 3 and 4. Thus parameter estimates, excluding mobility costs, are not affected much from the introduction of unobserved heterogeneity. Another interesting parameter is α , which is estimated as high as 0.75. This can be interpreted as, 75 percent of workers can not move either because of search frictions or time persistence of shocks. Finally, we find that $\gamma_1 = 0.47$, thus it can be inferred that unobserved types show some persistence, since it is much smaller than 0.75. When we repeat the simulation exercise for the extended model, we find that inclusion of unobserved heterogeneity does not change the qualitative implications of the main model (figures available upon request).

6 Conclusion

We introduced a model which can be used to analyze distributional effects of trade liberalization. Our initial setting was somehow similar to ACM, but we followed a completely different econometric strategy which allowed us to introduce richer ex-ante and endogenous worker heterogeneity. Although this strategy prevented us from using their compact Euler-equation conditions, we simplified the estimation process by discretizing state-space. Using NLSY and CPS, we estimated mobility parameters and human capital accumulation process jointly. With estimates of these structural parameters and calibrated production functions, we simulated a counterfactual trade shock in metal manufacturing sector (which was subject

Table 6: Estimation - Moving Cost (Unobserved Heterogeneity).

Panel A: Idiosyncratic Shock Parameter			
		<i>Coefficient</i>	<i>t-stat</i>
	ν	1.300	7.633

Panel B: Age specific cost			
	<i>Age</i>	<i>Coefficient</i>	<i>t-stat</i>
C_1^1	<i>Age 26</i>	1.36	2.39
C_1^2	<i>Age 33</i>	2.10	3.58
C_1^3	<i>Age 40</i>	2.03	2.99
C_1^4	<i>Age 47</i>	2.34	3.27
C_1^5	<i>Age 54</i>	3.08	3.99

Panel C: Additional sector specific cost			
	<i>Sector</i>	<i>Coefficient</i>	<i>t-stat</i>
C_2^1	<i>Manuf</i>	0.00	N/A
C_2^2	<i>Metal</i>	2.84	7.10
C_2^3	<i>Service</i>	-1.32	-6.99
C_2^4	<i>Trade</i>	-0.49	-5.13

Panel D: Additional education specific cost			
	<i>Education</i>	<i>Coefficient</i>	<i>t-stat</i>
C_3	<i>College</i>	0.19	1.79

Panel E: Types			
	<i>Probability</i>	<i>Coefficient</i>	<i>t-stat</i>
α	$Pr(II)$	0.75	18.25
γ_1	$Pr(I \text{ to } II)$	0.47	6.12
γ_2	$Pr(II \text{ to } I)$	0.16	N/A

Table 7: Estimation - Human Capital (Unobserved Heterogeneity).

Panel A: Std. Dev. Of Wage Shock			
		<i>Coefficient</i>	<i>t-stat</i>
	σ_z	0.4114	319.31
Panel B: Education Parameters			
	<i>Sectors</i>	<i>Coefficient</i>	<i>t-stat</i>
ϕ_1^1	<i>Manuf</i>	0.1200	8.13
ϕ_1^2	<i>Metal</i>	0.0501	1.92
ϕ_1^3	<i>Service</i>	0.1863	12.86
ϕ_1^4	<i>Trade</i>	0.1514	10.47
Panel C: Sectoral Experience Parameters			
	<i>Sectors</i>	<i>Coefficient</i>	<i>t-stat</i>
ϕ_2^1	<i>Manuf</i>	0.0233	12.52
ϕ_2^2	<i>Metal</i>	0.0136	2.88
ϕ_2^3	<i>Service</i>	0.0379	25.75
ϕ_2^4	<i>Trade</i>	0.0282	13.04
	<i>Education</i>	<i>Coefficient</i>	<i>t-stat</i>
ϕ_4	<i>College</i>	-0.0073	-4.30
Panel D: Market Experience Parameters			
	<i>Sectors</i>	<i>Coefficient</i>	<i>t-stat</i>
ϕ_3^1	<i>Manuf</i>	0.0104	7.28
ϕ_3^2	<i>Metal</i>	0.0109	3.32
ϕ_3^3	<i>Service</i>	0.0025	1.98
ϕ_3^4	<i>Trade</i>	0.0089	6.88
	<i>Education</i>	<i>Coefficient</i>	<i>t-stat</i>
ϕ_5	<i>College</i>	0.0125	6.06

to shocks recently, steel sector in particular.) We find that:

(1) The results show that estimated moving costs are large and increase further with age. Preference shocks are important in explaining labor mobility, therefore psychological or unobserved factors play a role in mobility decisions.

(2) High moving costs found in this paper (and in ACM) might be partially due to omission of unobserved heterogeneity, which may be caused by search frictions and persistence of preference and wage shocks.

(3) After a trade shock in the metal sector, mainly "metal" and "manufacturing" workers would be affected since output of metal sector is not consumed but used as input in "manufacturing" and "metal" sectors.

(4) "Metal" workers would be worse off in general. However, young workers would be much less compared to middle-aged, due to their ability to move to other sectors (hence high option values). On the other hand, "Manufacturing" workers would be better off. Again young workers much less compared to middle-aged because of the drop in their option values. The relevant figures display a mirror effect in "manufacturing" and "metal" sectors.

(5) As workers get close to retirement they should be unanimous since they have less time to enjoy or suffer from the effects of free trade on their wages. To analyze effects of trade shocks on very old workers, a more detailed modelling of savings and retirement benefits is required, which is left for future research.

Appendix A: Alternative Estimations

To analyze robustness of our results we have experimented with alternative specifications. The presentation of results and discussions are kept short to limit length of the paper.

Basic Model vs. Restricted Utility Shocks

In the labor literature utility shocks are not common; in similar discrete choice models, such as Keane and Wolpin (1997), labor allocations are mainly driven by wages shocks. To demonstrate the effect of inclusion of utility shocks we introduce a descriptive model with a very simple moving cost and human capital structure:

$$\begin{aligned} C_t^{mij} &= C_1 + C_2^j, \\ \log h_t^{ni} &= \phi_0^i + \phi_1 Coll^n + \phi_2 SecEx_t^{ni} + \phi_3 MktEx_t^n + z_t^{ni}, \end{aligned}$$

we estimate this model using only NLSY data. Then, we repeat the exercise with a restriction $\nu = 0.04$.

Table 8: Basic Model and Restricted Utility Shocks.

Panel A: Basic Model Estimates with NLSY						
	ν	C_1	C_2^1	C_2^2	C_2^3	C_2^4
Coef.	1.77	5.53	0.00	3.79	-1.85	-0.40
tstat	10.34	9.78	N/A	8.37	-6.92	-2.25
	σ_z	<i>Sec. Exp.</i>	<i>Mkt. Exp.</i>	<i>College</i>		
Coef.	0.41	0.03	0.01	0.22		
tstat	321.89	41.06	11.89	61.91		
Panel B: Estimates with NLSY (Restricted Nu)						
	ν	C_1	C_2^1	C_2^2	C_2^3	C_2^4
Coef.	0.04	0.34	0.00	0.39	-0.11	-0.20
tstat	N/A	76.02	N/A	50.32	-15.49	-33.42
	σ_z	<i>Sec. Exp.</i>	<i>Mkt. Exp.</i>	<i>College</i>		
Coef.	0.39	0.01	0.04	0.15		
tstat	372.04	57.36	147.22	58.99		

We do not set ν equal to zero because otherwise we need to make substantial changes in the computations. The results are shown in Table 8 Panels A and B respectively. Here,

we show the contribution of utility shocks to large moving costs. Wage shocks can be easily identified since wages are observed. We observe that wages do not fluctuate much, but workers change sectors very often, which implies very small moving costs when preference shocks are omitted.

Alternative initial distributions

We have to guess the initial distribution of sectoral experience for older workers in estimation process, because we do not observe workers' sectoral experience in CPS. We iterate labor allocation equations using year 1983 wages to calibrate initial distribution of CPS workers. Then alternatively, we iterate using average wages over the CPS sample (year 1983 to 2001). Using simple descriptive model (introduced above) we show that the initial distribution of workers does not affect our results significantly. Results shown in Table 9 Panels A and B.

Table 9: Alternative Initial Distributions.

Panel A: Estimates with NLSY and CPS						
	ν	C_1	C_2^1	C_2^2	C_2^3	C_2^4
Coef.	1.63	5.28	0.00	3.85	-2.22	-0.61
tstat	11.64	17.14	N/A	15.32	-14.32	-6.16
	σ_z	<i>Sec. Exp.</i>	<i>Mkt. Exp.</i>	<i>College</i>		
Coef.	0.41	0.03	0.01	0.18		
tstat	322.47	42.27	11.74	51.78		
Panel B: Estimates with NLSY and CPS (Alternative)						
	ν	C_1	C_2^1	C_2^2	C_2^3	C_2^4
Coef.	1.54	4.91	0.00	3.74	-1.93	-0.63
tstat	18.42	17.73	N/A	16.52	-13.62	-6.94
	σ_z	<i>Sec. Exp.</i>	<i>Mkt. Exp.</i>	<i>College</i>		
Coef.	0.41	0.03	0.01	0.18		
tstat	323.05	41.10	13.22	52.98		

Appendix B: Key Equations

The expected utility function used in programming can be expressed as:

$$\begin{aligned}
\bar{V}_t^i(s_t^n) &= E_{u,z} V_t^i(s_t^n, z_t^n, u_t^n) \\
&= E_z w_t^i(s_t^n, z_t^n, \bar{w}_t^i) + E \max_j \beta \{V_{t+1}^j(\eta_{t+1}^n | s_t^n) - C^{i,j}(\eta_{t+1}^n)\}, \\
&= \tilde{w}_t^i(s_t, \xi_t) + \beta \Omega_{t+1}^i(s_t^n) + \beta E_{s,u,z} \{V_{t+1}^i(s_{t+1}^n, z_{t+1}^n, u_{t+1}^n) | s_t^n\}, \\
&= \tilde{w}_t^i(s_t, \xi_t) + \beta \Omega_{t+1}^i(s_t^n) + \beta E_s \int_z \{\bar{V}_{t+1}^i(s_{t+1}^n) - \bar{w}_{t+1}^i(s_{t+1}^n) + w_{t+1}^i(s_{t+1}^n, z_{t+1}^n, \bar{w}_{t+1}^i)\} dz \\
&= \tilde{w}_t^i(s_t, \xi_t) + \beta \Omega_{t+1}^i(s_t^n) + \beta E_s \bar{V}_{t+1}^i(s_{t+1}^n)
\end{aligned}$$

where $\tilde{w}_t^i(s_t, \xi_t) = E_z w_t^i(s_t^n, z_t^n, \xi_t)$.

Define

$$\tilde{V}_t^i(s_t^n, z_t^n) = w_t^i(s_t^n, z_t^n, \bar{w}_t^i) + \beta \Omega_{t+1}^i(s_t^n) + \beta E_s \bar{V}_{t+1}^i(s_{t+1}^n)$$

gross flows from state s_t to s_{t+1} can be represented as:

$$m^{s_t s_{t+1}} = E_s \int_z \frac{\exp \left\{ \left(\tilde{V}_{t+1}^j(s_{t+1}^n, z_{t+1}^n) - \tilde{V}_{t+1}^i(s_{t+1}^n, z_{t+1}^n) - C^{i,j}(s_{t+1}^n) \right) / \nu \right\}}{\sum_k \exp \left\{ \left(\tilde{V}_{t+1}^k(s_{t+1}^n, z_{t+1}^n) - \tilde{V}_{t+1}^i(s_{t+1}^n, z_{t+1}^n) - C^{i,k}(s_{t+1}^n) \right) / \nu \right\}} dz,$$

if agent stays same age; or

$$m^{s_t s_{t+1}} = \frac{1}{7} E_s \int_z \frac{\exp \left\{ \left(\tilde{V}_{t+1}^j(s_{t+1}^n, z_{t+1}^n) - \tilde{V}_{t+1}^i(s_{t+1}^n, z_{t+1}^n) - C^{i,j}(s_{t+1}^n) \right) / \nu \right\}}{\sum_k \exp \left\{ \left(\tilde{V}_{t+1}^k(s_{t+1}^n, z_{t+1}^n) - \tilde{V}_{t+1}^i(s_{t+1}^n, z_{t+1}^n) - C^{i,k}(s_{t+1}^n) \right) / \nu \right\}} dz,$$

if agent is older at s_t . Note that s_{t+1} should have the correct sectoral experience given s_t following the process in (5). Finally the option value can be expressed as

$$\Omega(s_t) = -\nu E_s \int_z \log \left(\frac{1}{\sum_k \exp \left\{ \left(\tilde{V}_{t+1}^k(s_{t+1}^n, z_{t+1}^n) - \tilde{V}_{t+1}^i(s_{t+1}^n, z_{t+1}^n) - C^{i,k}(s_{t+1}^n) \right) / \nu \right\}} \right) dz.$$

ACM present derivation of equations similar to the ones above in detail. The main difference

here is having an additional non-linear shock, z_t , hence we take integrals over that shock using simulations.

Appendix C: A Brief Analysis of the Pew Survey

Pew Global Attitudes survey is consist of interviews conducted in 44 countries with 38,263 individuals in 2002. It includes approximately 100 questions on various popular issues and personal background. We are not using the survey data to estimate our main model but to estimate a simple descriptive probit model to illustrate our motivation for this research. A question on international trade points out a very interesting yet unexplored issue. The question is: "And what about the different products that are now available from different parts of the world - do you think this is a very good thing, somewhat good, somewhat bad or a very bad thing for our country?" We find that as people get older they are less likely to answer this question as "good" and "somehow good". We set up a simple probit model to demonstrate the correlation between age and probability of supporting free trade.

Consider that $A = 1$ if the individual, i , answers the question as "good" and else $A = 0$. We assume that $A = 1$ if and only if gains from trade u is greater than a certain threshold $\bar{u}$. We use a simple linear form

$$u_i = \beta_0 + \beta_1 Age_i + \beta_2 Age_i^2 + \beta_3 Age_i^3 + \beta_4 Female_i + \beta_5 Employed_i + \varepsilon_i,$$

Where ε is a iid shock, Employed is a dummy for employment status which is one for employed people and zero for unemployed, Female is a dummy variable which is one for female and zero for male, and Age means age in last birthday minus eighteen. Estimates show that probability of a person's gains from trade being larger than the threshold decrease with age (in a linear fashion). See Table 10 - Panel A for the estimates. The percentage of people from different age groups supporting free trade is reported in Panel B of Table 10.

In addition to Pew data, General Social Survey, conducted in US starting from 1972, also has questions related to people's perception of free trade. The negative correlation between age and supporting free trade is also observed in GSS, but the evidence is not conclusive since the number of respondents to these questions in General Social Survey is much smaller compared to Pew data. For example 1348 people gave a valid response to the question: "Does America benefit from being a member of NAFTA?" the probability of answering "Yes" again, in general, decreases with age. See Table 10 - Panel C.

Table 10: Pew Statistics.

Panel A: Pew Probit Results						
	<i>Coefficient</i>		<i>Std. Error</i>			
<i>Constant</i>	-0.298		0.021			
<i>Age</i>	-0.008		0.003			
<i>Age</i> ²	0.000		0.000			
<i>Age</i> ³	0.000		0.000			
<i>Female</i>	-0.020		0.014			
<i>Employed</i>	0.053		0.015			

Panel B: Probability of Supporting Free Trade in the Pew Sample						
<i>Age</i>	<i>20's</i>	<i>30's</i>	<i>40's</i>	<i>50's</i>	<i>60's</i>	<i>70's</i>
<i>Probability</i>	0.374	0.353	0.316	0.302	0.277	0.238

Panel C: Probability of Supporting NAFTA in the GSS sample						
<i>Age</i>	<i>20's</i>	<i>30's</i>	<i>40's</i>	<i>50's</i>	<i>60's</i>	<i>70's</i>
<i>Probability</i>	0.661	0.610	0.571	0.602	0.449	0.447

It should be noted that the questions asked in these surveys are very general; the answers given depend on many factors not observed from the data such as one's perception of free trade, consumption preferences, recent changes in trade policy in their countries, skill level, worker's industry, and many other things which would differ from country to country and person to person. The probit analysis and tables only show that there is, in general, a negative correlation between age and supporting free trade in most countries for most of the people. In the next section we set up a model to explain why age and gains from trade are correlated. We will show that welfare effects of trade liberalization depend on people's age, education and experience level as well as the type of liberalization.

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Figure 1: Flows Out of Sectors - Young Workers without Experience .

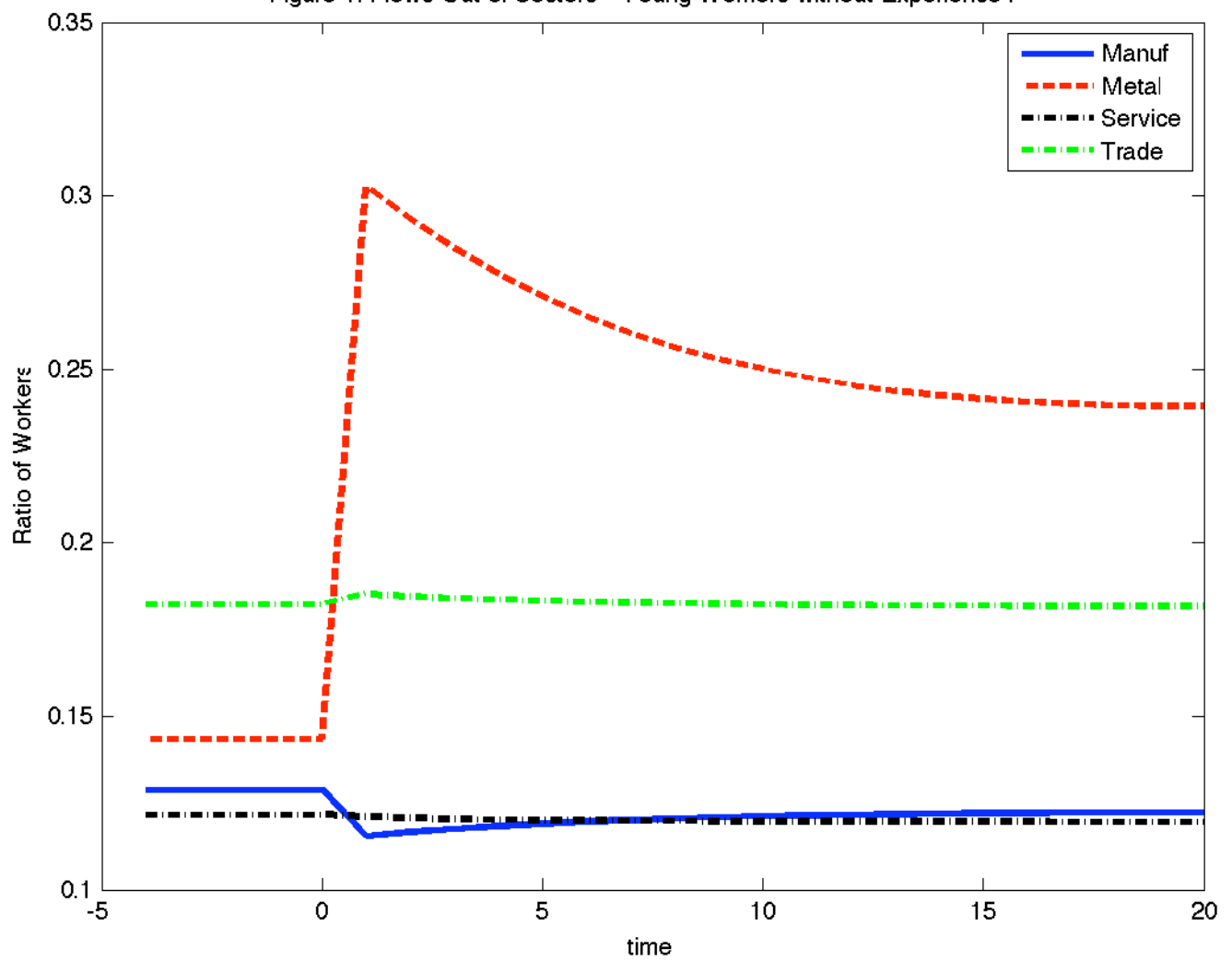


Figure 2: Flows Out of Sectors - Old Workers without Experience .

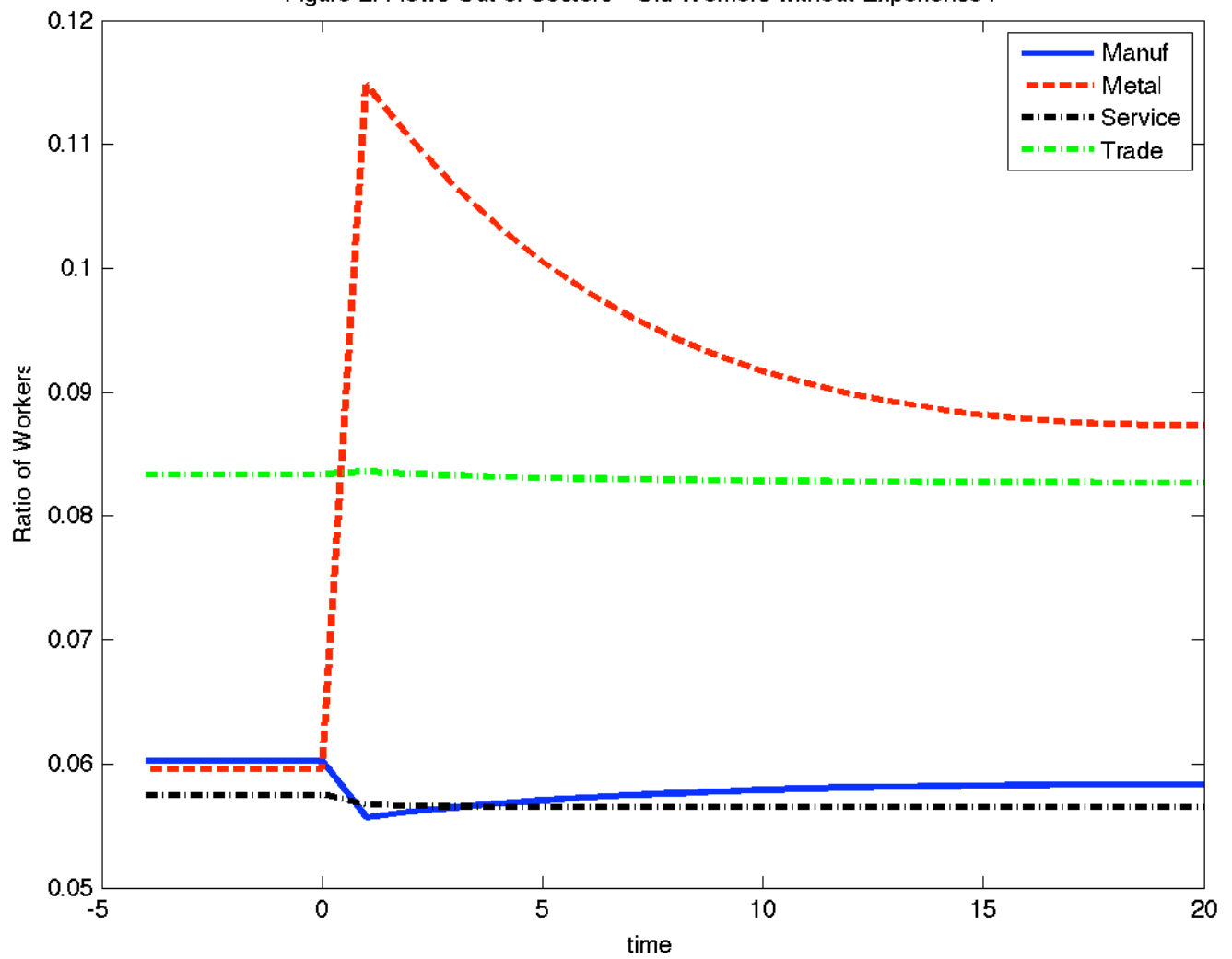


Figure 3: Flows Out of Sectors - Old Workers with Experience .

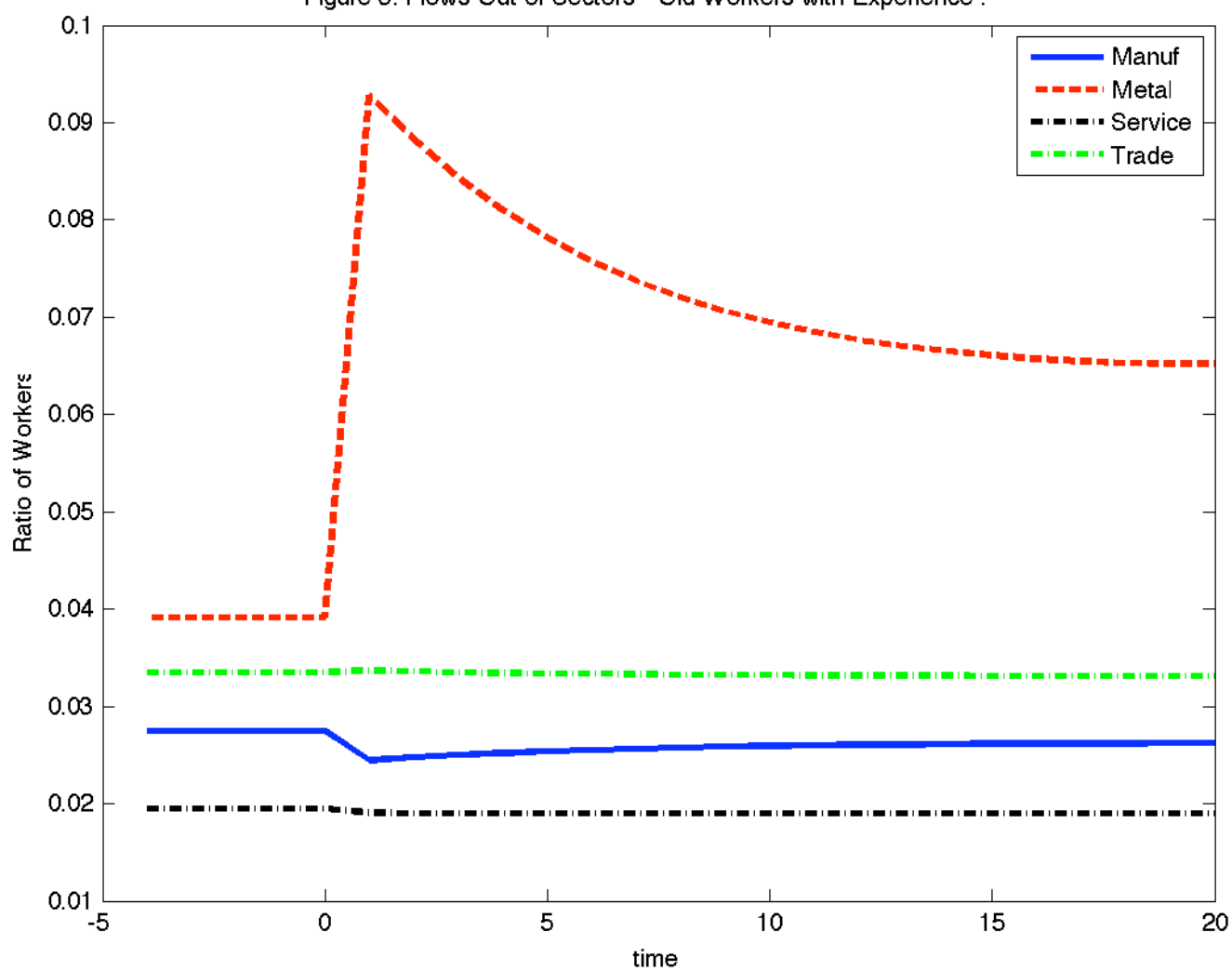


Figure 4: Adjustment of Wages .

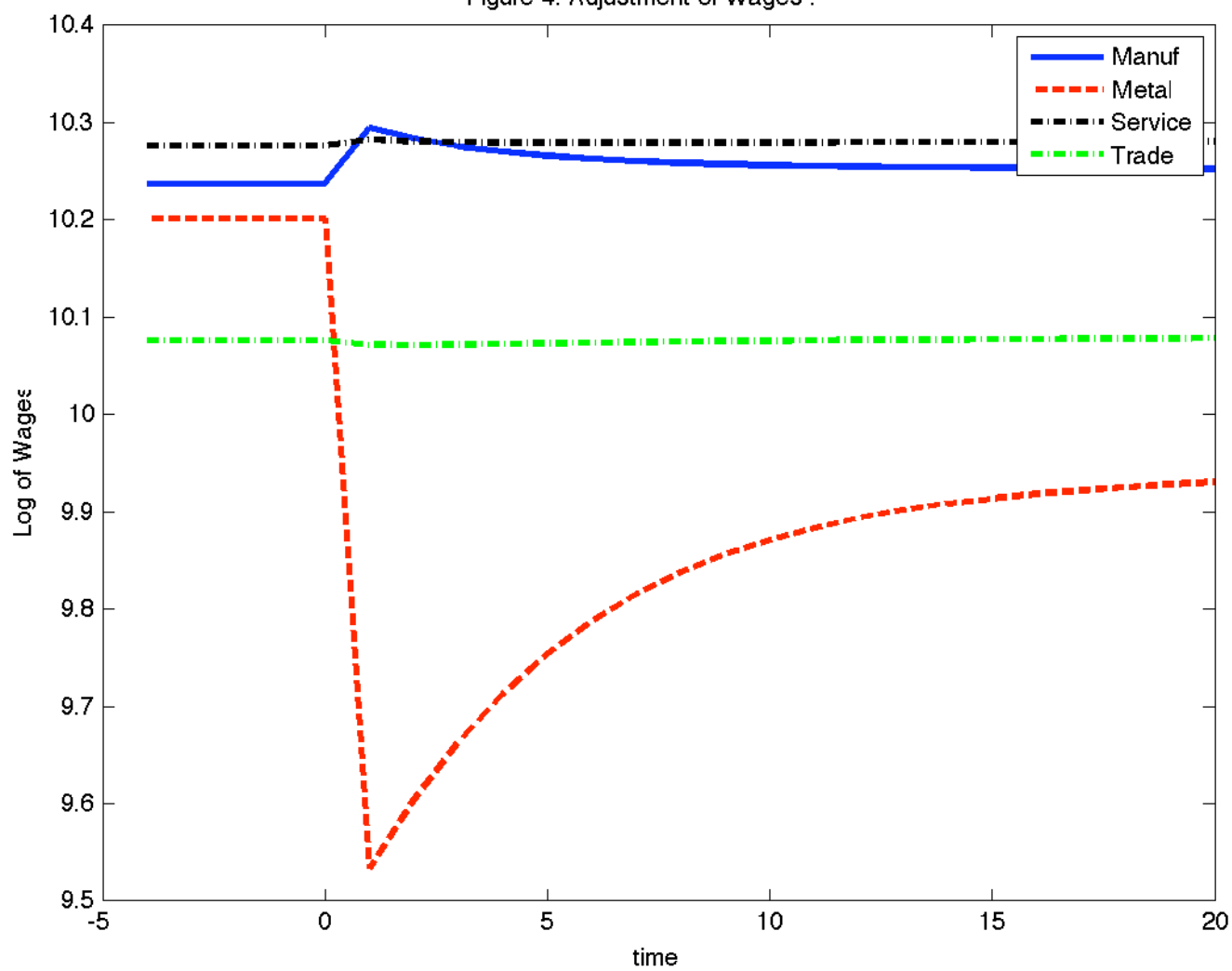


Figure 5: Percentage Change in Output .

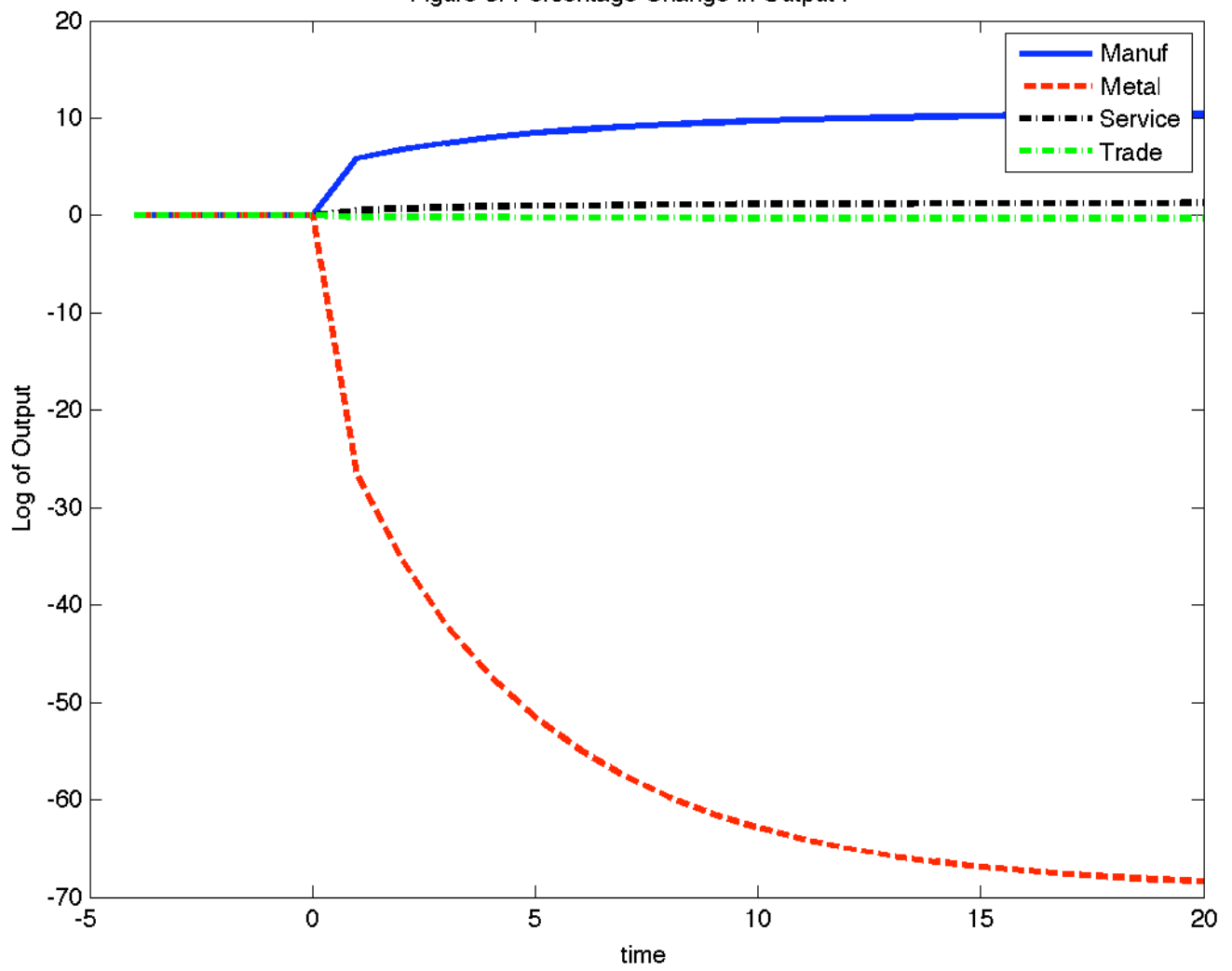


Figure 6: Percentage Change in Demand .

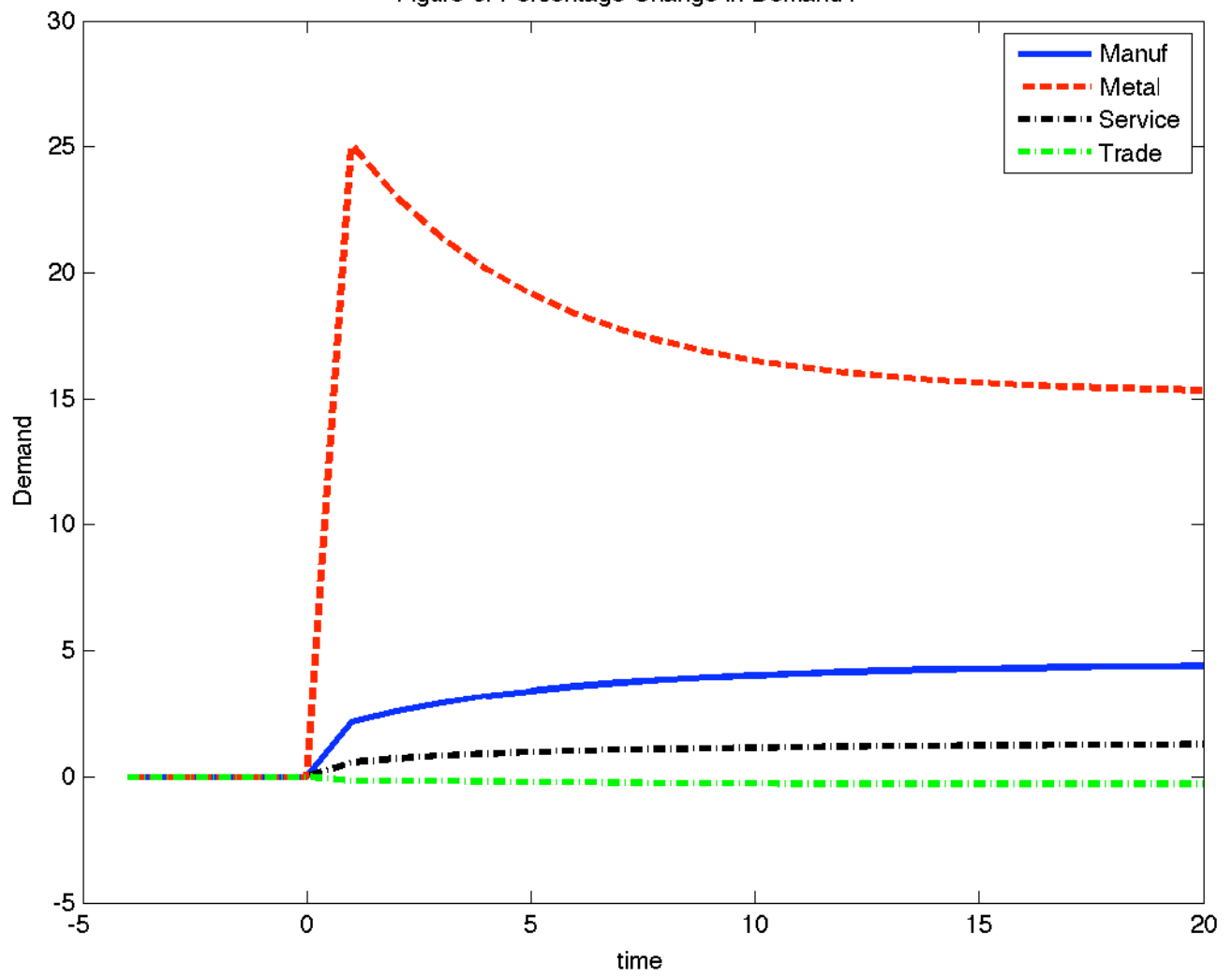


Figure 7: Percentage Change in Price .

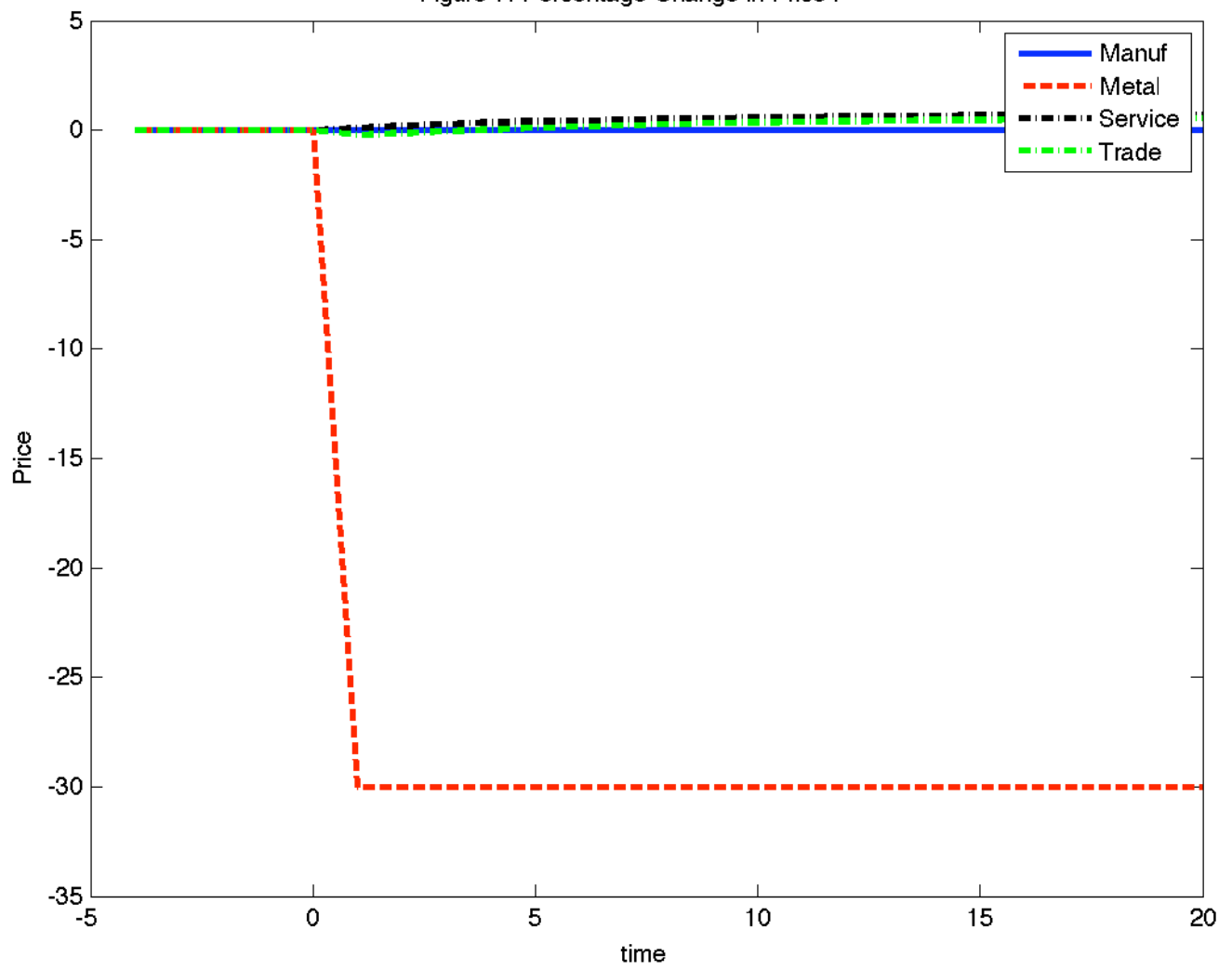


Figure 8: Change in Present Discounted Value - Manufacturing (No-College) .

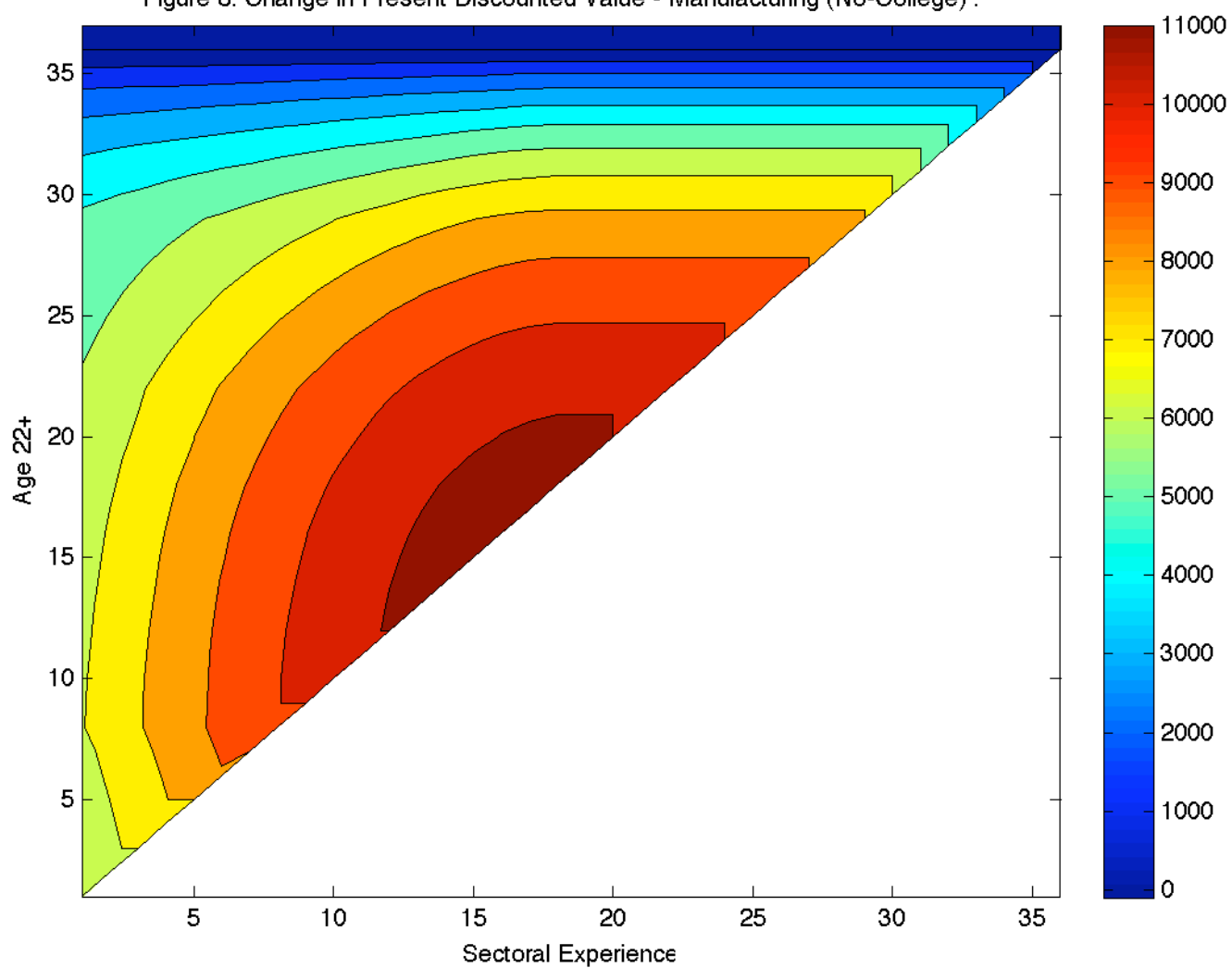


Figure 9: Change in Present Discounted Value - Metal (No-College) .

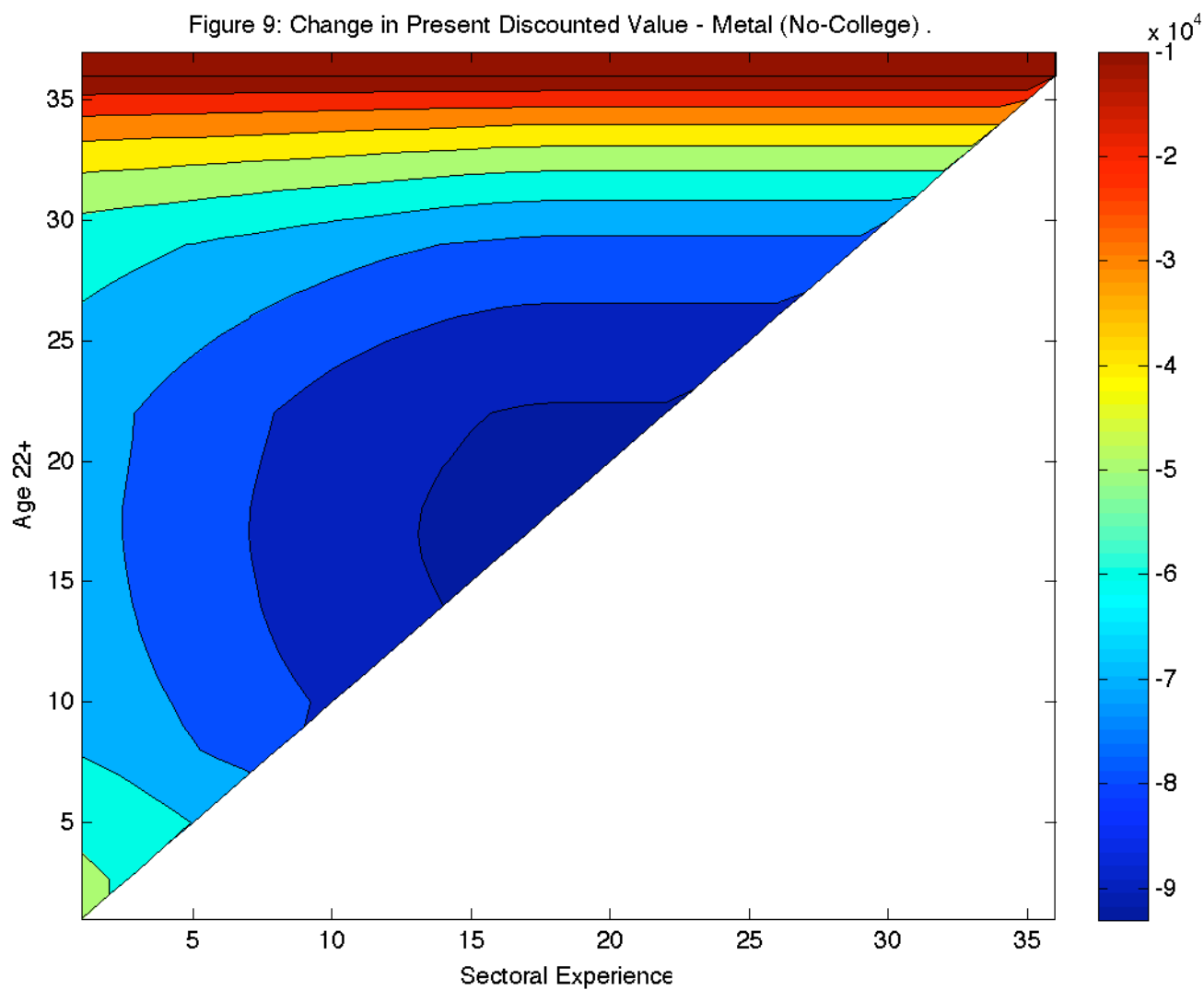


Figure 10: Change in Present Discounted Value - Service (No-College) .

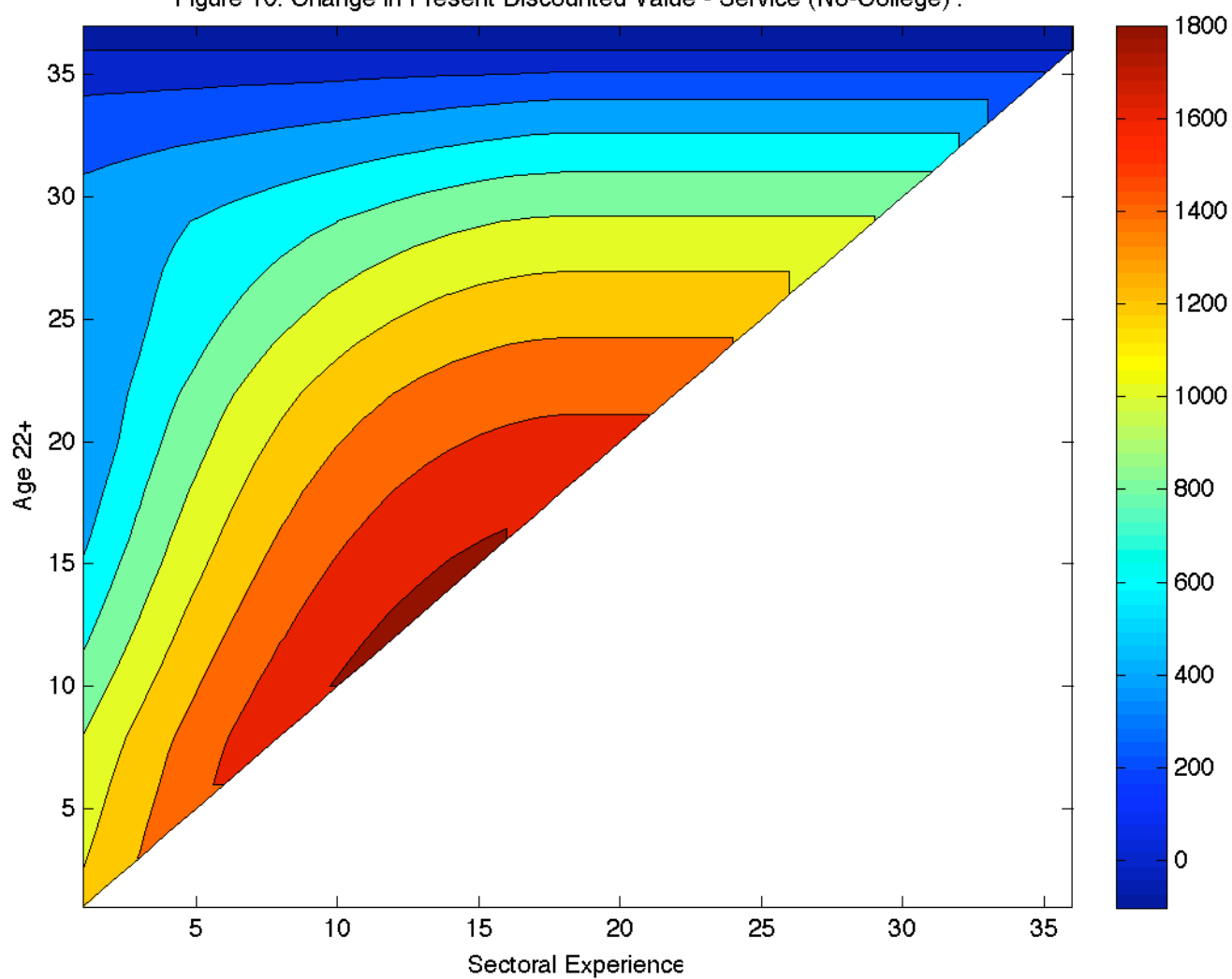


Figure 11: Change in Present Discounted Value - Trade (No-College) .

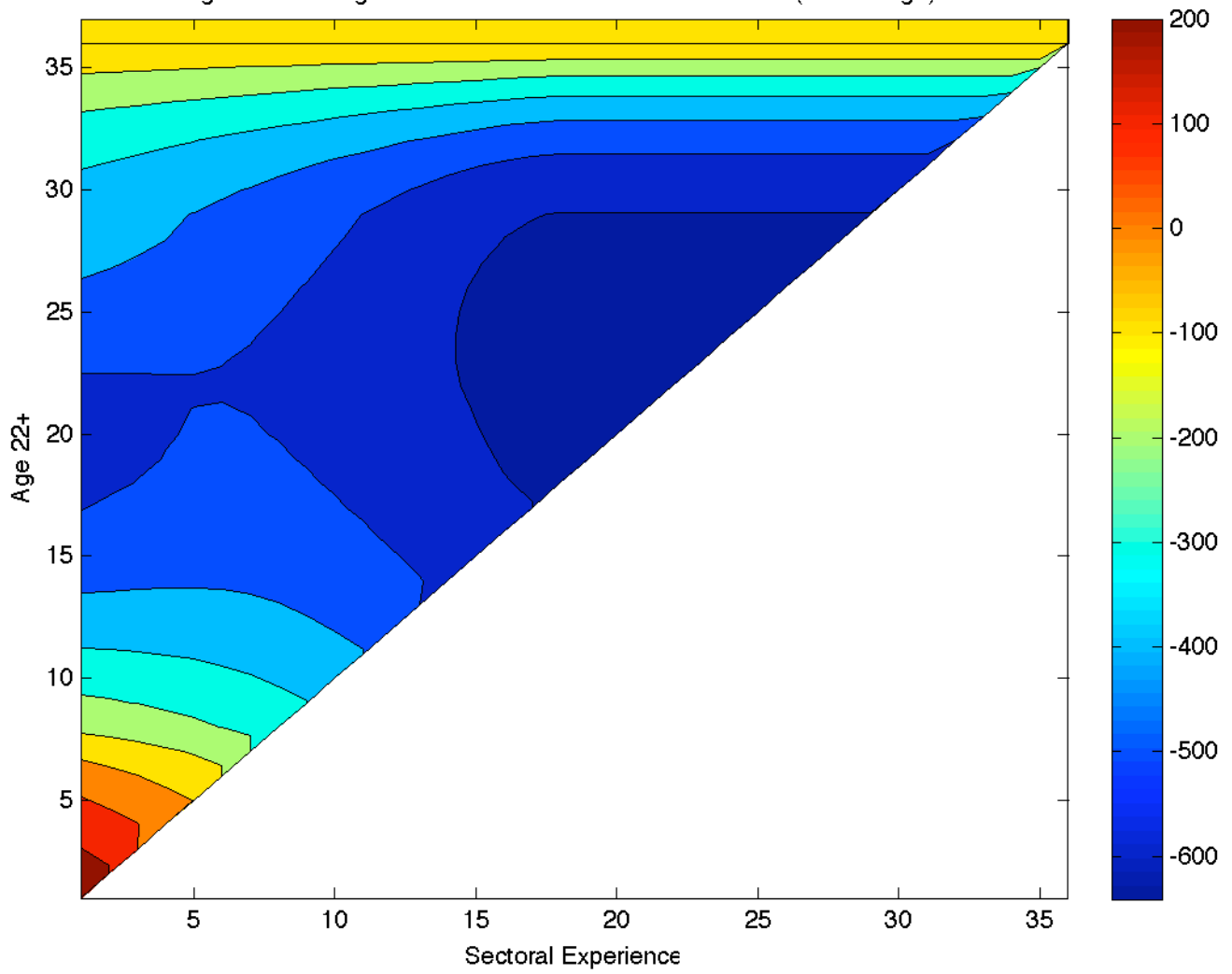


Figure 12: Change in Present Discounted Value - Manufacturing (College) .

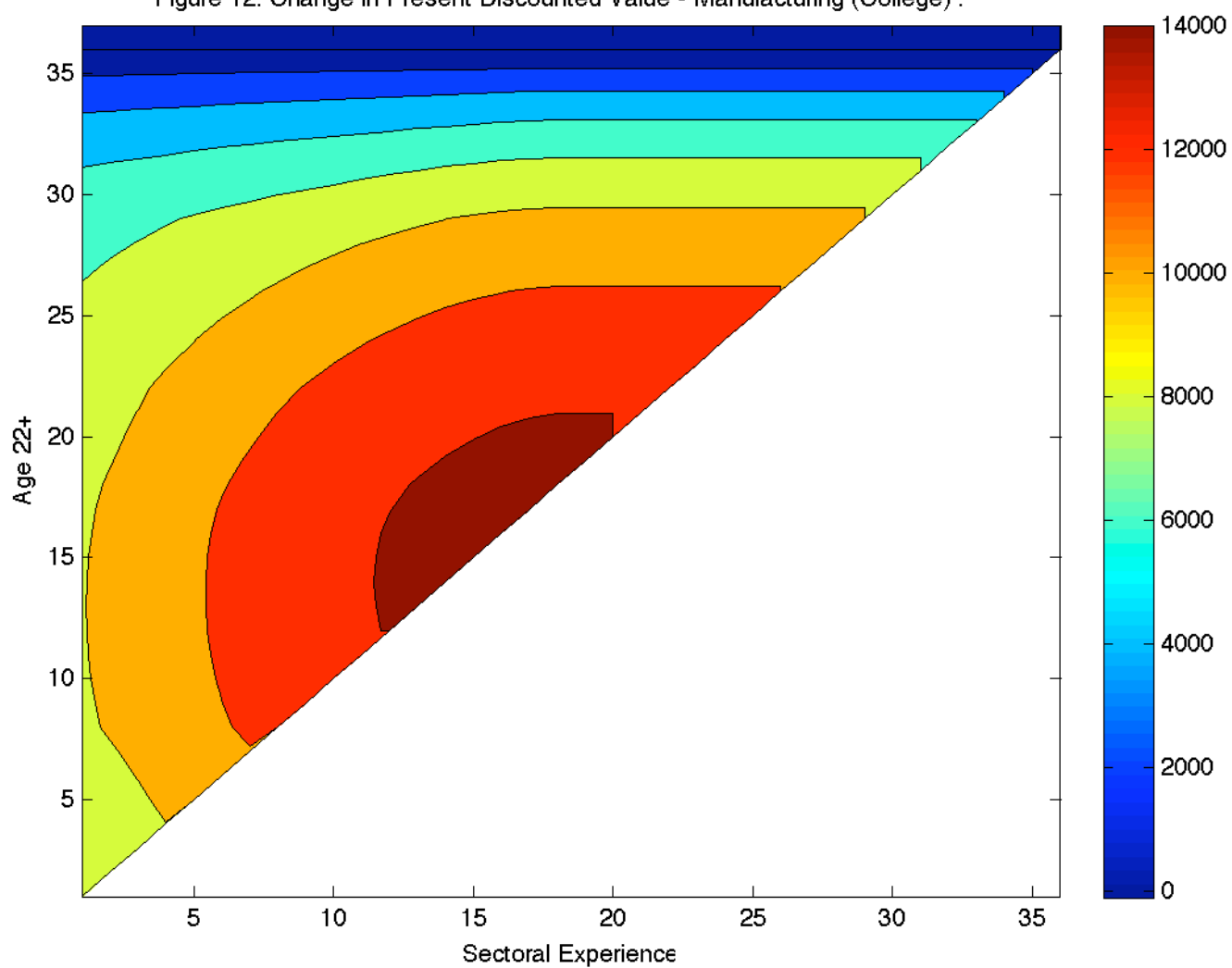


Figure 13: Change in Present Discounted Value - Metal (College) .

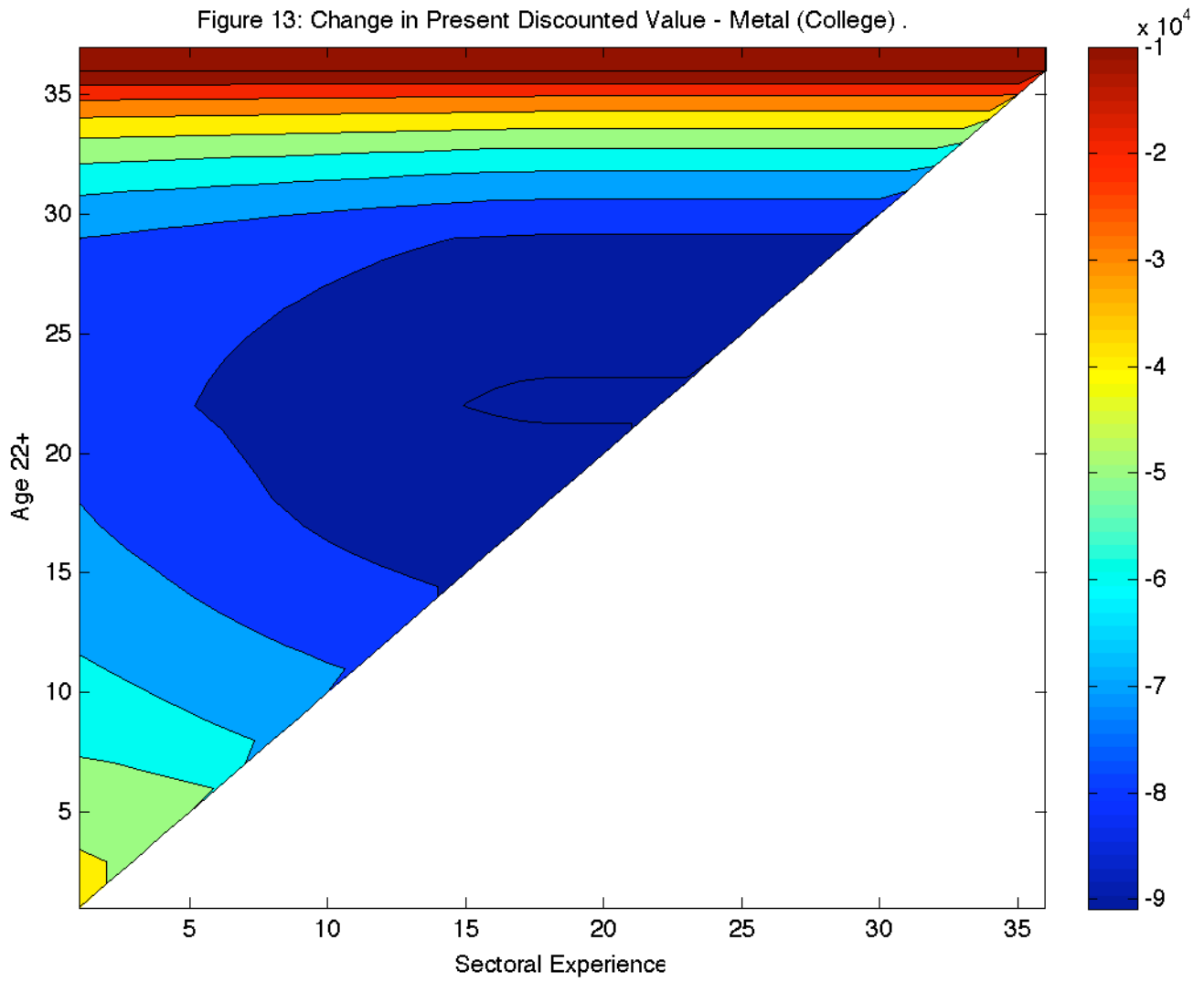


Figure 14: Change in Present Discounted Value - Service (College) .

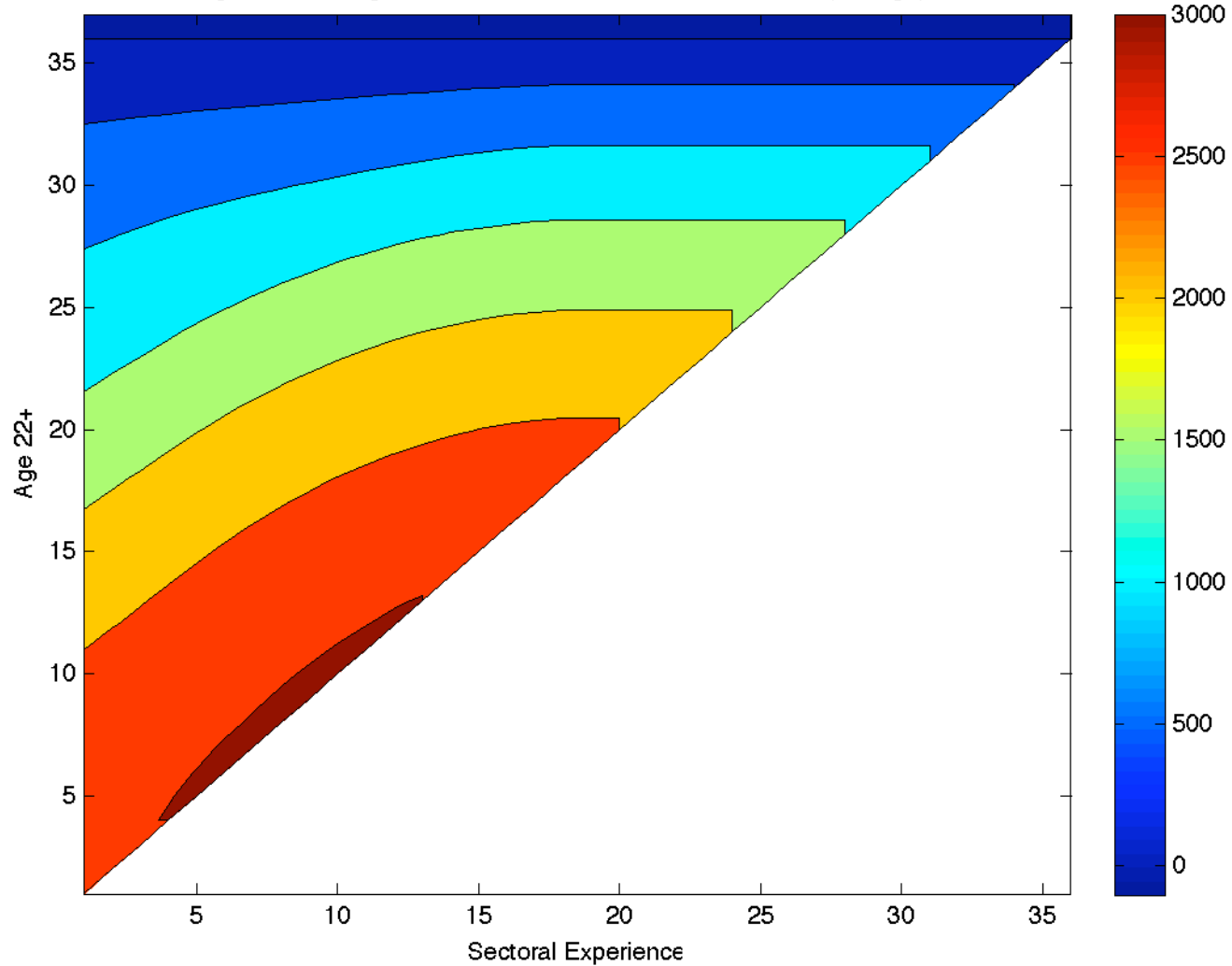


Figure 15: Change in Present Discounted Value - Trade (College) .

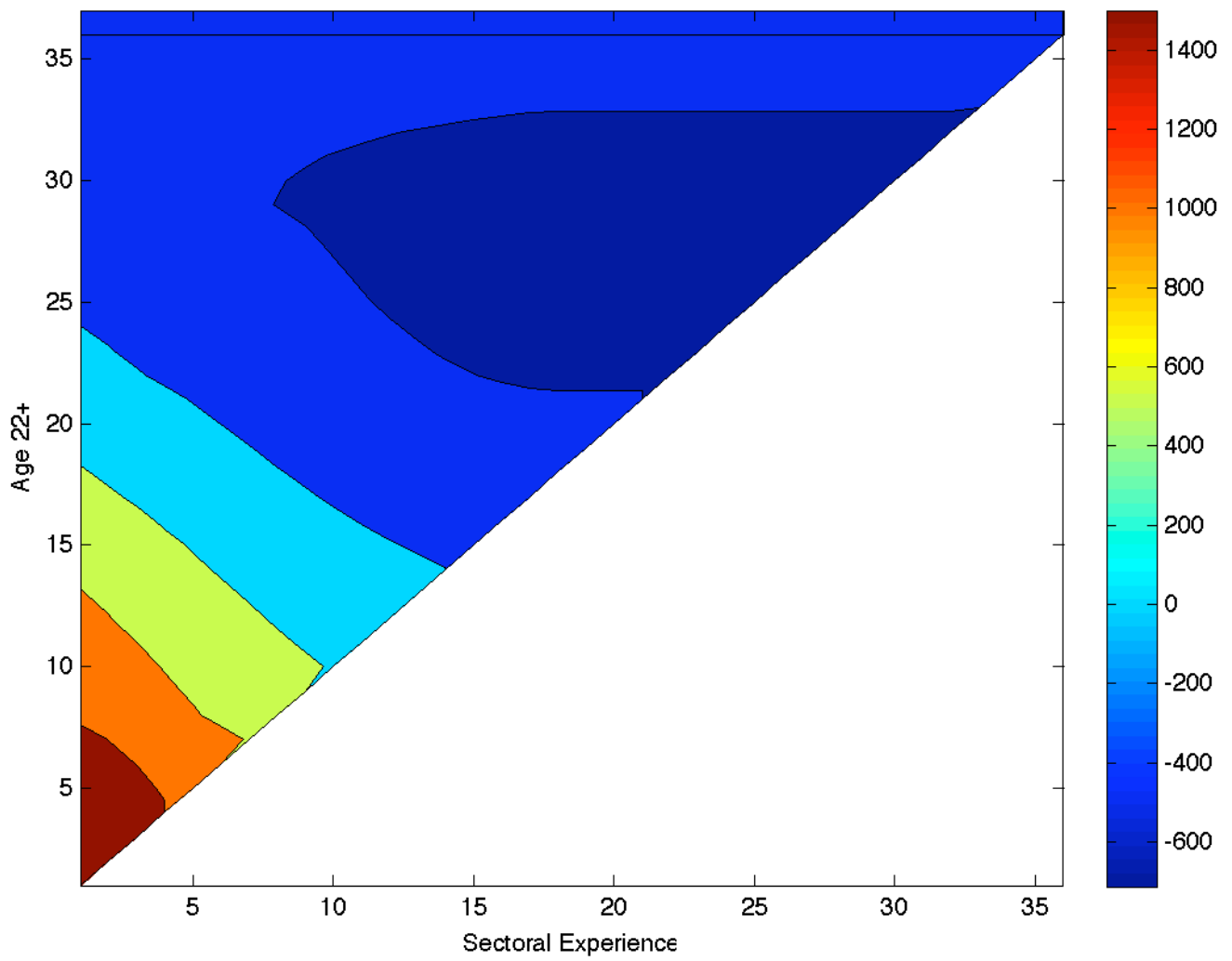


Figure 16: Actual Value Functions vs. Approximated Value Functions

