Trade Policy and Wage Inequality: A Structural Analysis with Occupational and Sectoral Mobility*

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Abstract

A number of authors have argued that a worker's occupation of employment is at least as important as the worker's industry of employment in determining whether the worker will be hurt or helped by international trade. We investigate the role of occupational mobility on the effects of trade shocks on wage inequality in a dynamic, structural econometric model of worker adjustment. Each worker in our specification can switch either industry, occupation, or both, paying a time-varying cost to do so in a rational-expectations optimizing environment. We find that the costs of switching industry and occupation are both high, and of similar magnitude, but in simulations we find that a worker's industry of employment is much more important than either the worker's occupation or skill class in determining whether or not she is harmed by a trade shock.

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Among the key questions trade economists need to be able to answer is: When a trade shock strikes such as liberalization, trade agreement, or expansion of a foreign export power, who benefits and who is hurt, and by how much? There are as many ways of approaching these questions as there are ways of dividing people into economically meaningful subgroups. The oldest literature divided people by what can be called 'class' lines, making a distinction between workers and the owners of physical or human capital – the Stolper-Samuelson approach. More recent approaches have divided up workers based on their industry of employment (Revenga (1992), Pavcnik, Attanasio and Goldberg (2004), Artuç, Chaudhuri and McLaren (2010)); region of residence (Topalova (2007), Kovak (2010), Hakobyan and McLaren (2010)); and age (Artuç (2009)), in each case attempting to quantify how trade shocks affect people in the different groups differently.

More recently, several studies have focussed on a division of workers by *occupations*, often making use of a data set explored by Autor, Levy, and Murnane (2003) that breaks down the 'task' composition of a wide range of occupations in US labor data. Authors who exploit these distinctions to look at the differential effects of trade shocks on workers with different types of occupations include Peri and Sparber (2009), Ebenstein, Harrison, McMillan, and Phillips (2009), and Liu and Trefler (2011). Some of the results in Ebenstein et. al. (2009), in particular, suggest that occupational distinctions may be more important than industry in identifying who loses from globalization, that it is workers in vulnerable occupations (namely, those that are the most offshorable) in affected industries who lose. If this is right, it is important information for policymakers to have to be able to target compensation programs effectively.

We take the focus on occupations in a new direction. Building on earlier work (Artuç, Chaudhuri and McLaren (2010)) (henceforth ACM) in which we estimated the costs to workers of switching industries in a dynamic model in order to measure the welfare effects of trade shocks on workers in different industries, we expand our framework to allow workers to change *both* their industry *and* their occupations, estimating the costs of doing so in an integrated dynamic structural econometric model. Our strategy is to specify a rational-expectations model in which industry and occupational switching is a forward-looking investment decision by long-lived workers; estimate the key structural parameters (particularly means and variances of moving costs) on worker data; and then simulate the effects of trade shocks using these estimates to analyze welfare and the time-path of the labor market's adjustment.

This approach has a number of advantages. First, it allows us to incorporate a real dynamic analysis into the effect on different occupations. Workers can and do change occupation, but it is costly to do so, and the degree of cost will affect the wage effects of a trade shock as well as how those wage changes translate into welfare changes. Importantly, a dynamic analysis allows us to identify the role of option value, which has been shown to have a large effect on the welfare analysis of trade shocks (Artuç, Chaudhuri and McLaren (2010)). If one's wage in one's own industry and occupation is reduced by a policy change, but wages in other occupations and industries to which one might consider switching are increased, then the positive option-value effect brought about by the latter may dominate the negative direct effect of the former. One needs a dynamic model with option value built in in order to find out what the net effect is.

Second, we will argue that a full account of occupational choice can have a significant effect on the whole pattern of gains and losses from trade shocks. Take a simple thought experiment as an example. Consider an economy with two goods and two types of worker, skilled and unskilled. Each good is produced by workers doing either of two tasks; output is a function of how many hours of each task are done, and the two goods differ in their task intensity. A worker's 'occupation' is defined by which task he or she performs. Consider three cases.

Case 1. If skilled workers can all do task 1 but unskilled workers can do only task 2 and it is easy for a worker of either occupation to switch between industries, then this model is merely a thinly disguised Heckscher-Ohlin model, and standard Stolper-Samuleson results will obtain. If the country involved is skilled-labor abundant compared to the rest of the world, then trade opening will increase wage inequality. Further, to know whether a given worker gains or loses, all one needs to know is that worker's skill class. The occupation and industry of employment are superfluous.

Case 2. Now, suppose that a worker of either skill class can choose either occupation, and the choice is partly determined by idiosyncratic preferences; but once that choice has been made, it is very costly to switch to another occupation. At the same time, it is easy for a worker of either occupation to switch industries. In that case, there will be both skilled and unskilled workers in both occupations. Stolper-Samuelson logic will ensure that the occupation that is intensive in the import-competing industry will be made worse off due to trade opening, while the other occupation will benefit. In this case, to know whether a given worker gains or loses, all one needs to know is that worker's occupation. The worker's skill class and industry of employment are superfluous.

Case 3. However, if either kind of worker can do either task with equal ease, and can switch between them readily, then skilled and unskilled workers will have the same wage, with or without trade, and so a trade shock will raise (or lower) all boats equally.

Clearly, even if all we are interested in is the effect of trade on income inequality as between skilled and unskilled workers, the degree of occupational mobility has an enormous effect.

To anticipate results, we find that both inter-sectoral and inter-occupational switching costs are large, and that they are similar in magnitude. Nonetheless, idiosyncratic shocks to the switching decision are also large, so that a non-negligible fraction of US workers switch along both dimensions every year. We also find that these costs are sub-additive, in the sense that the cost of switching both sector and occupation is much less than the cost of switching only industry plus the cost of switching only occupation. In addition, these costs are quite different in character for college-educated and non-college-educated workers. Finally, despite the extremely high costs of switching occupation, the main determinant of whether a worker benefits from trade liberalization or not is that worker's industry. In our simulations, one's occupation of employment makes almost no difference to the direction of welfare effect once industry has been taken into account.

Aside from our previous efforts in ACM, this equilibrium approach is related to some other work on the relationship between occupational choice and income distribution. Liu and Trefler (2011) use an equilibrium Roy-type model with endogenous matching of workers to occupations to interpret patterns of occupational adjustment in tradeable services occupations in response to international offshoring. They show that increased competition with foreign workers tends to lead to increased switching to lower-wage occupations. Kambourov and Manovskii (2009) use a general-equilibrium model with optimal dynamic occupational choice to show that rises in the volatility of occupation-specific productivity can help explain increases in income inequality in the data.

The next section lays out our model and estimation method. The following section shows the data and estimations, and the last section details the simulation results.

1 Model

We extend the model presented in ACM and Cameron Chaudhuri McLaren (2009) to include occupations along with sectors. Each worker chooses her sector i and occupation k jointly in each period in order to maximize her expected present discounted utility. Assume that there are I industries (sectors) and K occupations. There are two skill groups, indexed by s: College-educated workers, indicated by $s = c$, and non-college educated workers, indicated by $s = n$. Assume that workers cannot change their skill status.

For the moment, we take wages as exogenously given, because it simplifies the discussion of the empirics. However, in Section 3 we will endogenize wages in each sector by specifying a spot market for labor in each sector that clears in each period (and of course the endogenous effect of trade shocks on wages is a major focus of this inquiry). Each period t, the wage w_t^{iks} for each sector i, occupation k and skill class s is realized and observed by all. Each worker understands the distribution of future wages and optimizes accordingly.

In order to accommodate the fact that workers who appear identical to the econometrician often do different things, we introduce idiosyncratic shocks to workers' preferences. If worker n in skill class s spends period t working in occupation k in sector i, her instantaneous utility is $w_t^{iks}+\eta_t^{iks}+\epsilon_t^{nik}$, where ϵ_t^{nik} is a cell-specific iid utility shock with extreme value distribution with variance parameter ν which are drawn separately by each worker in every period,[1] and η_t^{iks} is an iid shock to the attractiveness of working in industry-occupation cell (i,k) that is common to all workers of skill class s. We will henceforth refer to these two shocks as the 'idiosyncratic shock' and the 'common shock,' respectively. We adopt the timing assumption that a worker in sector-occupation cell (i,k) at the beginning of period t enjoys wage w_t^{iks} and non-pecuniary benefit η_t^{iks} for sure, but will receive the idiosyncratic benefit ϵ_t^{nik} only if she remains in that cell. If she switches to cell (j,l) during period t, then at the end of the period she will receive idiosyncratic benefit ϵ_t^{njl} instead.

We assume that a worker learns $\epsilon_t^n = [\epsilon_t^{n11}, \epsilon_t^{n12}, ..., \epsilon_t^{nIK}]'$, and then decides to move or stay, with moving cost $C(i,k,j,l,s,\xi_t^{ikjls})$, where i and k are the worker's initial sector and occupation, and j and l are her final sector and occupation, and ξ_t^{ikjls} are mean-zero iid shocks common to all workers. If a worker does not change her sector or occupation then the moving cost is equal to zero, so $C(i,k,i,k,s,\xi_t^{ikjls}) = 0$. In principle, we could assume a different value for the moving cost for each value of (i,j,k,l,s) and estimate each one, but this would create a vast number of parameters. In practice, we need to parameterize the moving cost function somehow. We specify the function as follows:

$$
\begin{aligned}
C_t(i,k,j,l,s,\xi_t^{ikjls}) &= 0 \text{ if } i=j,\ k=l; && (1)\\
&= C_t^{1,j,s} + \xi_t^{ikjls} \text{ if } i \neq j,\ k=l; && (2)\\
&= C_t^{2,l,s} + \xi_t^{ikjls} \text{ if } i=j,\ k\neq l; && (3)\\
&= C_t^{1,j,s} + C_t^{2,l,s} + C_t^{3,s} + \xi_t^{ikjls} \text{ if } i\neq j,\ k\neq l, && (4)
\end{aligned}
$$

where $C_t^{1,j,s}$, $C_t^{2,l,s}$ and $C_t^{3,s}$ are parameters common to all workers and the ξ_t^{ikjls} are mean-zero iid shocks. The value $C_t^{1,j,s}$ is the cost of switching sectors. We assume that it depends on the destination sector j but not the origin sector i (so it may be interpreted as an 'entrance cost' for the sector). The value $C_t^{2,l,s}$ is the cost of switching occupations. We assume that it depends on the destination occupation l but not the origin occupation k (so it may be interpreted as an 'entrance cost' for the occupation). We allow for the possibility that the cost of switching in one dimension is affected by whether or not the worker is switching in the other dimension. For example, if a worker is switching sectors, that may raise the cost of also switching occupations, since there is a rising marginal cost of additional complexity in decision making; or it may *lower* the cost of switching occupations, since switching sectors already creates as much disruption in the worker's life as it is possible to create. In other words, we allow for the possibility that these switching costs are not simply additive. The

[1]More precisely, we set the parameters for this two-parameter family of distributions equal to $(-\gamma\nu, \nu)$, which ensures a mean of zero and a variance equal to $\frac{\pi^2\nu^2}{6}$. See Patel, Kapadia, and Owen (1976).

parameter $C_t^{3,s}$ captures this, and could be positive (as in the first case just mentioned) or negative (as in the second). All of these parameters may differ by skill class s.

1.1 Equilibrium relationships.

The optimization problem for worker n can be summarized by the following Bellman equation, in which $U_t^{iks}(\epsilon_t^n, \eta_t^{iks}, \xi_t^s)$ is the *ex post* payoff to the worker in period t conditional on the realization of that period's shocks, and V_t^{iks} is the *ex ante* expected payoff to a worker, where the expectation is taken with respect to that period's shocks: the vector of idiosyncratic shocks, ϵ_t^n, the common preference shock η_t^{iks}, and the matrix ξ_t^s of common switching-cost shocks ξ_t^{ikjls}.

$$\begin{aligned} U_t^{iks}(\varepsilon_t^n, \eta_t^{iks}, \xi_t^s) &= w_t^{iks} + \eta_t^{iks} + \max_{j,l}\{\varepsilon_t^{njl} - C_t(i,k,j,l,s,\xi_t^{ikjls}) + \beta E_t[V_{t+1}^{jls}]\} \\ &= w_t^i + \eta_t^{iks} + \beta E_t[V_{t+1}^{iks}] + \max_{j,l}\{\varepsilon_t^{njl} - C_t(i,k,j,l,s,\xi_t^{ikjls}) + \beta V_{t+1}^{jls} - \beta V_{t+1}^{iks}\}. \end{aligned}$$

Taking expectations with respect to all three shocks, this yields:

$$\begin{aligned} V_t^{iks} &= E\left[w_t^{iks} + \eta_t^{iks}\right] + \beta E_t[V_{t+1}^{iks}] + E\left[\max_{j,l}\{\varepsilon_t^{njl} - C_t(i,k,j,l,s,\xi_t^{ikjls}) + \beta\left(V_{t+1}^{jls} - V_{t+1}^{iks}\right)\}\right] \\ &\equiv E\left[w_t^{iks} + \eta_t^{iks}\right] + \beta E_t[V_{t+1}^{iks}] + \Omega_t^{iks}, \end{aligned} \tag{5}$$

where Ω_t^{iks} is interpreted as an option-value term. In other words, the expected payoff to a worker in a given cell at a given date is equal to the current wage plus common non-pecuniary benefit, plus the continuation value if the worker stays in that cell next period, plus the value of the option of moving to another sector and/or occupation.

Due to the extreme value distribution of the ϵ_t, it can be shown that workers' optimal choice of sector-occupation cell in each period will satisfy:

$$m_t^{ikjls} = \frac{exp\left[\frac{1}{\nu}\left(\beta E_t\left(V_{t+1}^{jls} - V_{t+1}^{iks}\right) - C_t(i,k,j,l,s,\xi_t^{ikjls})\right)\right]}{\Sigma_{j'=1\ldots I, l'=1\ldots K} exp\left[\frac{1}{\nu}\left(\beta E_t\left(V_{t+1}^{j'l's} - V_{t+1}^{iks}\right) - C_t(i,k,j',l',s,\xi_t^{ikj'l's})\right)\right]}, \tag{6}$$

where m_t^{ikjls} denotes the fraction of workers of s type in sector-occupation cell (i,k) who choose to move to cell (j,l) in period t, which we will call the *gross flow* from that origin cell to that destination cell. This is the same as the functional form familiar from multinomial logit problems (a full algebraic derivation can be found in the appendix of Artuç, Chaudhuri and McLaren (2007)). Essentially, (6) says that the more attractive (j,l) is expected to be in the future relative to other cells, and the lower is the cost of switching to it from (i,k), then the larger is the fraction of workers who will choose that location. Crucially, however, this response of the gross flow to the future relative attractiveness or current switching cost is determined by the parameter ν, which we may recall is proportional to the variance of the idiosyncratic shocks ϵ_t^n. A large value of ν implies that idiosyncratic preference shocks tend to be large; in the limit, those shocks are all workers care about, and so workers will disregard relative future profitability in choosing their sectors and occupations. More generally, the m_t^{ikjls} will respond more to future expected wage differentials the smaller is ν. This point will be useful in identifying ν econometrically.

1.2 Econometric method.

The estimation method is described in detail with full derivations in Artuç (2012). We need to estimate the parameters of the moving costs, the C_t^{1js}, C_t^{2ls}, and C_t^{3s} as well as the idiosyncratic variance ν. In addition, we need to estimate the means $\bar{\eta}^{iks}$ of the common preference shocks η_t^{iks}. We do this in two stages, using the two equations discussed above, the gross-flows equation (6) and the Bellman equation (5).

The first stage uses (6) with data on actual gross flows to estimate $\lambda_t^{iks} \equiv \frac{1}{\nu}\left(\beta E_t\left(V_{t+1}^{iks} - V_{t+1}^{11s}\right)\right)$ as well as $\frac{1}{\nu}C_t^{1js}$, $\frac{1}{\nu}C_t^{2ls}$, and $\frac{1}{\nu}C_t^{3s}$ for all i, k, s and t, using a Poisson regression approach similar to that detailed in Santos Silva and Tenreyro (2006). The values ξ_t^{ikjls} are essentially like error terms to allow us to fit the first-stage regression equation. This estimation can be done for each year of the data as a separate cross section.

These parameters for the first-stage regression can be identified from gross flows alone. Consider, for example, a model with many cells, and suppose that at time t a large fraction of type-s workers in every other cell moves to cell (i, k) and a large fraction also move to cell i', k' (so that m_t^{jliks} and $m_t^{jli'k's}$ are both fairly big for $(j, l) \neq (i, k), (i', k')$). However, only a low fraction of workers in (i, k) switch to other cells in period t, while a large fraction of workers in (i', k') switch cells (in other words, m_t^{ikiks} is large while $m_t^{i'k'i'k's}$ is small). Equation (6) then implies that λ_t^{iks} is large relative to λ_t^{jls} for $(j, l) \neq (i, k)$ (so that the numerator of m_t^{jliks} is large and the denominator of m_t^{ikiks} is small), while $C_t(j, l, i', k', s, \xi_t^{jli'k's})/\nu$ is small relative to switching costs for other destinations (so that the numerator of $m_t^{jli'k's}$ can be large at the same time as the denominator of $m_t^{i'k'i'k's}$ is large).

Further, once these have been estimated, the option value terms $\frac{1}{\nu}\Omega_t^{iks}$ can be calculated from them (the algebraic derivation is in Artuç (2012)).

The second stage uses the difference between (5) as written out for cell (i, k) and the same equation as written out for cell (j, l), multiplied by $\frac{\beta}{\nu}$:

$$\lambda_t^{iks} - \lambda_t^{jls} = \frac{\beta}{\nu} E_t\left(w_t^{iks} - w_t^{jls} + \eta_t^{ik,s} - \eta_t^{jl,s}\right) + \beta(\lambda_{t+1}^{iks} - \lambda_{t+1}^{jls}) + \frac{\beta}{\nu}\left(\Omega_t^{iks} - \Omega_t^{jls}\right). \quad (7)$$

In (7), all of the variables are either in the data (namely, the wages) or estimated from Stage 1, except for the η_t^{iks}'s and the parameters β and ν. Recalling that η_t^{iks} is equal to $\bar{\eta}^{iks}$

plus an iid disturbance, we can treat (7) as a linear regression to estimate $\bar{\eta}^{iks}$ and $\frac{1}{\nu}$ with the data from all years pooled. The disturbance term to the η_t^{iks} acts as the error term for the regression.

Roughly, the idea is as follows. Stage 1 uses the observed gross flows of workers to infer the (i) 'pull' λ_t^{iks} of each sector/occupation cell at each date, which is a combination of the future relative profitability of each cell with the responsiveness $\frac{\beta}{\nu}$ of workers to that future profitability; and (ii) the cost of switching. But that does not allow us to separate out the future relative profitability from the responsiveness. Having, then, a panel of such 'pull' estimates and the costs, we can put them together in Stage 2 with wages to see how much the 'pull' is affected by changes in wage differentials. This allows us to separate out the 'responsiveness' factor $\frac{\beta}{\nu}$ and complete the estimation. Essentially, if gross flows do not respond very much to future wage differentials, a low value of $\frac{\beta}{\nu}$ will be indicated, otherwise a high value.

A qualification that should be noted is that in principle equation (7) can be used to estimate β as well as ν, but in practice it turns out to be difficult to do so. The reason is that significant changes in β induce only small changes in equilibrium aggregates. As a result, we impose a value of β that seems reasonable based on the literature, and examine how robust results are to changes in its value.

2 Data and Regression Analysis

We use the March Current Population Surveys (CPS) from 1975 to 2000 of the US Census to estimate the model. Dimensionality issues force us to aggregate sectors and occupations, with the result that we consider 4 sectors and 3 occupations. The sectors are: 1. Agriculture and Construction, 2. Manufacturing, 3. Non-traded Service and 4. Traded Service. We have divided services into two categories because certain services are more skill intensive than others and those are usually traded (exported). The occupations we use are: 1. White collar, 2. Service-related blue collar and 3. Production-related blue collar. We group workers into two education groups, workers with no college education, workers with some college education.

We normalize annual real wages so that the average real wage across all workers in the sample is unity. Table 1 shows the distribution of normalized wages across occupations, sectors and education groups along with the number of observations for each type. As one would expect, college-educated workers have higher incomes in every sector-occupation cell than non-college educated workers.

Tables 2 and 3 summarize occupational and sectoral mobility of the workers in our sample respectively, showing transition from row to column. The main diagonal of Table 2 shows the fraction of workers in each occupation who stay in that occupation each year, on average. This varies from 96.3% for production-related blue-collar to 97.8% for white collar. Clearly, most workers do not switch industry in a given year, which is hardly surprising, but the

Table 1: Normalized Wages and Number of Observations

				Number of observations		
			Wage	Mean	Min	Max
No College	White	Agr/Cons	1.19	252	172	410
		Manuf	1.22	587	309	1002
		Non-traded	0.99	603	322	1214
		Traded	1.08	934	612	1439
	Blue S	Agr/Cons	0.89	1172	901	1584
		Manuf	0.94	1845	933	2649
		Non-Traded	0.83	2139	1519	2509
		Traded	0.83	2510	1858	3029
	Blue P	Agr/Cons	0.66	788	534	1073
		Manuf	0.78	1856	993	2616
		Non-Traded	0.68	457	301	644
		Traded	0.79	1058	750	1223
College	White	Agr/Cons	1.48	189	111	255
		Manuf	1.57	799	460	1009
		Non-Traded	1.31	648	470	902
		Traded	1.34	2456	1936	3149
	Blue S	Agr/Cons	1.04	82	46	117
		Manuf	1.23	249	166	390
		Non-Traded	1.03	393	171	508
		Traded	1.21	741	395	987
	Blue P	Agr/Cons	0.78	49	37	72
		Manuf	0.85	57	29	80
		Non-Traded	0.73	23	11	36
		Traded	0.83	57	23	93

fraction who do varies from 2.8% to 3.7% which is significant. In addition, note that the off-diagonal elements are all positive, ranging from the 0.4% of service-related blue-collar workers who move to production-related blue-collar each year to the 3.1% of production-related blue-collar who move in the opposite direction. The biggest inflows are into the services-related blue-collar occuptions.

Table 2: Occupational Mobility Martix

	White	Blue S	Blue P
White	0.978	0.018	0.004
Blue S	0.014	0.972	0.014
Blue P	0.006	0.031	0.963

The matrix for sectoral mobility is similar. The rate of switching varies from 2.9% for manufacturing and traded services to 5.4% for agriculture and construction. The off-diagonal elements range from the 0.6% of manufacturing workers who switch to agriculture and construction each year to the 2.8% of non-traded services workers who switch to traded services each year. The biggest inflows are into traded services.

Table 3: Sectoral Mobility Matrix

	Agr/Cons	Manuf	Non-Traded	Traded
Agr/Cons	0.946	0.014	0.014	0.026
Manuf	0.006	0.971	0.007	0.016
Non-Traded	0.007	0.009	0.956	0.028
Traded	0.007	0.010	0.013	0.971

We are, of course, interested in *joint* mobility decisions, and so we need to think about the possibility that a worker will move along both dimensions at once. Table 4 shows how frequently this occurs compared to switching along only one dimension. For each of the twelve sector-occupation cells, the third column of the table shows the average fraction of workers who change sector but not occupation each year, the fourth column shows the fraction who change occupation but not sector, and the fifth column shows the fraction who change both. The fraction who change along both dimensions is consistently similar in magnitude to the number who change in either dimension alone. Indeed, for some cells sectoral switches alone are more frequent than occupational switches alone; for other cells the pattern is the reverse; but for most cells the frequency of switching along both dimensions is in either between the frequency of switching only sector and the frequency of switching only occupation or higher than either. Put differently, the probability that a worker switches sector is quite similar to the probability that a worker switches occupation, and a worker who switches in one dimension is at least as likely also to switch in the other dimension as not. This all suggests that the costs of switching along either dimension are likely quite similar, and the cost of switching both is likely not significantly greater than the cost of switching only one, which would imply a negative value of $C^{3,s}$. This is all borne out in the estimates, as will be seen shortly.

In Table 5, we present the ratio of industry-occupation cells for each industry and occupation and the ratio of college graduates in each cell. The first column shows the ratio of each occupation in the corresponding sector. For example manufacturing has the highest ratio of "production related blue collar" workers, which is 0.35. This means more than one third of manufacturing workers have "BlueP" occupation. The second column shows the ratio of a specific occupation working in a given sector. For example, only 7 percent of "white collar" workers are in the "agriculture and construction" sector. The last column shows the ratio of college graduates in each industry-occupation cell. For example, 72 percent of traded services sector white collar workers are college graduates.

The estimation results from the first stage are presented in Table 6, and the results from the second stage are presented in Table 7. Recalling that estimation in Stage 2 depends on β, and that we are not estimating β, the results in Table 7 are presented for an assumed value of $\beta = 0.97$ and also for $\beta = 0.9$. These two values bracket the great majority of discount factors used in the literature. For our purposes, the results are virtually identical (which underscores the difficulty of estimating β). For simplicity, we will unless otherwise stated refer to the $\beta = 0.97$ estimates.

The estimated moving costs are all very large, as found in ACM. For example, the ratio C^{2js}/ν corresponding to the cost of entering a white-collar occupation for a non-college educated worker is 6.209, which, given our estimate of $\frac{1}{\nu}$ as 1.63 (from Table 7) and hence $\nu = 0.61$ implies $C^{2js} = 3.79$. In other words, given our normalization of wages, the cost of entering a white-collar occupation for a non-college educated worker is almost four times the average worker's annual income. This should not be taken literally, but rather indicates that there are large frictions in the reallocation of labor that are picked up by the estimation – gross flows of workers do respond to future wage differentials, but only weakly. At the same time, as indicated by the mobility matrix tables, a small but positive fraction of workers do switch both sector and occupation each year. This is possible within the model because of a large value of ν. The implied value of $\nu = 0.61$, given the extreme-value distribution, amounts to a standard deviation for ϵ_t^{nik} of 0.79. In other words, the standard deviation of the idiosyncratic preference shock for non-pecuniary enjoyment of a given sector-occupation cell is 79% of average annual income, indicating that occasionally, even with no differences in wages across cells at all, a worker will be willing to incur a large cost in order to switch from the low-idiosyncratic-benefit cell to the high-benefit cell.

In interpreting results, it should be pointed out that the moving cost for any worker is actually $C_t^{ikjls} + \epsilon_t^{iks} - \epsilon_t^{jls}$, the common moving cost plus the idiosyncratic part. As a result,

Table 4: Sector and Occupation Change

No-College					
Sector	**Occupation**	**Change Sec**	**Change Occ**	**Change Both**	**Stay**
Aggr/Cons	**White**	1.10%	1.76%	1.99%	95.15%
Manuf	**White**	1.16%	1.11%	1.23%	96.49%
NonTraded	**White**	1.12%	1.75%	2.63%	94.50%
Traded	**White**	0.92%	1.95%	1.67%	95.45%
Aggr/Cons	**BlueS**	2.94%	1.67%	1.87%	93.52%
Manuf	**BlueS**	1.65%	1.00%	0.96%	96.39%
NonTraded	**BlueS**	2.47%	0.69%	1.65%	95.18%
Traded	**BlueS**	2.16%	1.19%	1.20%	95.45%
Aggr/Cons	**BlueP**	3.40%	2.11%	3.22%	91.28%
Manuf	**BlueP**	1.35%	0.73%	1.73%	96.18%
NonTraded	**BlueP**	2.82%	1.62%	2.53%	93.03%
Traded	**BlueP**	2.64%	1.63%	1.90%	93.83%

College					
Sector	**Occupation**	**Change Sec**	**Change Occ**	**Change Both**	**Stay**
Aggr/Cons	**White**	2.93%	0.55%	1.18%	95.34%
Manuf	**White**	1.94%	0.40%	0.71%	96.94%
NonTraded	**White**	3.14%	0.83%	1.12%	94.91%
Traded	**White**	1.13%	0.89%	0.63%	97.35%
Aggr/Cons	**BlueS**	4.05%	1.88%	4.47%	89.59%
Manuf	**BlueS**	2.82%	1.86%	1.89%	93.44%
NonTraded	**BlueS**	2.96%	1.03%	2.77%	93.24%
Traded	**BlueS**	1.95%	3.30%	1.42%	93.33%
Aggr/Cons	**BlueP**	2.35%	1.72%	9.85%	86.08%
Manuf	**BlueP**	0.67%	2.22%	5.93%	91.17%
NonTraded	**BlueP**	2.46%	3.61%	7.54%	86.39%
Traded	**BlueP**	2.17%	5.22%	3.66%	88.95%

Table 5: Ratio of Industry-Occupation Cells

		Share in Sector	Share in Occupation	Ratio of College Grads.
White	Agri/Cons	0.17	0.07	0.43
	Manuf	0.26	0.21	0.58
	Non-Traded	0.29	0.19	0.52
	Traded	0.44	0.52	0.72
BlueS	Agri/Cons	0.5	0.14	0.07
	Manuf	0.39	0.23	0.12
	Non-Traded	0.59	0.28	0.16
	Traded	0.42	0.36	0.23
BlueP	Agri/Cons	0.33	0.19	0.06
	Manuf	0.35	0.44	0.03
	Non-Traded	0.11	0.11	0.05
	Traded	0.14	0.26	0.05

for workers who actually move, the cost incurred will generally be less than C^{ikjls}, since it is workers with low idiosyncratic costs who will chose to move.

At the same time, note that the cost of entering white-collar occupations for a college-educated worker is substantially less, at $(5.031)(0.61) = 3.07$. As one might have expected, it is easier for a college-educated worker to get a white-collar job than for a non-college-educated worker. The easiest occupation for either type of worker to enter is service-oriented blue-collar, while the hardest to enter is white-collar for non-college educated and production blue-collar for college-educated. The easiest sector for either type of worker to enter is traded services, while the hardest for non-college educated is manufacturing and for college-educated is agriculture and construction. The sector and occupation switching costs all range in between 2.6 (3.7 times 0.61) and 3.8 (6.2 times 0.61).

Clearly, these estimates do not imply any tendency for wages to be equated across sectors or occupations, either in the short run or in the long run. A worker chasing high wages would need to see a very substantial wage difference, expected to persist quite a long time, in order to justify incurring switching costs of the magnitude observed here. In addition, the high variance of the idiosyncratic shocks, as measured by ν, suggests that workers behave as if they take factors other than wages into account in their career decisions. This is true despite the fact that workers are quite mobile in the sense that there are always workers switching sector and occupation, as shown in Tables 2 to 4. This feature of this sort of model is discussed at some length in Artuç, Chaudhuri and McLaren (2008).

Importantly, note that the last row of Table 6 shows a value for C^3 that is always negative, with a value around 4. This means that the cost of switching both sector and occupation is roughly the same as switching either sector or occupation, which is consistent with the patterns noted in Table 4.

Table 6: Regression Results - Stage 1

C/ν - Non-College						
Sector/Occ	***Mean***	***Change***	***Min***	***Max***	***Max StdE***	***Min StdE***
White	6.209	-0.102	5.576	6.902	*(0.199)*	*(0.332)*
BlueS	3.712	-0.647	3.269	4.605	*(0.198)*	*(0.327)*
BlueP	5.546	0.308	4.972	5.947	*(0.198)*	*(0.328)*
Aggr/Cons	5.130	0.739	4.708	5.654	*(0.170)*	*(0.242)*
Manuf	5.616	-0.342	5.303	6.155	*(0.167)*	*(0.244)*
NonTraded	4.866	-0.066	4.532	5.226	*(0.165)*	*(0.228)*
Traded	4.254	-0.207	3.885	4.590	*(0.157)*	*(0.213)*
Ch All	-4.124	0.004	-4.623	-3.866	*(0.125)*	*(0.179)*

C/ν - College						
Sector/Occ	***Mean***	***Change***	***Min***	***Max***	***Max StdE***	***Min StdE***
White	5.031	0.821	4.469	5.982	*(0.323)*	*(0.534)*
BlueS	3.836	-0.486	2.787	4.400	*(0.324)*	*(0.536)*
BlueP	5.652	0.932	4.448	6.548	*(0.338)*	*(0.581)*
Aggr/Cons	5.972	-0.357	4.800	7.154	*(0.296)*	*(0.574)*
Manuf	5.710	-0.434	5.007	6.557	*(0.253)*	*(0.417)*
NonTraded	5.028	0.257	4.299	5.737	*(0.236)*	*(0.416)*
Traded	3.799	-0.305	2.850	4.432	*(0.225)*	*(0.390)*
Ch All	-3.886	0.259	-4.269	-3.445	*(0.179)*	*(0.278)*

3 Simulations

We can now turn to simulation of a trade liberalization. For this, we need to complete the general-equilibrium model and calibrate it. We specify production functions for each sector below, and assume a spot market for labor in each sector that clears each period given the number of workers in each cell as of the beginning of the period. We will also specify trade policy that determines the prices of all tradeable goods for each date, and assume that all workers know that sequence. In addition, for this exercise, we suppress the shocks to the (C_t^{1is})'s, (C_t^{2ls})'s, (C_t^{3s})'s and (η_t^{iks})'s, since they are a distraction from our interest in the effects of a trade shock. Consequently, we set the value of each of these variables equal to the mean across years of its estimated value.

Table 7: Regression Results - Stage 2

	$\beta = 0.97$		$\beta = 0.90$	
	Estim	***StdE***	***Estim***	***StdE***
$1/\nu$	1.630	*(0.638)*	1.683	*(0.623)*
$\bar{\eta}^{21,n}/\nu$	-0.008	*(0.032)*	0.024	*(0.031)*
$\bar{\eta}^{31,n}/\nu$	0.374	*(0.071)*	0.394	*(0.069)*
$\bar{\eta}^{41,n}/\nu$	0.255	*(0.047)*	0.275	*(0.045)*
$\bar{\eta}^{12,n}/\nu$	0.539	*(0.108)*	0.509	*(0.105)*
$\bar{\eta}^{22,n}/\nu$	0.488	*(0.095)*	0.483	*(0.092)*
$\bar{\eta}^{32,n}/\nu$	0.642	*(0.126)*	0.628	*(0.122)*
$\bar{\eta}^{42,n}/\nu$	0.655	*(0.123)*	0.629	*(0.120)*
$\bar{\eta}^{13,n}/\nu$	0.872	*(0.169)*	0.903	*(0.165)*
$\bar{\eta}^{23,n}/\nu$	0.772	*(0.137)*	0.847	*(0.133)*
$\bar{\eta}^{33,n}/\nu$	0.808	*(0.165)*	0.819	*(0.162)*
$\bar{\eta}^{43,n}/\nu$	0.694	*(0.135)*	0.707	*(0.132)*
$\bar{\eta}^{21,c}/\nu$	-0.074	*(0.071)*	-0.043	*(0.136)*
$\bar{\eta}^{31,c}/\nu$	0.297	*(0.075)*	0.308	*(0.145)*
$\bar{\eta}^{41,c}/\nu$	0.280	*(0.060)*	0.297	*(0.116)*
$\bar{\eta}^{12,c}/\nu$	0.716	*(0.133)*	0.668	*(0.259)*
$\bar{\eta}^{22,c}/\nu$	0.463	*(0.098)*	0.427	*(0.187)*
$\bar{\eta}^{32,c}/\nu$	0.728	*(0.148)*	0.699	*(0.288)*
$\bar{\eta}^{42,c}/\nu$	0.482	*(0.105)*	0.419	*(0.204)*
$\bar{\eta}^{13,c}/\nu$	1.114	*(0.238)*	1.123	*(0.461)*
$\bar{\eta}^{23,c}/\nu$	1.063	*(0.207)*	1.065	*(0.405)*
$\bar{\eta}^{33,c}/\nu$	1.093	*(0.253)*	1.054	*(0.493)*
$\bar{\eta}^{43,c}/\nu$	0.952	*(0.216)*	0.892	*(0.422)*

Given this structure, an equilibrium can be described as follows. (i) Consider a sequence V of matrices of cell payoffs $V_t \equiv \{V_t^{iks}\}_{i=1,...I,k=1,...K}$ from $t = 0$ to ∞ and an initial allocation of workers across the cells given by the matrix $L_0 \equiv \{L_0^{iks}\}_{i=1,...I,k=1,...K}$ for $s = c, n$. (ii) Given L_0 and product prices at $t = 0$, marginal value products of labor for each type of labor in each cell and hence period-0 wages can be computed, and given expected next-period values V_1, the gross-flows matrix can be computed from (6). Therefore, the next-period allocation of labor L_1 and next-period wages can also be computed. Proceeding in this way, the whole infinite sequence of labor allocations and wages can be computed, and from (5), the implied sequence of cell payoffs can be computed, and can be denoted $\tilde{V}$. (iv) The value sequence V is, then, an equilibrium with initial allocation L_0 if and only if $V = \tilde{V}$. Existence and uniqueness of equilibrium are proven for a very similar model in Cameron, Chaudhuri and McLaren (2007), and a slight modification of the proof would ensure the same result here. Computational details are discussed in Artuç, Chaudhuri and McLaren (2008).

We assume Cobb-Douglas production functions for each sector i:

$$y_t^i = A^i (L_t^{i,White})^{\alpha^{i1}} (L_t^{i,BlueS})^{\alpha^{i2}} (L_t^{i,BlueP})^{\alpha^{i3}}, \tag{8}$$

where y_t^i is the output, $L_t^{i,k}$ is the effective human capital in sector i and occupation k, which is the human-capital-adjusted sum of number of college graduates and non-college graduates: $L_t^{i,k} = \psi^{ik} L_t^{i,k,c} + L_t^{i,k,n}$.[2] We do not require the α^{ik} weights in (8) to sum to unity for any sector, in order to allow for sector-specific capital, which is absorbed by the A^i factor. The consumers have identical Cobb-Douglas preferences with shares θ^i. This matters because all wages are real wages, meaning the marginal value product of the particular kind of labor in the particular sector-occupation cell, divided by the consumer price index (CPI) derived from the common utility function. For example, real wages in a non-import-competing sector will tend to rise with liberalization because it tends to lower the prices of other sectors' output and therefore the CPI.

We set the values A^i and α^{ik} to minimize a loss function; specifically, for any set of parameter values, we can compute the predicted wage for each sector and that sector's predicted share of GDP using (8) and its derivatives together with empirical employment levels for each sector and our assumptions about prices as described below. The loss function is then the sum across sectors and across years of the square of each sector's predicted wage minus mean wage in the data, plus the square of the sector's predicted minus its actual share of GDP. (The sector GDP figures are from the BEA, but the wages are from our sample.) In addition, we assume that all workers have identical Cobb-Douglas preferences, using consumption shares from the BLS consumer price index calculations for the consumption weights. The values of ψ^{ik} are given by the average skill premium within each cell. The calibration results are presented in Table 8.

[2]We examined a more flexible CES within-occupation aggregation of the two types of labor, but our estimates of the elasticity of substitution between the two types of labor within occupations produced very high values, 60 and above. Perfect substitutability within occupations seems like a good approximation.

Table 8: Parameters for Simulation

	A	α^1	α^2	α^3	θ
Aggr/Cons	1.31	0.17	0.32	0.16	0.37
Manuf	1.82	0.20	0.20	0.15	0.30
NonTraded	1.43	0.24	0.36	0.05	0.10
Traded	2.05	0.24	0.16	0.05	0.23

ψ	***Aggr/Cons***	***Manuf***	***NonTraded***	***Traded***	
White	1.24	1.29	1.33	1.25	
BlueS	1.18	1.31	1.24	1.46	
BlueP	1.18	1.10	1.07	1.06	

We treat manufacturing and traded services as goods whose products are determined on world prices, while the other two sectors produce non-traded output whose prices adjust to clear the domestic market. Our simulation is not intended to reproduce the historical data in detail, but to provide an example of a liberalization that produces changes in trade volumes roughly of the same order of magnitude as what has been experienced in the period of the data. With that in mind, the liberalization experiment is set up as follows. The world prices of manufactures and traded services are 0.875 and 1 respectively. Initially, there is a 0.25 tariff on manufactures, so the domestic price is 1.125, and this is expected by all to continue permanently. From that initial steady state, suddenly at $t = 0$ the tariff is eliminated, and is expected to stay at zero permanently. Our simulation, then, begins at date $t = 0$, with initial allocation of labor given by the old steady state. We run the simulation under the assumptions $\beta = 0.9$ and $\beta = 0.97$.

The results from the simulation with $\beta = 0.97$ are shown in the figures. (The figures for $\beta = 0.9$ are almost identical.) Figure 1 shows the evolution of the allocation of labor across the four sectors in the data from 1975 to 2000, while Figure 2 shows the same evolution in our simulation, starting 5 years before the liberalization. Although our simulation has not been calibrated to match this time-path for labor allocations, the broad patterns in the data are echoed in the simulation. The driving force in the simulation is a simple elimination of the manufacturing tariff, while in the historical data the same effect – a dwindling manufacturing labor force and relocation of workers especially to traded services – has been driven by progressive reduction in trade barriers together with the rise of manufactured exports from low-wage economies.

Note that despite the liberalization as a sudden shock with immediate elimination of the tariff, the simulation mimics the data with a *gradual* movement of labor out of manufacturing. This is because of the idiosyncratic shocks in the model, and is reflected in the structure of the gross flows equation (6). Immediately after the liberalization, wages in manufacturing are much lower than wages in other sectors, but only a portion of workers leave. Those who leave are the ones whose current idiosyncratic moving costs (the difference in the ϵ_t^{nik} values across sectors) are particularly low. Workers with higher idiosyncratic moving costs bide their time, and wait for a better moment to move to another sector. As a result, no matter how large the wage differential is between sectors, only a fraction of workers leave the disadvantaged sector in any one year.

Figure 3 shows the allocation of labor in the data from the point of view of occupations. Despite the large-scale sectoral reallocation shown in Figure 1, there has not been much change along the occupational dimension. Blue-collar service-related occupations still are by far the largest category, with blue-collar production-related occupations by far the smallest. That pattern and its overall stability are reproduced in the simulation, as shown in Figure 4, with the exception that the simulation shows a partial exodus from the blue-collar production occupations.

Figures 5 through 7 show the effect of the trade liberalization on real wages in the simulation. Figure 5 shows the average wage for each skill group, as well as the skill premium (which here means the percentage gap between the average college-educated wage and the average non-college-educated wage). The real wage jumps up slightly for both groups due to the liberalization, with barely any change in the skill premium, which remains slightly above 50%. (Of course, by construction, the skill premium within a sector-occupation cell does not change, but wages across cells can change and the allocation of each type of worker across cells can change, so in principle the aggregate skill premium could change.) Figure 6 shows the average wage for workers in each occupation class. The liberalization causes a small increase in average real wages for white-collar workers, with a slight increase in wages for blue-collar service-related workers. At the same time, average wages for workers in blue-collar production-related occupations fall. In each case, gradual adjustment following the initial jump in wages moves in the opposite direction of the initial jump.

The most dramatic wage effects show up in Figure 7, which plots average wages by sector. At the date of the liberalization, manufacturing wages drop abruptly. This drop is well-understood with the help of Figure 8, which plots the changes in prices. The price of manufactured output falls by 25% when the tariff is eliminated. This causes a direct drop in the consumer price index (CPI) because manufactures are consumed, but it also causes an indirect drop in the CPI because consumer demand shifts toward manufactures and away from the two non-traded sectors, forcing reductions in those two sectors' prices as well. Consequently, CPI falls by about 13%. The net effect on the price of manufactures relative to CPI is therefore a drop of about $25\% - 13\%$, or 12%. Since at date $t = 0$ no labor reallocation has yet had a chance to occur, the marginal products of labor are unchanged and so the percentage change in real wages is exactly the percentage change in each sector's relative price. Manufacturing wages fall by 12%, while real wages in tradeable service rise by the drop in CPI, or about 13%. Since the prices of output in agriculture and construction and in non-traded services have been forced down, the wage increases in those sectors are much smaller. Figure 8 makes it clear that, unlike wage changes by educational class or by occupation, wage changes by sector due to the liberalization are not subtle. Once again, however, the large initial jumps in wage are attenuated by subsequent gradual adjustment. As workers leave the manufacturing sector, for example, the marginal product of labor in the various occupations rises, gradually raising manufacturing wages.

Figure 9 shows the effect of the liberalization on the manufacturing sector's share of GDP, both in the simulation and in the data. The loss of tariff protection results in a progressive reallocation of labor out of manufacturing and a consequent reduction of manufacture's GDP share by approximately 4 percentage points over fifteen years, a shift that is closely parallel to the actual trend observed in the data.

We present some key statistics from the simulation in Table 9 and Table 10. Table 9 shows the impact effect of the liberalization on wages and welfare for each group at date 0, while Table 10 shows the long-run effect, meaning the comparison of the new steady state with the old one. This is all done for the two different assumed values for β, $\beta = 0.9$ and $\beta = 0.97$. The first three boxes of Table 9 show, respectively, the date-0 percentage change in wage, percentage change in welfare for non-college-educated workers, and percentage change in welfare for college-educated workers for each sector-occupation cell, all for $\beta = 0.97$. The remaining three boxes provide the same information for $\beta = 0.9$, and Table 10 follows the same format but for steady-state changes. The welfare changes in Table 9 are the most relevant for our purposes because they measure the change in expected discounted lifetime utility starting from the moment of the policy change into the infinite future, and thus take full account of the transition to the new steady state.

Note that, for both values of β, wages for all occupations in manufacturing drop at date 0 (by exactly the drop in the relative price of manufacturing output, 12.33%), while real wages for all occupations not in manufacturing rise at date 0 (benefitting from the reduction in the consumer price of manufactured output). However, over time workers of all occupations leave manufacturing and wages there rise, so that in the long run manufacturing wages for all occupations are slightly higher than their original values (first and fourth box of Table 10). At the same time, workers enter the other sectors, especially traded services, pushing down the marginal products of labor there, and also pushing down the prices of non-traded sector output. Therefore, wages in sectors other than manufacturing *fall* gradually after date 0, coming to rest just slightly above their old steady-state value (the smallest steady-state wage increase is 1.24% for white-collar workers in agriculture/mining, and the largest is 2.85% for blue-collar production-related workers in the traded-services sector).

The question that has animated this paper is the welfare question: Who benefits from the trade liberalization? For manufacturing workers, the liberalization sharply reduces their wages in the short run, very modestly increasing them in the long run. In addition, it raises the wages of workers in all other sectors in both the short and the long run. This is important for each manufacturing worker, because in each period there is a chance that she will choose to switch to those sectors. As a result, the current wage for a manufacturing-sector worker is reduced, but her option value is improved. Whether the manufacturing worker benefits from the liberalization or not depends on the balance between these two effects. The last two boxes of Table 9 show that if workers are relatively impatient ($\beta = 0.9$), the short-run manufacturing wage effect dominates, and welfare is lowered for manufacturing workers, in all occupations, by approximately 2%. The second and third boxes of the same table show that with more patient workers ($\beta = 0.97$) the two effects roughly cancel each other out; the net welfare effect on manufacturing workers is close to zero (with the largest change in either direction being -0.22% for non-college-educated blue-collar workers). With the higher weight on the future, the welfare effect turns positive for one group of manufacturing workers: college-educated blue-collar production-related workers, but the effect is under one tenth of a percentage point. For workers in all other sectors, the welfare effect of the liberalization is positive and of significant magnitude for all occupations, ranging from approximately one percent to approximately four percent.

In other words, with a low discount factor, workers in the manufacturing sector suffer significant harm from the liberalization, regardless of occupation; while with a high discount factor, workers in the manufacturing sector have welfare that is barely affected by the liberalization, regardless of occupation. For either discount factor, workers in all other sectors enjoy a significant welfare improvement from the liberalization, regardless of occupation. This speaks to the question raised in the introduction: Is a worker's occupation more or less important than the worker's industry for determining whether or not she gains from a trade liberalization? Despite the high costs of switching occupations, for the most part it is still what industry the worker is in and not what occupation she works in that is key.

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Table 9: Simulation Results - Short Run Effects (Percent Change)

Change in Wages, $\beta = 0.97$				
	Aggr/Cons	***Manuf***	***NonTraded***	***Traded***
White	2.57	-12.33	2.57	12.72
BlueS	2.57	-12.33	2.57	12.72
BlueP	2.57	-12.33	2.57	12.72

Change in Welfare, No-College, $\beta = 0.97$				
	Aggr/Cons	***Manuf***	***NonTraded***	***Traded***
White	1.46	-0.02	1.41	2.24
BlueS	1.33	-0.09	1.32	1.95
BlueP	1.23	-0.22	1.24	1.84

Change in Welfare, College, $\beta = 0.97$				
	Aggr/Cons	***Manuf***	***NonTraded***	***Traded***
White	1.56	-0.12	1.56	2.37
BlueS	1.45	0.00	1.48	2.26
BlueP	1.33	0.08	1.40	1.82

Change in Wages, $\beta = 0.90$				
	Aggr/Cons	***Manuf***	***NonTraded***	***Traded***
White	2.58	-12.34	2.58	12.71
BlueS	2.58	-12.34	2.58	12.71
BlueP	2.58	-12.34	2.58	12.71

Change in Welfare, No-College, $\beta = 0.90$				
	Aggr/Cons	***Manuf***	***NonTraded***	***Traded***
White	1.92	-2.33	1.82	4.16
BlueS	1.58	-2.41	1.57	3.43
BlueP	1.31	-2.53	1.33	3.08

Change in Welfare, College, $\beta = 0.90$				
	Aggr/Cons	***Manuf***	***NonTraded***	***Traded***
White	2.09	-2.54	2.08	4.41
BlueS	1.79	-2.26	1.83	4.15
BlueP	1.48	-1.81	1.68	3.01

Table 10: Simulation Results - Long Run Effects (Percent Change)

Change in Wage, $\beta = 0.97$				
	Aggr/Cons	***Manuf***	***NonTraded***	***Traded***
White	1.24	0.84	1.45	1.75
BlueS	1.69	0.94	1.78	2.25
BlueP	2.18	1.17	2.12	2.57

Change in Welfare, No-College, $\beta = 0.97$				
	Aggr/Cons	***Manuf***	***NonTraded***	***Traded***
White	1.21	1.06	1.19	1.32
BlueS	1.21	0.97	1.20	1.30
BlueP	1.19	0.94	1.19	1.32

Change in Welfare, College, $\beta = 0.97$				
	Aggr/Cons	***Manuf***	***NonTraded***	***Traded***
White	1.29	1.07	1.30	1.40
BlueS	1.28	1.06	1.30	1.47
BlueP	1.25	1.02	1.27	1.33

Change in Wage, $\beta = 0.90$				
	Aggr/Cons	***Manuf***	***NonTraded***	***Traded***
White	1.35	0.63	1.58	2.08
BlueS	1.71	0.50	1.83	2.57
BlueP	2.20	0.56	2.12	2.85

Change in Welfare, No-College, $\beta = 0.90$				
	Aggr/Cons	***Manuf***	***NonTraded***	***Traded***
White	1.30	0.79	1.26	1.62
BlueS	1.26	0.59	1.25	1.58
BlueP	1.21	0.51	1.22	1.58

Change in Welfare, College, $\beta = 0.90$				
	Aggr/Cons	***Manuf***	***NonTraded***	***Traded***
White	1.38	0.80	1.41	1.73
BlueS	1.34	0.71	1.37	1.87
BlueP	1.27	0.66	1.32	1.56

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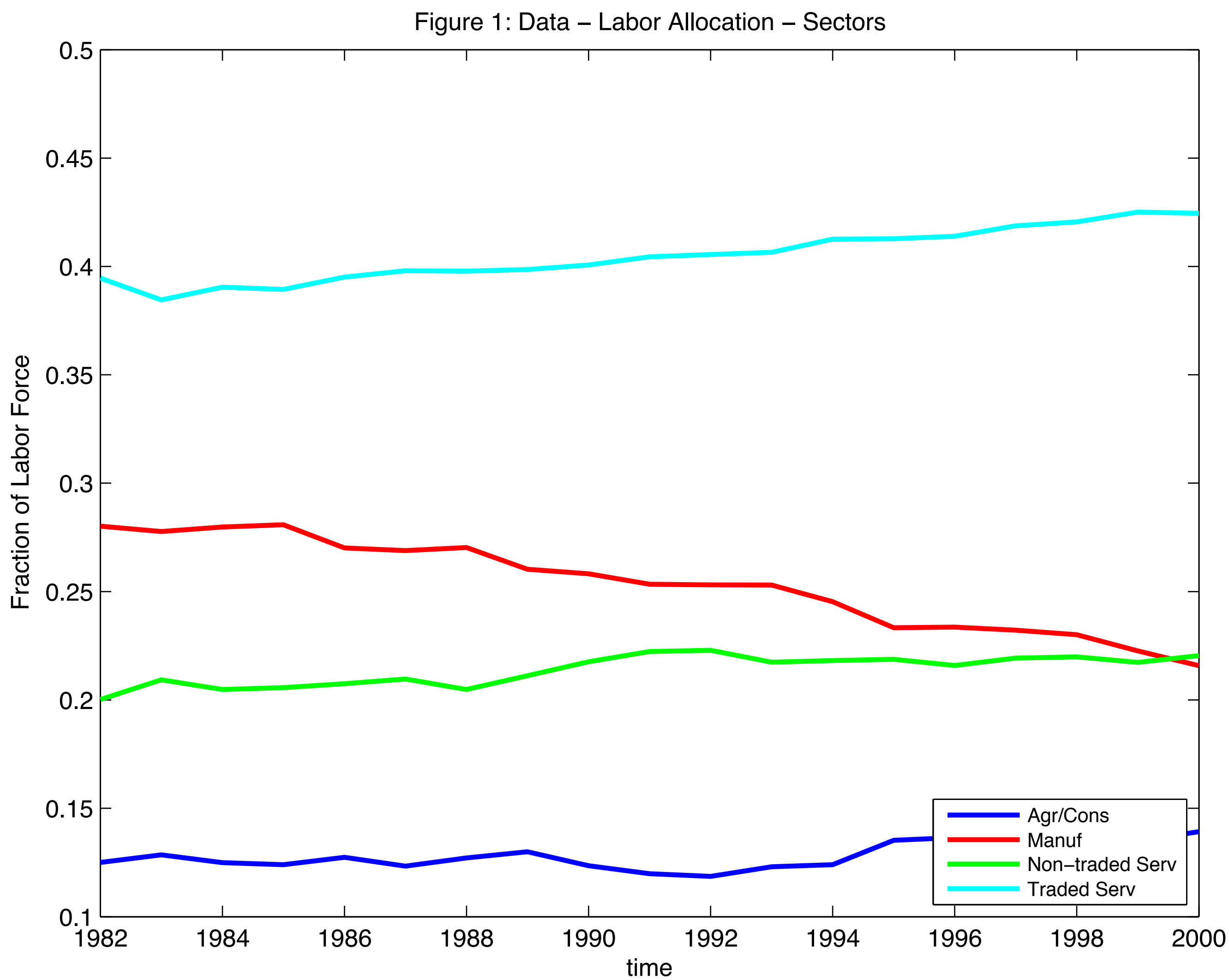


Figure 1: Data – Labor Allocation – Sectors
Fraction of Labor Force
time
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
Agr/Cons
Manuf
Non–traded Serv
Traded Serv

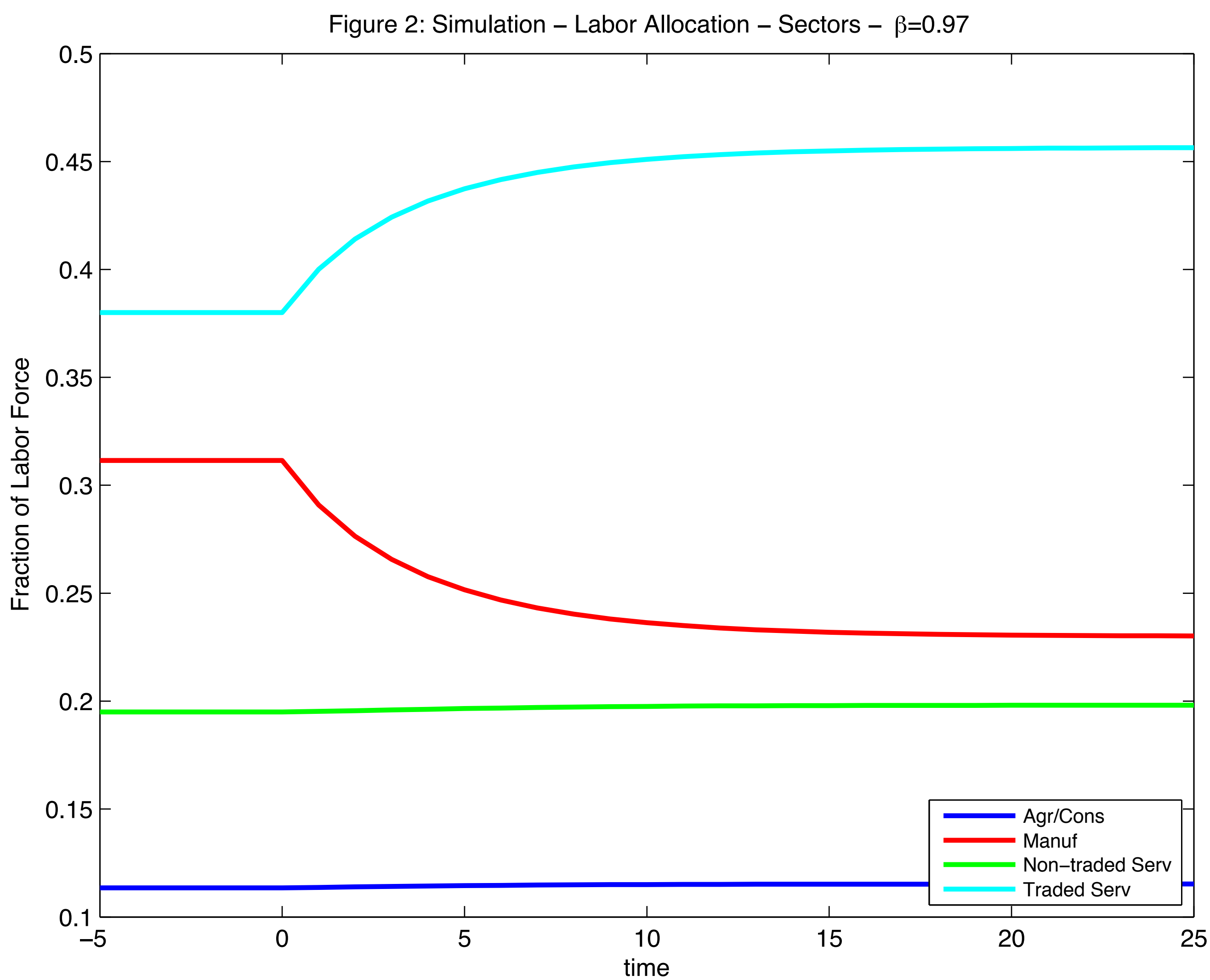


Figure 2: Simulation – Labor Allocation – Sectors – β=0.97
Fraction of Labor Force
time
Agr/Cons
Manuf
Non–traded Serv
Traded Serv
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
–5
0
5
10
15
20
25

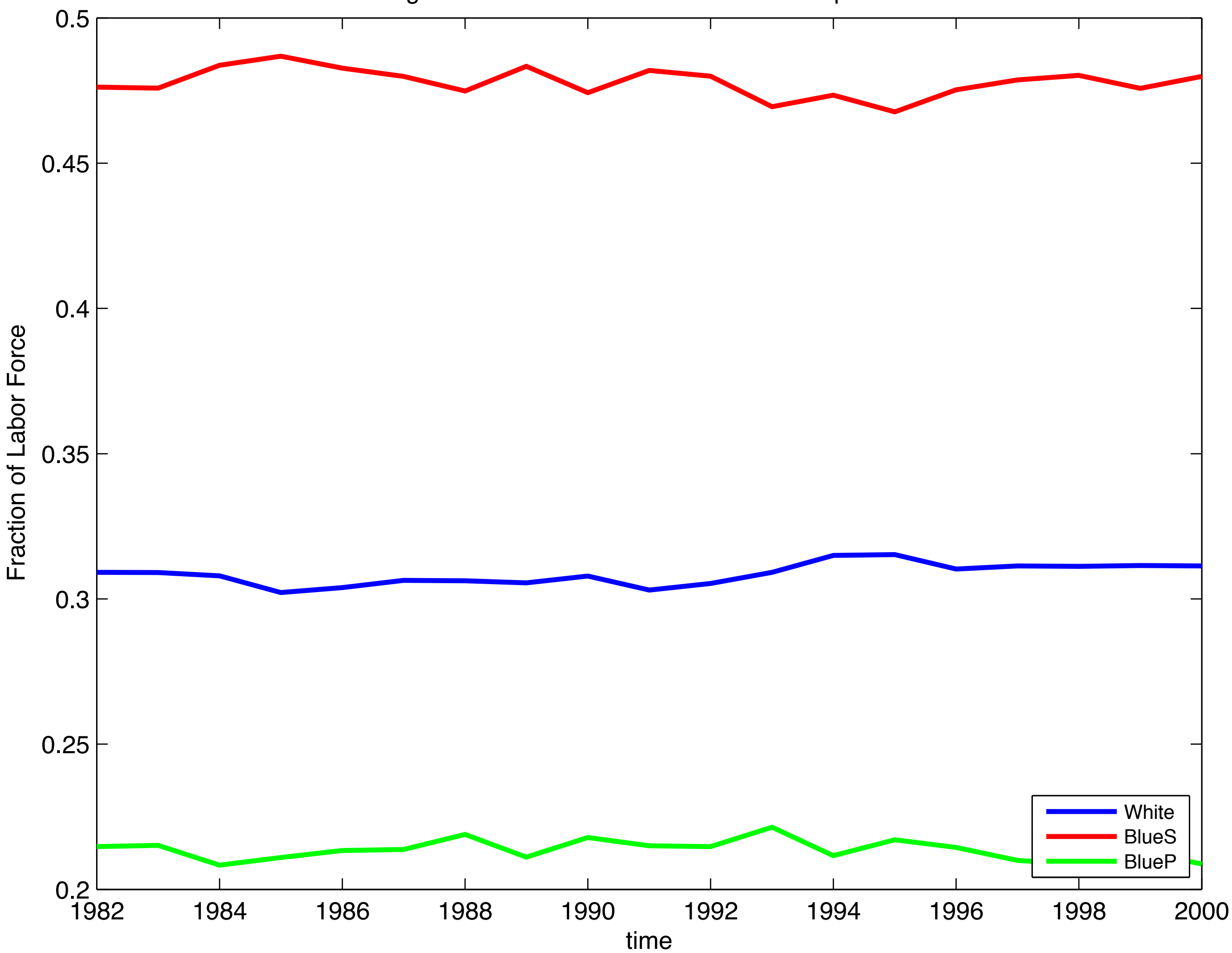


Figure 3: Data – Labor Allocation – Occupations

Figure 4: Labor Allocation – Occupations – β=0.97

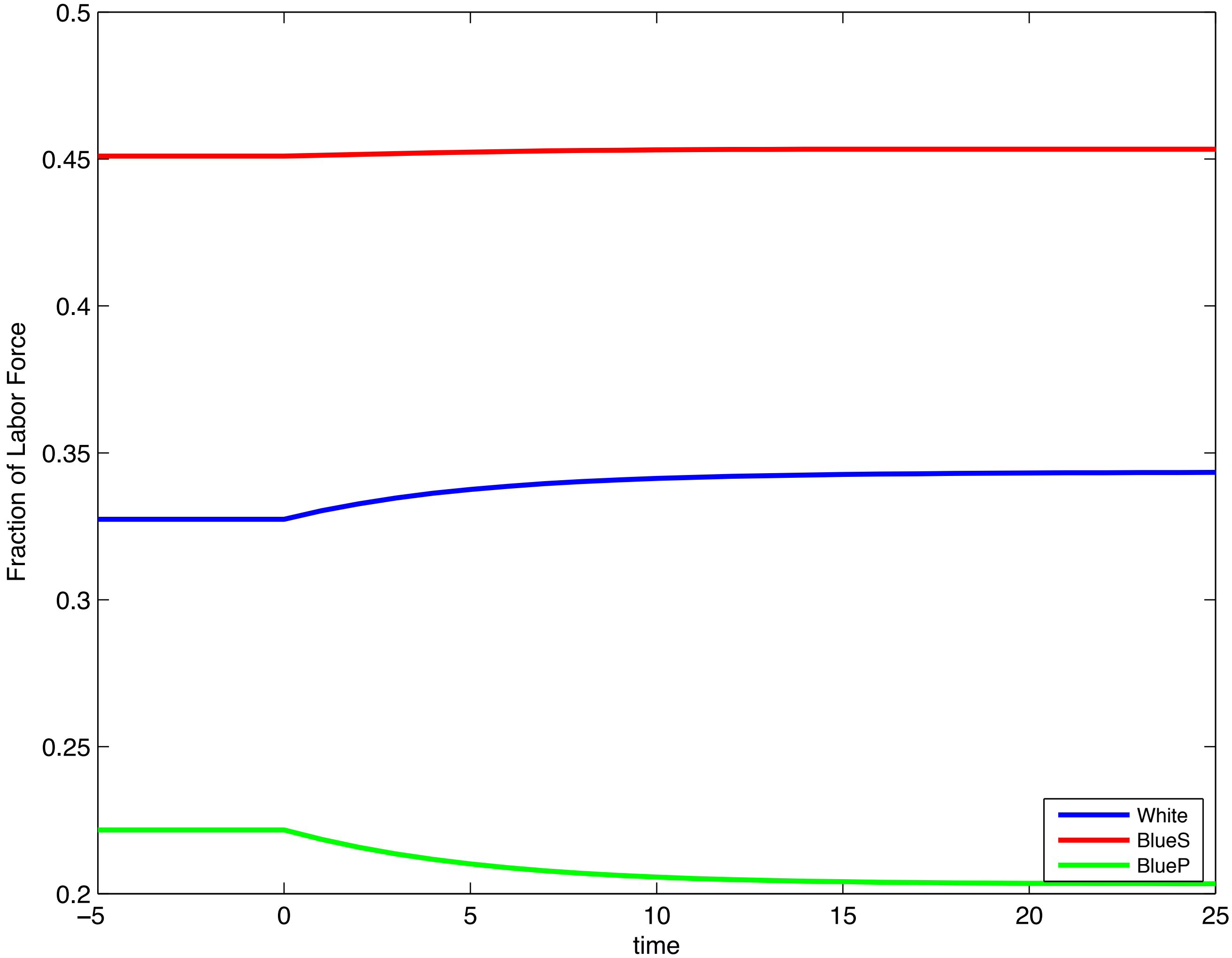


Figure 5: Average Real Wages – Education Level – β=0.97

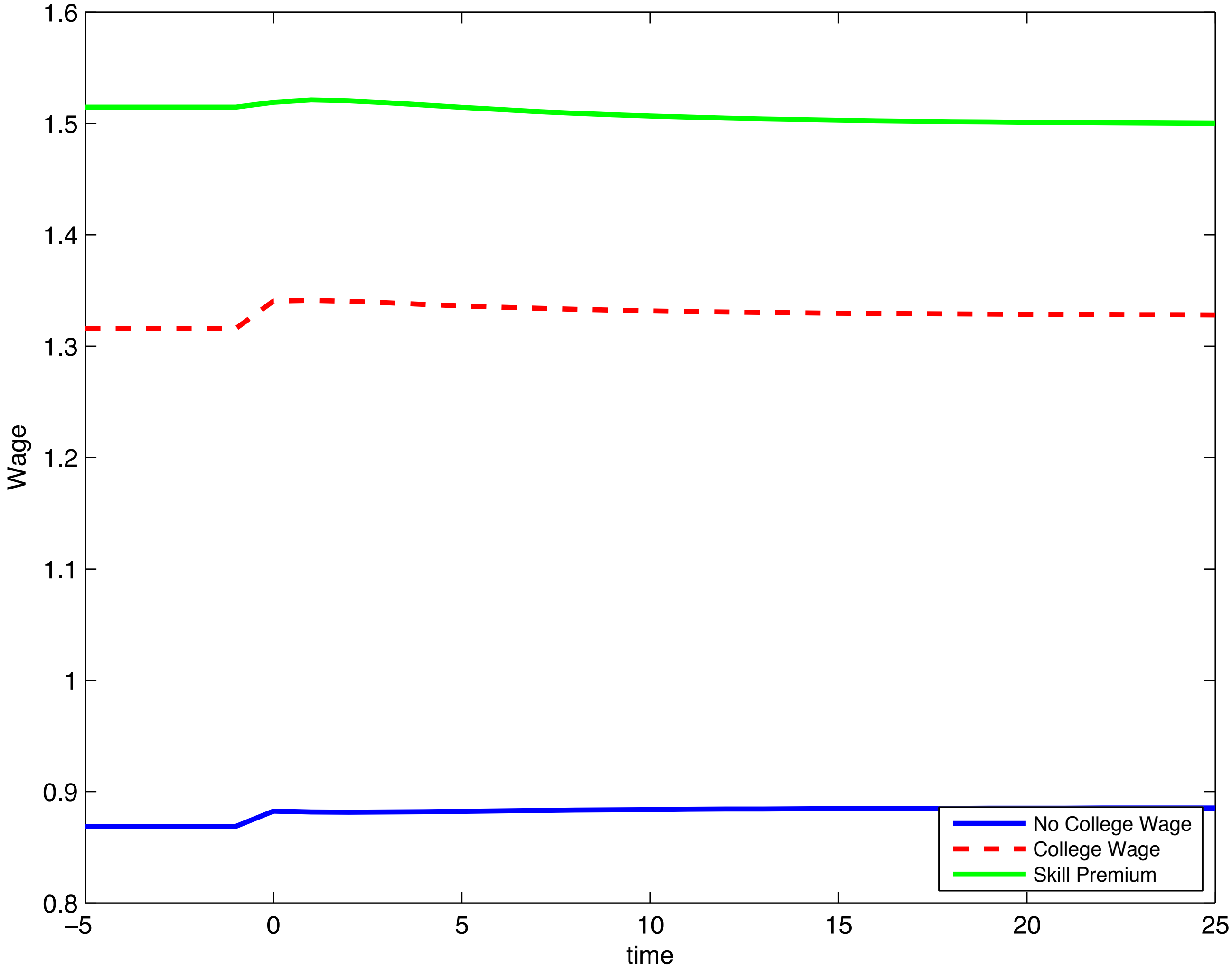


Figure 6: Average Real Wages – Occupation – β=0.97

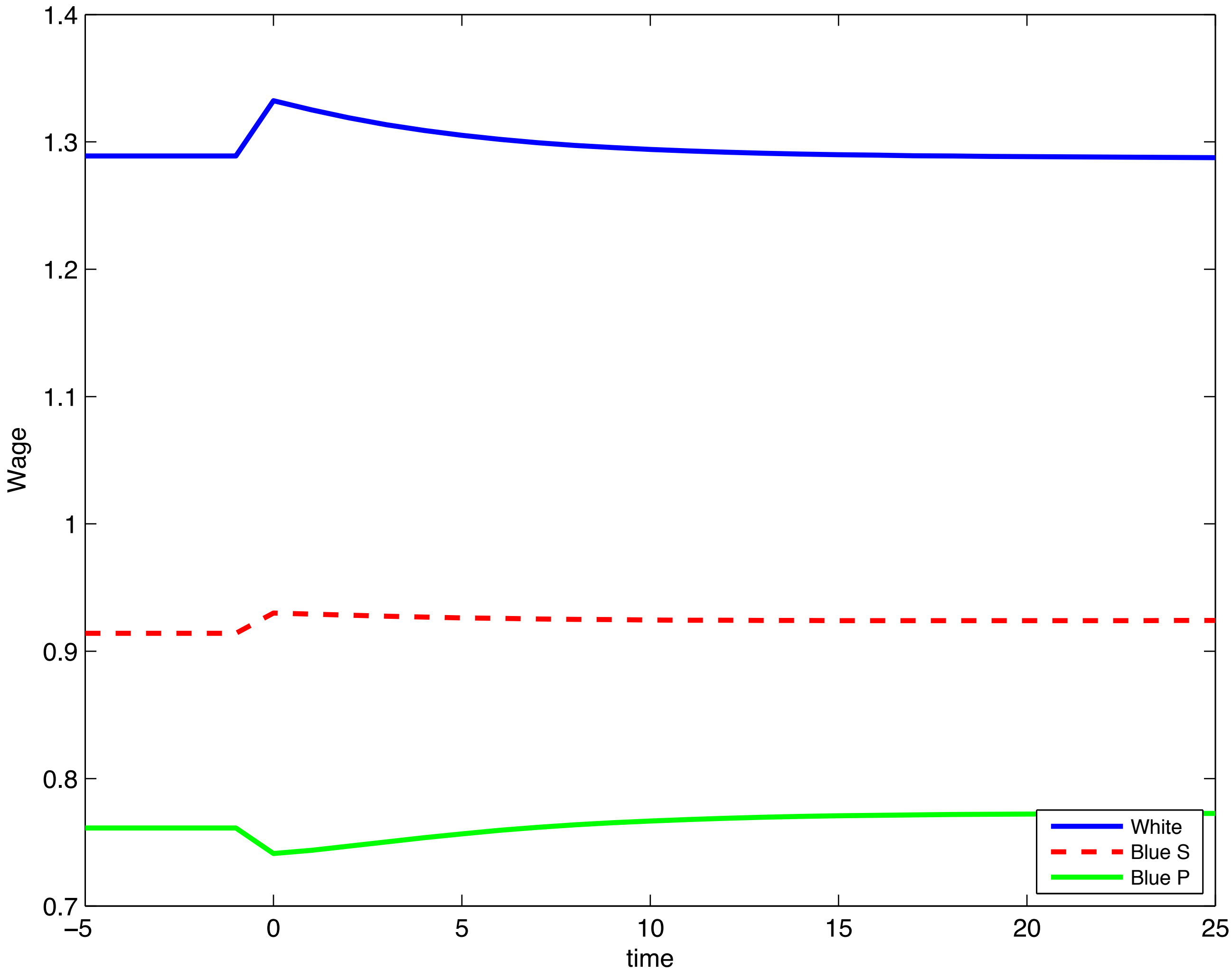


Figure 7: Average Real Wages – Sector – β=0.97

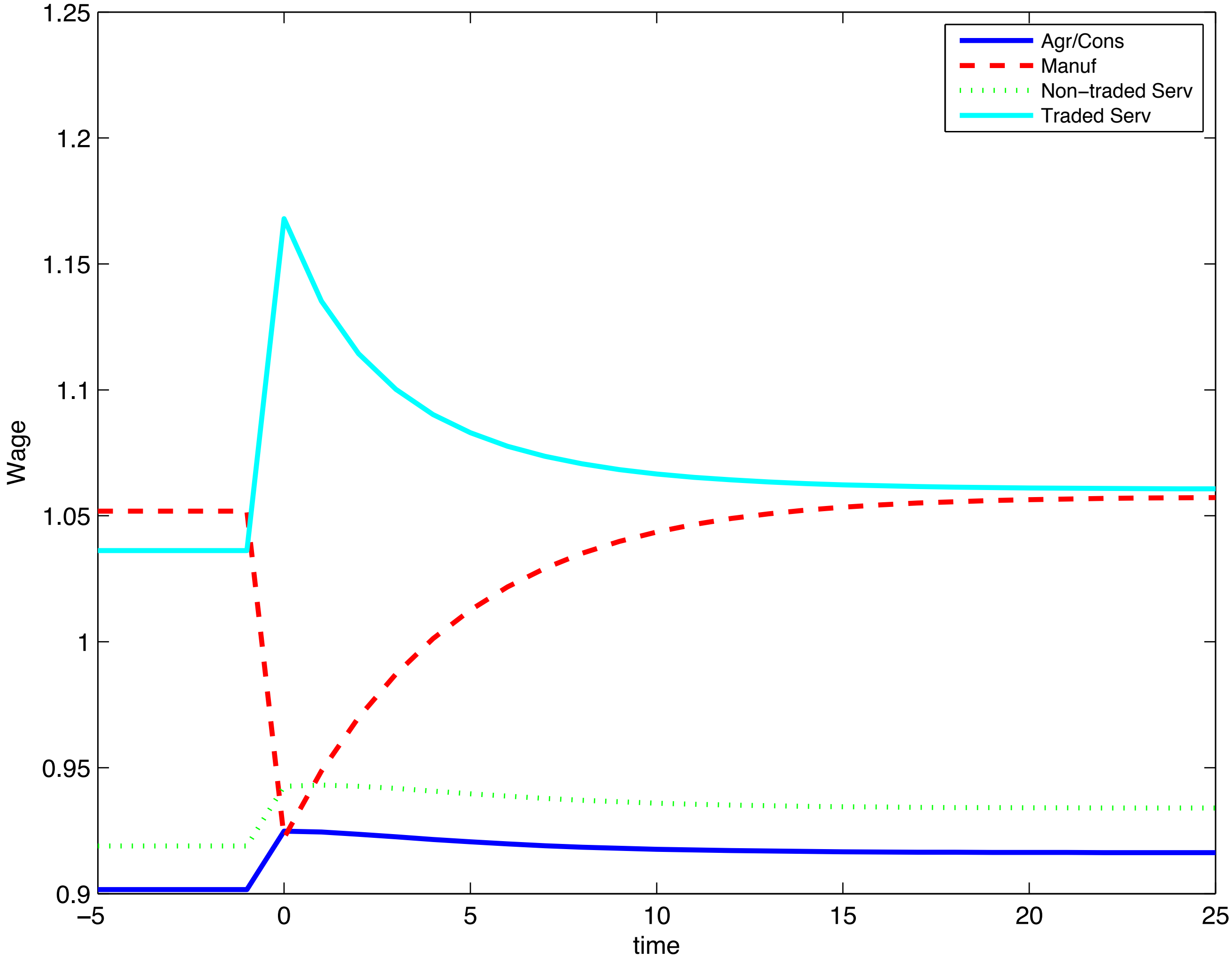
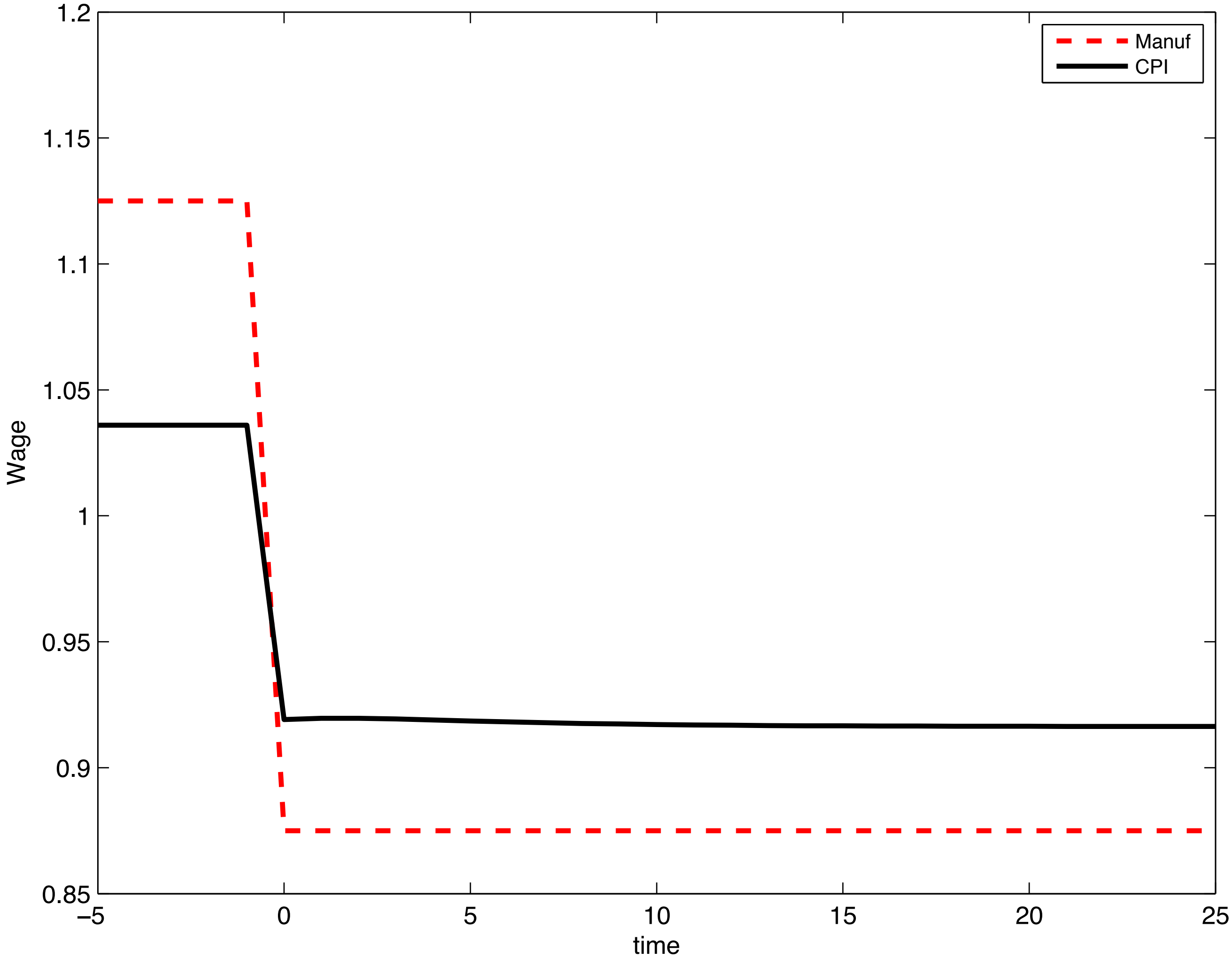


Figure 8: Manufacturing Price and CPI – β=0.97



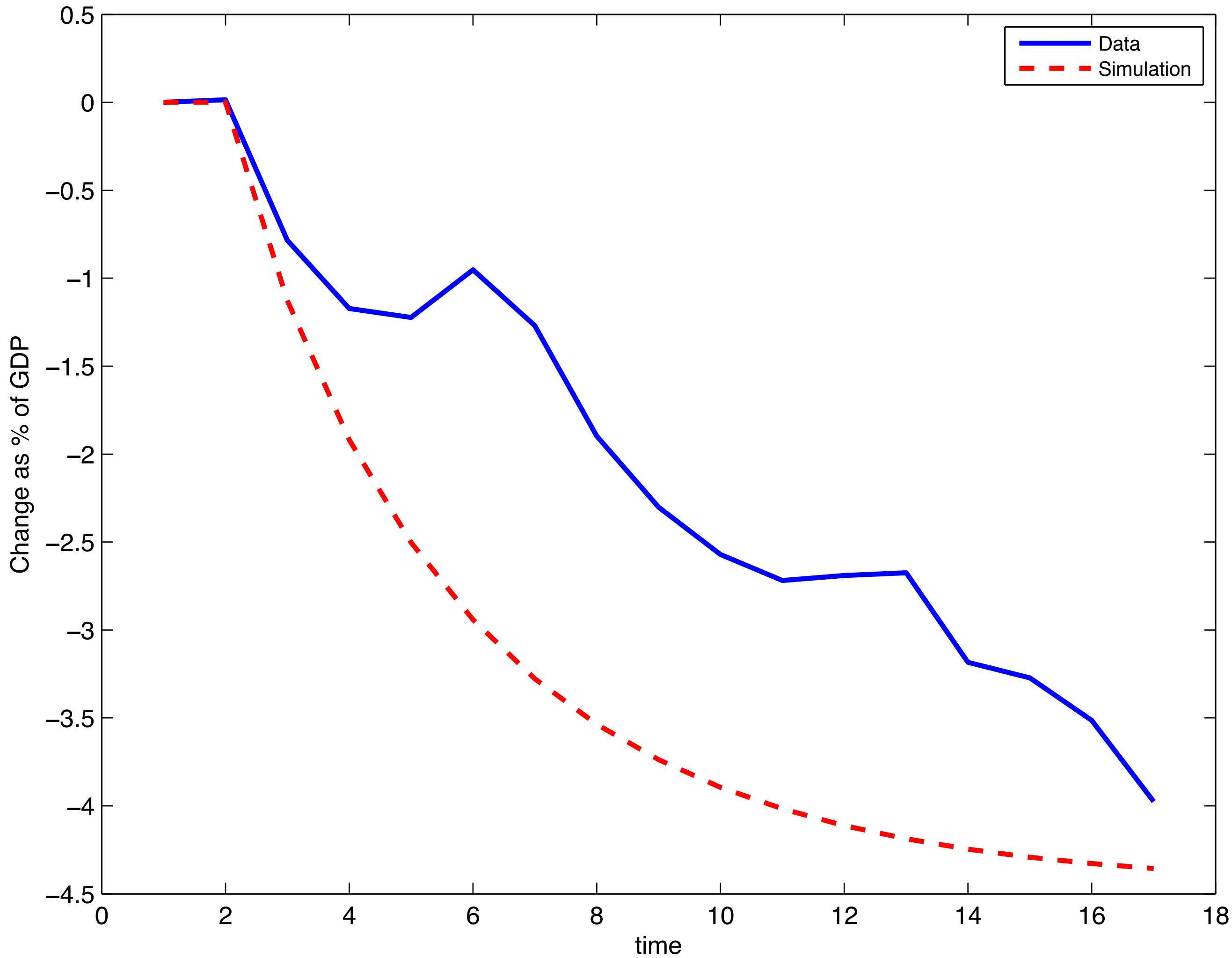


Figure 9: Change in Manufacturing Sector Output – β=0.97