A Structural Empirical Approach to Trade Shocks and Labor Adjustment: An Application to Turkey. *

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Abstract

Using three years of a Turkish labor force survey, we show how the structural parameters of an equilibrium model of labor adjustment can be estimated using limited data. This enables us to study the welfare effects of a hypothetical trade liberalization on the Turkish labor market, taking into account the full rational-expectations transition path and each worker's assessment of option value over his or her whole lifetime. We find that industry-switching costs implied by the Turkish data are high, and as a consequence it takes a decade to reach the new steady state; in the meantime, wages for the liberalizing sector fall sharply. However, the welfare losses for workers in that sector are attenuated by the subsequent rise in the sector's wages and by workers' option value. None of these effects could be captured by a reduced-form regression, or by a static model. Computational requirements are very modest, and the estimation is very simple, although it is structural estimation of a rich dynamic equilibrium model. Consequently, the techniques could be applied in many other settings.

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In trade liberalization, in trade shocks, in dealing with large-scale public-sector downsizing, a major issue facing policy analysts is the how to asses the costs faced by workers in moving from the afflicted sector of the economy to another sector. If it is prohibitively costly to switch industries, for example, a trade liberalization that decimates an import-competing sector may raise the present discounted value of real GDP but cause serious harm to the population of workers who had grown dependent on the sector, and this harm needs to be assessed and taken into account.

In this paper, we summarize a method for estimating these costs based on a dynamic rational-expectations model of labor adjustment, and for using these estimates in policy simulations to try and assess exactly these distributional impacts of policy. The approach has been developed in a number of papers by Cameron, Chaudhuri, and McLaren (2007), Chaudhuri and McLaren (2007) and Artuç, Chaudhuri and McLaren (2007, 2008, 2009). The method can be summarized as follows. First, specify a model of the labor market for the whole economy in which each period each worker has the opportunity to switch sectors, but at a cost, which varies for each worker over time according to a distribution whose parameters are to be estimated. (The time-varying idiosyncratic costs allow for gradual reallocation of workers to a shock, and they also allow for anticipatory reallocation to an expected future shock, both of which are important features of real-world labor adjustment.) Second, derive from this model an equilibrium condition analogous to an Euler equation, which can then be brought to the data to estimate the underlying parameters of the distribution of idiosyncratic moving-cost shocks. Third, estimate those parameters by fitting this equilibrium condition to data on gross flows of workers and wages, across sectors of the economy and across time. Fourth, use these estimated parameters to simulate policy experiments.

Artuç, Chaudhuri and McLaren (forthcoming) apply this method to the Current Population Surveys of the US Census, but they are applicable to a wide array of other countries.[1] We will demonstrate the techniques here on a data set from Turkey. In particular, we use a very limited data set – a worker survey with modest sample sizes and only three years of data. Nonetheless, structural parameters of the labor adjustment process can be easily estimated and a rich variety of questions can then be explored using convenient simulation methods. We thus show that a well-grounded analysis of the dynamic response to trade shocks can be

[1] Another example is Artuc (2009), which applies a different estimation method but the same simulation method to National Longitudinal Survey of Youth data.

accomplished quite easily, without much computer power and with very modest data.

1 A Summary of the Model.

The model is developed in detail in Cameron, Chaudhuri, and McLaren (2007) and Chaudhuri and McLaren (2007). Essentially, the basic model is a Ricardo-Viner trade model with the addition of costly inter-industry labor mobility.[2] The essential idea can be summarized as follows. Workers can always change their sector of employment, but must incur costs to do so. At the same time, each individual worker faces time-varying idiosyncratic shocks that either make it either costly for that worker to change sectors, or, at times, costly *not* to change sectors. As a result, a certain fraction of workers are always changing sectors – the labor market exhibits gross flows. When a trade shock hits a sector adversely, the workers whose idiosyncratic moving costs are currently low leave the sector while those currently with high moving costs wait. This induces gradual adjustment to a trade shock. It also implies that option value is important in workers' utilities, as each worker is aware that no matter what sector he or she is in at present, there is some probability that he or she will choose to move to another sector in the future.

1.1 Basic setup

Consider an n-good economy, in which all agents have preferences summarized by the indirect utility function $v(p, I) \equiv I/\phi(p)$, where p is an n-dimensional price vector, I denotes income, and ϕ is a linear-homogeneous consumer price index. Assume that in each industry i there are a large number of competitive employers, and that their aggregate output in any period t is given by $x_t^i = X^i(L_t^i, K^i, s_t)$, where L_t^i denotes the labor used in industry i in period t, K^i is a stock of sector-specific capital,[3] and s_t is a state variable that could capture the effects of policy (such as trade protection, which might raise the price of the output), technology shocks, and the like. Assume that X^i is strictly increasing, continuously

[2] In principle, the model can accommodate geographic as well as inter-industry mobility. Instead of n industries, we could have n industry-region cells, for example; all of the logic below would carry through without amendment. In practice, we have limited the discussion to inter-industry mobility because we have not found enough inter-regional mobility in the data to identify the parameters of interest.

[3] Adjustment of capital over time is obviously important, but in this study we set it aside to focus on labor.

differentiable and concave in its first two arguments. Its first derivative with respect to labor is then a continuous, decreasing function of labor, holding K^i and s_t constant. Assume that s follows a stationary process on some state space S.[4]

The economy's workers form a continuum of measure $\overline{L}$. All workers are homogeneous, and each of them at any moment is located in one of the n industries. Denote the number of workers in industry i at the beginning of period t by L_t^i. If a worker, say, $l \in [0, \overline{L}]$, is in industry i at the beginning of t, she will produce in that industry, collect the market wage for that industry, and then may move to any other industry. In order for the labor market to clear, the real wage w_t^i paid in industry i at date t must satisfy $w_t^i = (p_t^i(s_t)/\phi(p_t(s_t)))\,(\partial X^i(L_t^i, K^i, s_t)/\partial L_t^i)$ at all times, where the $p_t^i(s_t)$ are the domestic prices of the different industries' outputs and may depend on s_t as, for example, in the case in which s_t includes a tariff.

If worker l moves from industry i to industry j, she incurs a cost $C^{ij} \geq 0$, which is the same for all workers and all periods, and is publicly known. In addition, if she is in industry i at the end of period t, she collects an idiosyncratic benefit $\varepsilon_{l,t}^i$ from being in that industry. These benefits are independently and identically distributed across individuals, industries, and dates, with density function $f : \Re \longmapsto \Re^+$, $f(\varepsilon) > 0 \forall \varepsilon$, and cumulative distribution function $F : \Re \longmapsto [0, 1]$. Without loss of generality, assume that $\int \varepsilon f(\varepsilon) d\varepsilon \equiv 0$. Thus, the full cost for worker l of moving from i to j can be thought of as $\varepsilon_{l,t}^i - \varepsilon_{l,t}^j + C^{ij}$. The worker knows the values of the $\varepsilon_{l,t}^i$ for all i before making the period-t moving decision.[5] We adopt the convention that $C^{ii} = 0$ for all i.

Note that the mean cost of moving from i to j is given by C^{ij}, but its variance and other moments are determined by f. It should be emphasized that these higher moments are important both for estimation and for policy analysis, as will be discussed below.

All agents have rational expectations and a common constant discount factor $\beta < 1$, and are risk neutral.

[4]We need to allow for shocks to sectoral labor demand to estimate the model, because otherwise the model would predict that all aggregates would converge non-stochastically to a steady state over time. Obviously, the data do not behave in that way, because of ongoing aggregate shocks. However, these exogenous shocks to labor demand are a distraction from our questions of interest and would generate enormous computational difficulties in simulations, so we drop them in our simulation exercises.

[5]It is useful to think of the timeline as follows: The worker observes s_t at the beginning of the period, produces output and receives the wage, then learns the vector $\varepsilon_{l,t}$ and decides whether or not to move. At the end of the period, she enjoys $\varepsilon_{l,t}^j$ in whichever sector j she has landed.

An equilibrium then takes the form of a decision rule by which, in each period, each worker will decide whether to stay in her industry or move to another, based on the current allocation vector L_t of labor across industries, the current aggregate state s_t, and that worker's own vector $\varepsilon_{l,t}$ of shocks. In the aggregate, this decision rule will generate a law of motion for the evolution of the labor allocation vector, and hence (by the labor market clearing condition just mentioned) for the wage in each industry. Each worker understands this behaviour for wages, and thus how L_t and the wages will evolve in the future in response to shocks; and given this behaviour for wages, the decision rule must be optimal for each worker, in the sense of maximizing her expected present discounted value of wages plus idiosyncratic benefits, net of moving costs.

To close the model, we need to determine the prices p_t^i. We do this in two ways in two different versions of the model. In the first version, all industries produce tradeable output, whose world prices are determined by world supply and demand and are exogenous to this model; the domestic prices p_t^i are then equal to the world price plus a tariff. In the second version of the model, a subset of the industries produce non-tradeable output, whose prices are determined endogenously. At each moment, the allocation of labor L_t determines the quantity of each industry's output, and hence the supply of each non-tradeable good; this, combined with the prices of the tradeable goods, allows us to compute the price of each non-tradeable good that equates domestic demand with that supply. Note that we do not need to concern ourselves with any of these price-determination issues for the *estimation* of the model, but we will need them later for the general-equilibrium *simulation* of the model.

1.2 The key equilibrium condition.

Suppose that we have somehow computed the maximized value to each worker of being in industry i when the labor allocation is L and the state is s. Let $U^i(L, s, \varepsilon)$ denote this value, which, of course, depends on the worker's realized idiosyncratic shocks. Denote by $V^i(L, s)$ the average of $U^i(L, s, \varepsilon)$ across all workers, or in other words, the expectation of $U^i(L, s, \varepsilon)$ with respect to the vector ε. Thus, $V^i(L, s)$ can also be interpreted as the expected value of being in industry i, conditional on L and s, but before the worker learns her value of ε.

Assuming optimizing behavior, i.e., that a worker in industry i will choose to remain at or move to the industry j that offers her the greatest expected benefits, net of moving costs, we can write:[6]

$$\begin{aligned} U^i(L_t, s_t, \varepsilon_t) &= w_t^i + \max_j\{\varepsilon_t^j - C^{ij} + \beta E_t[V^j(L_{t+1}, s_{t+1})]\} \\ &= w_t^i + \beta E_t[V^i(L_{t+1}, s_{t+1})] + \max_j\{\varepsilon_t^j + \overline{\varepsilon}_t^{ij}\} \end{aligned} \tag{1}$$

where:

$$\overline{\varepsilon}_t^{ij} \equiv \beta E_t[V^j(L_{t+1}, s_{t+1}) - V^i(L_{t+1}, s_{t+1})] - C^{ij}. \tag{2}$$

Note that L_{t+1} is the next-period allocation of labor, derived from L_t and the decision rule, and s_{t+1} is the next-period value of the state, which is a random variable whose distribution is determined by s_t. The expectations in (1) and (2) are taken with respect to s_{t+1}, conditional on all information available at time t.

Taking the expectation of (1) with respect to the ε vector then yields:

$$V^i(L_t, s_t) = w_t^i + \beta E_t[V^i(L_{t+1}, s_{t+1})] + \Omega(\overline{\varepsilon}_t^i), \tag{3}$$

where $\overline{\varepsilon}_t^i = (\overline{\varepsilon}_t^{i1}, ..., \overline{\varepsilon}_t^{iN})$ and:

$$\Omega(\overline{\varepsilon}_t^i) = \sum_{j=1}^N \int_{-\infty}^{\infty} (\varepsilon^j + \overline{\varepsilon}_t^{ij}) f(\varepsilon^j) \prod_{k \neq j} F(\varepsilon^j + \overline{\varepsilon}_t^{ij} - \overline{\varepsilon}_t^{ik}) d\varepsilon^j. \tag{4}$$

The average value to being in industry i can therefore be decomposed into three terms: (1) the wage, w_t^i, that a industry-i worker receives; (2) the base value of staying on in industry i, i.e., $\beta E_t[V^i(L_{t+1}, s_{t+1})]$; and (3) the additional value, $\Omega(\overline{\varepsilon}_t^i)$, derived from having the option to move to another industry should prospects there look better (and which is simply equal to the expectation of $\max_j\{\varepsilon^j + \overline{\varepsilon}_t^{ij}\}$ with respect to the ε vector). We will call this the 'option value' associated with being in that industry at that time. Note that, since $\overline{\varepsilon}_t^{ii} \equiv 0$, this is always positive.

Using (3), we can rewrite (2) as:

$$\begin{aligned} C^{ij} + \overline{\varepsilon}_t^{ij} &= \beta E_t[V^j(L_{t+1}, s_{t+1}) - V^i(L_{t+1}, s_{t+1})] \\ &= \beta E_t[w_{t+1}^j - w_{t+1}^i + \beta E_{t+1}[V^j(L_{t+2}, s_{t+2}) - V^i(L_{t+2}, s_{t+2})] \\ &\quad +\Omega(\overline{\varepsilon}_{t+1}^j) - \Omega(\overline{\varepsilon}_{t+1}^i)], \text{ or} \end{aligned}$$

$$C^{ij} + \overline{\varepsilon}_t^{ij} = \beta E_t[w_{t+1}^j - w_{t+1}^i + C^{ij} + \overline{\varepsilon}_{t+1}^{ij} + \Omega(\overline{\varepsilon}_{t+1}^j) - \Omega(\overline{\varepsilon}_{t+1}^i)]. \tag{5}$$

[6]From here on, we drop the worker-specific subscript, l.

Note that $\bar{\varepsilon}_t^{ij}$ is the value of $\varepsilon^i - \varepsilon^j$ at which a worker in industry i is indifferent between moving to industry j and staying in i. Condition (5) thus has the simple, common-sense interpretation that for the *marginal* mover from i to j, the cost (including the idiosyncratic component) of moving is equal to the expected future benefit of being in j instead of i at time $t+1$. This expected future benefit has three components. The first is the wage differential. The second is the revealed expected value to being in industry j instead of i at time $t+2$, as revealed by the cost borne by the marginal mover from i to j at time $t+1$, or $C^{ij} + \bar{\varepsilon}_{t+1}^{ij}$. The last component is the difference in option values associated with being in each industry. Thus, if I contemplate being in j instead of i next period, I take into account the expected difference in wages; then the difference in the expected values of continuing in each industry afterward; and finally, the differences in the values of the option to leave each industry if conditions call for it.

Put differently, condition (5) is an Euler equation. Given appropriate choice of functional forms, this can be implemented to estimate the moving-cost parameters. We turn to that task next.

1.3 The estimating equation.

Let m_t^{ij} be the fraction of the labor force in industry i at time t that chooses to move to industry j, i.e., the *gross flow* from i to j. With the assumption of a continuum of workers and i.i.d idiosyncratic components to moving costs, this gross flow is simply the probability that industry j is the best for a randomly selected i-worker. Now, make the following functional form assumption. Assume that the idiosyncratic shocks follow an extreme-value distribution with parameters $(-\gamma\nu, \nu)$:

$$\begin{aligned} f(\varepsilon) &= \frac{e^{-\varepsilon/\nu-\gamma}}{\nu} \exp\left\{-e^{-\varepsilon/\nu-\gamma}\right\} \\ F(\varepsilon) &= \exp\left\{-e^{-\varepsilon/\nu-\gamma}\right\}, \end{aligned}$$

implying:

$$\begin{aligned} E(\varepsilon) &= 0, \text{ and} \\ Var(\varepsilon) &= \frac{\pi^2\nu^2}{6}. \end{aligned}$$

Note that while we make the natural assumption that the ε's be mean-zero, we do not impose any restrictions on the variance. The variance is proportional to the square of ν, which is a free parameter to be estimated, and crucial for all of the policy and welfare analysis.

By assuming that the ε_t^i are generated from an extreme-value distribution we are able to obtain a particularly simple expression for the conditional moment restriction, which we then plan to estimate using aggregate data. Specifically, it is shown in the web-only Appendix to Artuç, Chaudhuri and McLaren (forthcoming) and in the Appendix to the 2007 working paper) that, with this assumption:

$$\bar{\varepsilon}_t^{ij} \equiv \beta E_t[V_{t+1}^j - V_{t+1}^i] - C^{ij} = \nu[\ln m_t^{ij} - \ln m_t^{ii}] \tag{6}$$

and:

$$\Omega(\bar{\varepsilon}_t^i) = -\nu \ln m_t^{ii} \tag{7}$$

Both these expressions make intuitive sense. The first says that the greater the expected net (of moving costs) benefits of moving to j, the larger should be the observed ratio of movers (from i to j) to stayers. Moreover, holding constant the (average) expected net benefits of moving, the higher the variance of the idiosyncratic cost shocks, the lower the compensating migratory flows.

The second expression says that the greater the probability of remaining in industry i, the lower the value of having the option to move from industry i.[7] Moreover, as the variance of the idiosyncratic component of moving costs increases, so too does the value of having the option to move. This also makes good sense.

Substituting from (6) and (7) into (5) and rearranging, we get the following conditional moment condition:

$$E_t\left[\frac{\beta}{\nu}(w_{t+1}^j - w_{t+1}^i) + \beta(\ln m_{t+1}^{ij} - \ln m_{t+1}^{jj}) - \frac{(1-\beta)}{\nu}C^{ij} - (\ln m_t^{ij} - \ln m_t^{ii})\right] = 0. \tag{8}$$

This condition can be interpreted as a linear regression:

$$(\ln m_t^{ij} - \ln m_t^{ii}) = -\frac{(1-\beta)}{\nu}C^{ij} + \frac{\beta}{\nu}(w_{t+1}^j - w_{t+1}^i) + \beta(\ln m_{t+1}^{ij} - \ln m_{t+1}^{jj}) + \mu_{t+1}, \tag{9}$$

where μ_{t+1} is news revealed at time $t+1$, so that $E_t\mu_{t+1} \equiv 0$. In other words, the parameters of interest, C^{ij}, β and ν, can then be estimated by regressing current flows (as measured by

[7] Note that $0 < m_t^{ii} < 1$, so $\Omega(\bar{\varepsilon}_t^i) = -\nu \ln m_t^{ii} > 0$.

$(\ln m_t^{ij} - \ln m_t^{ii})$) on future flows (as measured by $(\ln m_{t+1}^{ij} - \ln m_{t+1}^{jj})$) and the future wage differential with an intercept.

The basic idea of the estimating equation (9) can be summarized as follows. We regress current flows of workers from i to j on next-period flows in the same direction and on next-period j-sector wages minus i-sector wages. If there are a lot of flows in all directions, that implies a high value for the intercept of this equation, which in turn implies a high variance for the idiosyncratic shocks ν relative to average moving costs C^{ij}. On the other hand, for a given overall *level* of flows, if those flows are very *responsive* to the expected next-period wage differential, that implies a large *slope* coefficient in the regression equation, which implies a low variance ν of the idiosyncratic shocks. That is how this simple regression can identify the mean and variance parameters of moving costs. In practice, for this exercise, we will constrain all average moving costs to be the same, or $C^{ij} = C \forall i, j$.

2 Data.

Our estimation strategy hinges on observing aggregate gross flows across industries. We construct gross flow measures from retrospective questions in the Hane Halkı İşgücü Anketi (HHİA) , or Household Employment Survey, of the Turkish Statistical Institute (TUIK), 2004-6. The survey asks, among other questions, what industry the worker is in at present and what industry the worker was in last year. This enables us to construct rates of flow, m_{t-1}^{ij}, for each date t. We also obtain industry wages w_t^i as the average wage reported in the HHİA samples for industry i at date t. These are deflated by the CPI, and normalized so that over the whole sample the average annualized wage is equal to unity. We restrict the sample to males aged 21 to 64 currently working full time or seasonal for wage (who do not own a business). Although agriculture is 30% of the economy, the number of workers who list themselves as full-time or seasonal agricultural workers is very small (3% of the sample). We include all full-time and seasonal agricultural workers but exclude those who own a farm, on the assumption that they are better treated as owners of a fixed, industry-specific factor than as a mobile worker. This selection process yields us 47,064 observations for 2004, 47,723 for 2005, and 49,394 for 2006.

If we have n industries, then there are n^2 rates of gross flow to keep track of each period (or $n(n-1)$ if one excludes the fraction of workers in each industry who do not move). Thus, the number of directions for gross flows proliferates rapidly as the number of industries increases, leading in finite samples to zero observations and observations with very small numbers of individuals. As a result, we need to aggregate industries, and we aggregate to the following four:

1. Agriculture, forestry, fisheries, hunting.
2. Manufacturing, mining, utilities, construction.
3. Trade, hotels and restaurants.
4. All other services including: education, public (administration, social security, military, etc.), health, finance, real estate, transportation, and communication.

As a result of our aggregation, the sample size for each regression is 24, since we have 3 years minus 1 to allow for lags, and 4 times 3 directions of flows.

Table 1: Descriptive Statistics: Gross Flows, 2004-6.

	Agric/Min	*Manuf/Const*	*Trade/Hotels*	*Service*
Agric/Min	0.8616	0.0669	0.0338	0.0376
Manuf/Const	0.0015	0.9770	0.0120	0.0095
Trade/Hotels	0.0011	0.0313	0.9482	0.0194
Service	0.0007	0.0085	0.0076	0.9832

(Origin sector is listed by row, destination sector by column. Each cell of table contains mean flow rate, averaged over the three years.)

Descriptive statistics for the resulting data are shown in Tables 1 and 2. Table 1 summarizes gross flows. Each cell of the table shows the fraction of workers, averaged across years, in the row sector who moved to the column sector in any given period; for example, on average, 3.38% of Agriculture/Mining workers in any year moved to Trade/Hotels. The rates of gross flow range from below 0.1% for the move from Service to Agriculture/Mining to 6.7% for the move from Agriculture/Mining to Manufacturing/Construction. A tendency for workers to exit Agriculture/Mining in favor of Manufacturing/Construction and Services is evident in the figures.

Table 2 shows descriptive statistics for wages. Wages vary a great deal across sectors. Normalized wages (that is, normalized to have a unit mean) averaged across time range from 0.5642 for Agriculture/Mining to 1.1882 for Services, suggesting that the shifts of workers observed in Table 1 are driven by a rise in the demand for labor in Services and Manufacturing/Construction relative to Agriculture/Mining.

Table 2: Descriptive Statistics: Wages, 2004-6 (normalized).

Agric/Min	0.5648
Manuf/Const	0.9253
Trade/Hotels	0.8046
Service	1.1882

3 Results.

Before showing estimations, we should point out that we do not attempt to estimate β. This model is not designed to estimate rates of time preference, and although it could be done in principle, in practice it turns out that that one parameter is very poorly identified. It turns out that estimating and simulating the model with different values of β produces nearly identical time-paths for key observable variables, so it is not surprising that it is hard to identify econometrically. We simply impose a value of β in all that follows; to check for sensitivity to the choice of β, we report estimations with both $\beta = 0.9$ and $\beta = 0.97$.

Table 3 shows the results from the basic regression. As mentioned above, we impose $C^{ij} \equiv C \forall i \neq j$, so that the mean moving cost for any transition from one industry to any other is the same. Throughout the table, the t-statistics are reported in parentheses.

Table 3: Regression Results for the Basic Model.

$\beta = 0.97.$		$\beta = 0.9.$	
ν	C	ν	C
2.56 (3.50***)	22.89 (3.23***)	1.62 (5.36***)	9.50 (5.36***)

(T-statistics are in parentheses. One-tailed significance: 1-percent***, 5-percent**, 10-percent*.)

The first two columns report results for $\beta = 0.97$, and the last two report results for $\beta = 0.9$. Notice that the estimated moving costs are enormous. Given our convention on normalizing wages, the value of C is estimated at 9.50 and 22.88 times average annual income, for the two cases respectively. The two values for ν translate to a standard deviation for the idiosyncratic shocks of just over one-year's average annual earnings. This reflects both the modest levels of gross flows observed in Table 1 and the fact that the flows respond only modestly to wage differentials across sectors. This suggests that the labor market will likely be sluggish in reallocating workers following a trade shock, as will be confirmed in the simulations.

Strictly speaking, OLS is likely to be biassed in this case, because the disturbance term, μ_{t+1}, contains any new information at date $t+1$ and so will in general be correlated with date-$t+1$ regressors. This implies a need for instrumental variables. The theory implies that past values of the flows and wages will be valid instruments, and the optimal weighting scheme can be derived as in the Generalized Method of Moments (GMM) (Hansen (1982)). This strategy is employed in Artuç, Chaudhuri and McLaren (forthcoming). However, in that study, the data set was 26 years long; in the present case, with only three years, that strategy is not available to us. We are hoping that after the Turkish Statistical Institute releases two more years of household survey data, we will be able to use instruments, which is left for future research. As an imperfect fix, we note that in the earlier paper with US data, estimating with OLS instead of with instruments increased the value of C by 67% and ν by 54% when $\beta = 0.97$, and C by 34% and ν by 31% when $\beta = 0.9$, so we divide our parameter estimates by 1.67, 1.54, 1.34 and 1.31 for an alternative set of simulations. After simulating the model with original estimates (for both $\beta = 0.9$ and $\beta = 0.97$), we repeat the simulation exercises with the corrected parameters, and show that the bias in the OLS estimates probably does not affect the adjustment path of workers and values significantly.

Another possible source of bias comes from the fact that we have imposed uniform moving costs for all sectors, so that $C^{ij} = C \forall i, j$. Degrees-of-freedom concerns prevent us from estimating the full set of C^{ij} parameters without restriction, but we have also estimated the model with a slightly richer specification allowing for sector-specific "entry costs." In this approach, $C^{ij} = C_j$ for $i = 1, \ldots, 4$. Table 4 shows the results of this regression.

Compared with the Basic Model regression from Table 3, we find that all sectors exhibit lower entry costs. However, we were not able to identify entry cost of Agriculture when

Table 4: Regression Results for Sector-Specific Entry Costs

	Beta=0.97		Beta=0.90	
	Estimate	t-statistic	Estimate	t-statistic
ν	1.60	(2.98***)	1.17	(3.95***)
$C^1(Agriculture)$	0.00	(0.00)	3.10	(1.53*)
$C^2(Manufacture)$	17.67	(2.41**)	7.17	(3.54***)
$C^3(Trade)$	9.90	(1.31)	5.55	(2.61***)
$C^4(Service)$	20.81	(5.52***)	8.65	(6.03***)

(T-statistics are in parentheses. One-tailed significance: 1-percent***, 5-percent**, 10-percent*.)

$\beta = 0.97$, therefore we are not using results from Table 4 in simulations. This identification problem probably arises because of our very small sample size. We find that entry to the Service sector (which includes government and professional sectors) is the most costly one, while entry to Agriculture (which includes only workers who do not own a farm) is the least costly.

4 Simulation: A Sudden Trade Liberalization.

Now, we use the estimates to study the effect of a hypothetical trade shock through simulations. Note that for the estimations, the only functional-form assumption we needed was the density for the idiosyncratic shocks, but to simulate the model we need to choose functional forms (and parameter values) for production and utility functions as well. We assume that each of the four sectors has a Cobb-Douglas production function, with labor and unmodelled sector-specific capital as inputs. Thus, for our purposes, the production function for sector i is given by:

$$y_t^i = A^i (L_t^i)^{\alpha^i} (K^i)^{1-\alpha^i}, \tag{10}$$

where y_t^i is the output for sector i in period t, K^i is sector-i's capital stock, and $A^i > 0$ and $\alpha^i > 0$ are parameters. Given the number of free parameters and our treatment of capital as fixed,[8] we can without loss of generality set $K^i = 1 \forall i$. This implies that the wages are given by:

$$w_t^i = p_t^i A^i \alpha^i (L_t^i)^{\alpha^i - 1}, \tag{11}$$

where p_t^i is the domestic price of the output of sector i.

For simulations, we need to choose values of production-function parameters to provide a plausible illustrative numerical example, broadly consistent with quantitative features of the data. To do this, we set the values A^i and α^i to minimize a loss function given our assumptions on prices (see below). 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 (11) and (10) 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 labor's predicted share of revenue minus the actual share, plus the square of the sector's predicted minus its actual share of GDP. The sectoral GDP and labor's share of revenue figures are from the Turkish Statistical Institute (www.turkstat.gov.tr) input output table for 2002, but the remaining figures are from our sample. In addition, we assume that all workers have identical Cobb-Douglas preferences, using consumption shares from 2002 input output table of the Turkish Statistical Institute for the consumption weights. The parameter values that result from this procedure are summarized in Table 5.

Table 5: Parameters for Simulation.

	A^i	α^i	Domestic price.	World price.
Agric/Min	0.2131	0.1330	1	1
Manuf/Const	1.3497	0.3708	1	0.7
Trade/Hotels	0.9379	0.2237	1	1*
Service	1.9494	0.3407	1	1

[8] We assume that capital is fixed in order to focus on the workers' problem and to keep the model manageable. Of course, that is an important limitation, since capital should also be expected to adjust to trade liberalization, and that should also be expected to affect wages.

Then, to provide a simple trade shock, we assume the following: (i) Units are chosen so that the domestic price of each good at date $t = -1$ is unity. (Given our available free parameters, this is without loss of generality.) (ii) There are no tariffs on any sector aside from manufacturing, at any date. (iii) The world price of manufacturing output is 0.7 at each date. The world price of all other tradeable goods is equal to unity at each date. (iv) There is initially a specific tariff on manufactures at the level 0.3 per unit, so that the domestic price of manufactures is equal to unity. (v) Initially, this tariff is expected to be permanent, and the economy is in the steady state with that expectation. (vi) At date $t = -1$, however, after that period's moving decisions have been made, the government announces that the tariff will be removed beginning period $t = 0$ (so that the domestic price of manufactures will fall from unity to 0.7 at that date), and that this liberalization will be permanent.

Thus, we simulate a sudden liberalization of the manufacturing sector. We compute the perfect-foresight path of adjustment following the liberalization announcement, until the economy has effectively reached the new steady state. This requires that each worker, taking the time path of wages in all sectors as given, optimally decides at each date whether or not to switch sectors, taking into account that worker's own idiosyncratic shocks. This induces a time-path for the allocation of workers, and therefore the time-path of wages, since the wage in each sector at each date is determined by market clearing from (11) given the number of workers currently in the sector. Of course, the time path of wages so generated must be the same as the time-path each worker expects. It is shown in Cameron, Chaudhuri and McLaren (2007) that the equilibrium exists and is unique. The computation method is described at length in Artuç, Chaudhuri and McLaren (2008), and programs for executing the simulations are contained in the web-only appendix for Artuç, Chaudhuri and McLaren (forthcoming). Simulations converge quickly and require modest computing power.

As a simplification, all goods are assumed to be traded, so all output prices are exogenous, and we use the case with $\beta = 0.97$.

The simulation output is plotted in the Figures. Figure 1 shows the time path of the allocation of workers. The Manufacturing/Construction sector has 32.8% of the workers in the tariff steady state, but under free trade has only 28.5%. All of the other sectors gain workers due to the liberalization. The adjustment is fairly slow, taking approximately a decade. Figure 2 shows the time path of real wages in each sector. With the abrupt drop in the price of manufacturers/construction output, real wages in all of the other sectors jump up at the liberalization date, but then gradually decline as workers stream into those sectors from manufacturing/construction and push the equilibrium down the labor-demand curve. Still, the real wage in each of those sectors is above the tariff steady-state level in the short run and the long run of the liberalization simulation. The story for manufacturing/construction wages is the reverse: An abrupt drop of about 20% on the date of the liberalization followed by a gradual improvement, as workers leave the sector and push the equilibrium up the labor-demand curve in that sector. Still, the real wage in manufacturing/construction is at each date below what it was in the tariff steady state.

Figure 3 shows the effect of the liberalization on life-time utility of the various workers. Each plot shows the expected present-discounted value of utility for a typical worker in each of the sectors at each date.[9] The main thing to notice is what happens at the sudden liberalization date. For all workers except those in Manufacturing/Construction the effect is positive: Lifetime utility jumps up, as should be expected, since those workers expect a rise in their real wages. Importantly, these lifetime utilities take into account the probability for each worker that he/she will move to another sector down the road due to idiosyncratic shocks. The only way a services sector worker, for example, would be hurt by the liberalization is if he/she moved into Manufacturing/Construction, which is a positive-probability event but not very likely.

On the other hand, the lifetime utility of a Manufacturing/Construction worker falls at the liberalization date by about 14%. The drop in utility is much smaller than the drop in wages for two reasons: The later increases in real wages in the sector, as noted above (see Figure 2), and the fact that workers in Manufacturing/Construction have the option to move to other sectors; this option value is increased by the liberalization, because it increases the real wage in the other sectors.

We repeat the exercise under the assumption that $\beta = 0.9$ and keep all other assumptions the same. Figures 6-10 show results of the case where $\beta = 0.9$. We find that unlike Artuç Chaudhuri and McLaren (2009) (which uses US data), changing the discount factor does not affect how much manufacturing workers are worse off. Figure 8 shows that, similar to the previous case, manufacturing workers are worse off by about 13%. This may be due to the fact that Turkish workers are less mobile compared to US workers, as reflected in the

[9]Note that this is different from the present discounted value of each sector's real wage, because it must take into account each worker's option value. The value is computed using equations (3) and (7) over the simulation; once again, see Artuç, Chaudhuri and McLaren (2008) for details.

parameter estimates of Tables 3 and 4.

In order to get a better understanding of the effects of OLS bias on the adjustment path of labor allocation, wages and values of workers, we repeat the simulations using adjusted estimates as we described in the previous section. The comparison of simulations with adjusted parameters and original OLS parameters are shown in Figures 11-16. The OLS bias seems to change the simulation results only slightly and qualitative results are robust. For example, for the $\beta = 0.97$ case, life-time utility of Manufacturing workers falls by 10% rather than 14% after the trade shock if we use corrected parameters (shown in Figure 13), while for the $\beta = 0.97$ case it falls by 12% rather than 13% with the corrected parameters (shown in Figure 16).

Therefore, this analysis suggests that since Turkish labor market data are consistent with very high intersectoral moving costs, workers in the liberalizing sector are likely to suffer a significant welfare loss that will be only partially alleviated over time. Workers in other sectors all enjoy a significant welfare benefit, as does the economy as a whole. Thus, the estimates suggest a significant political conflict over trade liberalization, with a strong motive for the government to find cost-effective ways to compensate the workers in the import-competing sector. Note that these simulations find much more scope for distributional conflict than the US simulations in Artuç, Chaudhuri and McLaren (forthcoming), because of the high estimated moving costs for Turkish workers. Note also that the nature of conflict is sharply different than the type highlighted by Heckscher-Ohlin-type models, in which the conflict would be between blue-collar and white-collar workers. In this paper, we find strong evidence of the potential for *inter-sectoral* conflict over trade policy.

In addition, we have identified a pitfall of reduced-form wage analysis: A regression of sectoral wages on sectoral tariffs using data at date $t = -1$ and $t = 1$ would significantly overestimate the long-run effect of the liberalization on the Manufacturing/Construction wage (and standard approaches would not even allow for an effect on the real wages in the other sectors). In addition, the wefare loss for those workers are considerably more modest than the reduction in wages, once the dynamics of the equilibrium adjustment and the effects of option value are taken into account.

Finally, it should be emphasized once again that this analysis has imposed very modest data requirements; the estimation requires only a simple regression; and the simulation requires very minimal computing power. As a result, this type of exercise is very portable across data sets and countries.

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[4] **Artuç, Erhan, Shubham Chaudhuri, and John McLaren.** (forthcoming). "Trade Shocks and Labor Adjustment: A Structural Empirical Approach." Forthcoming, *American Economic Review.*

[5] **Cameron, Stephen, Shubham Chaudhuri, and John McLaren.** 2007. "Trade Shocks and Labor Adjustment: Theory." NBER Working Paper 13463.

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[7] **Hansen, Lars P.** 1982. "Large Sample Properties of Generalized Method of Moments Estimators." *Econometrica,* 50: 1029-1054.

Figure 1: Simulated Trade Liberalization I - Labor Allocation

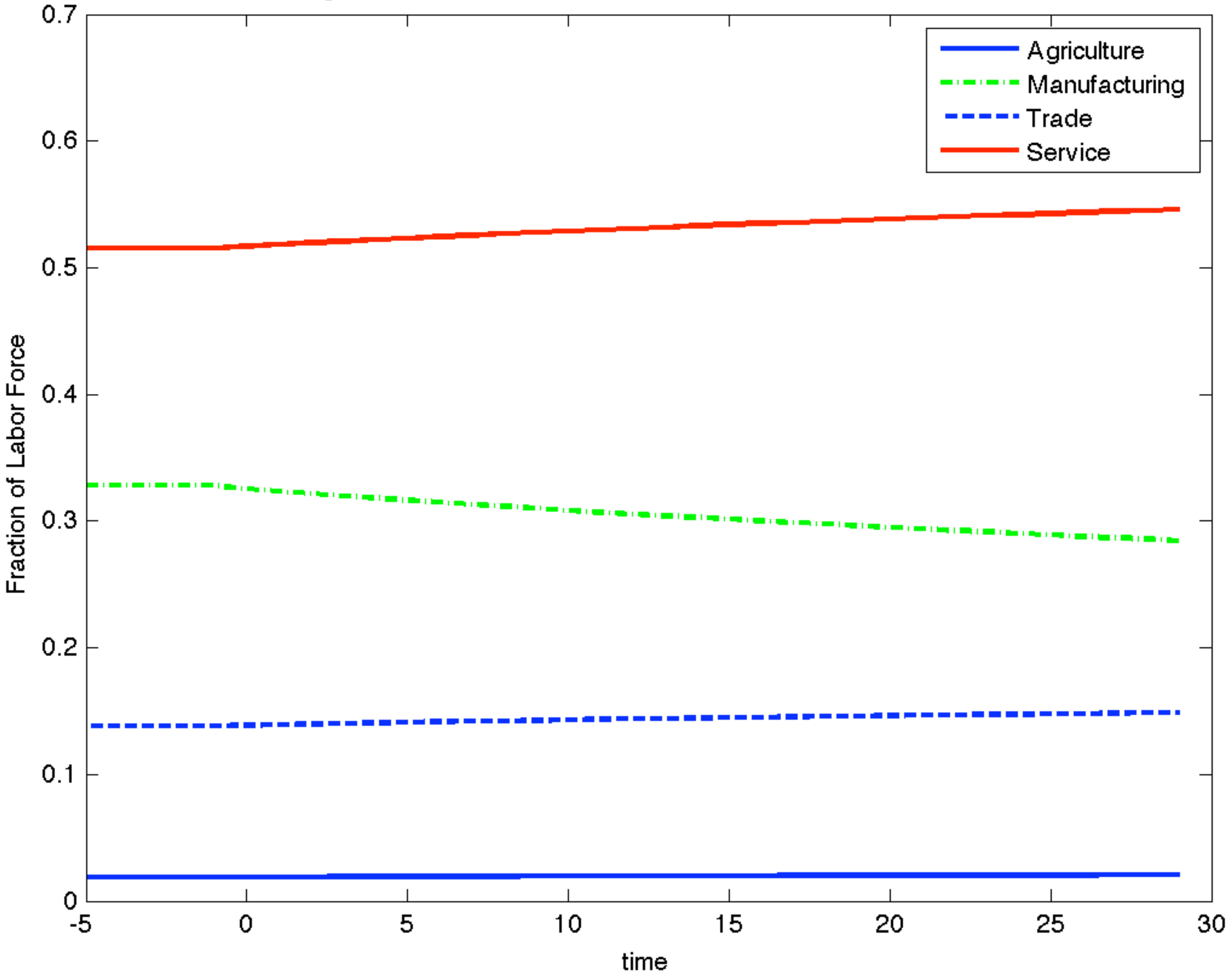


Figure 2: Simulated Trade Liberalization I - Wages

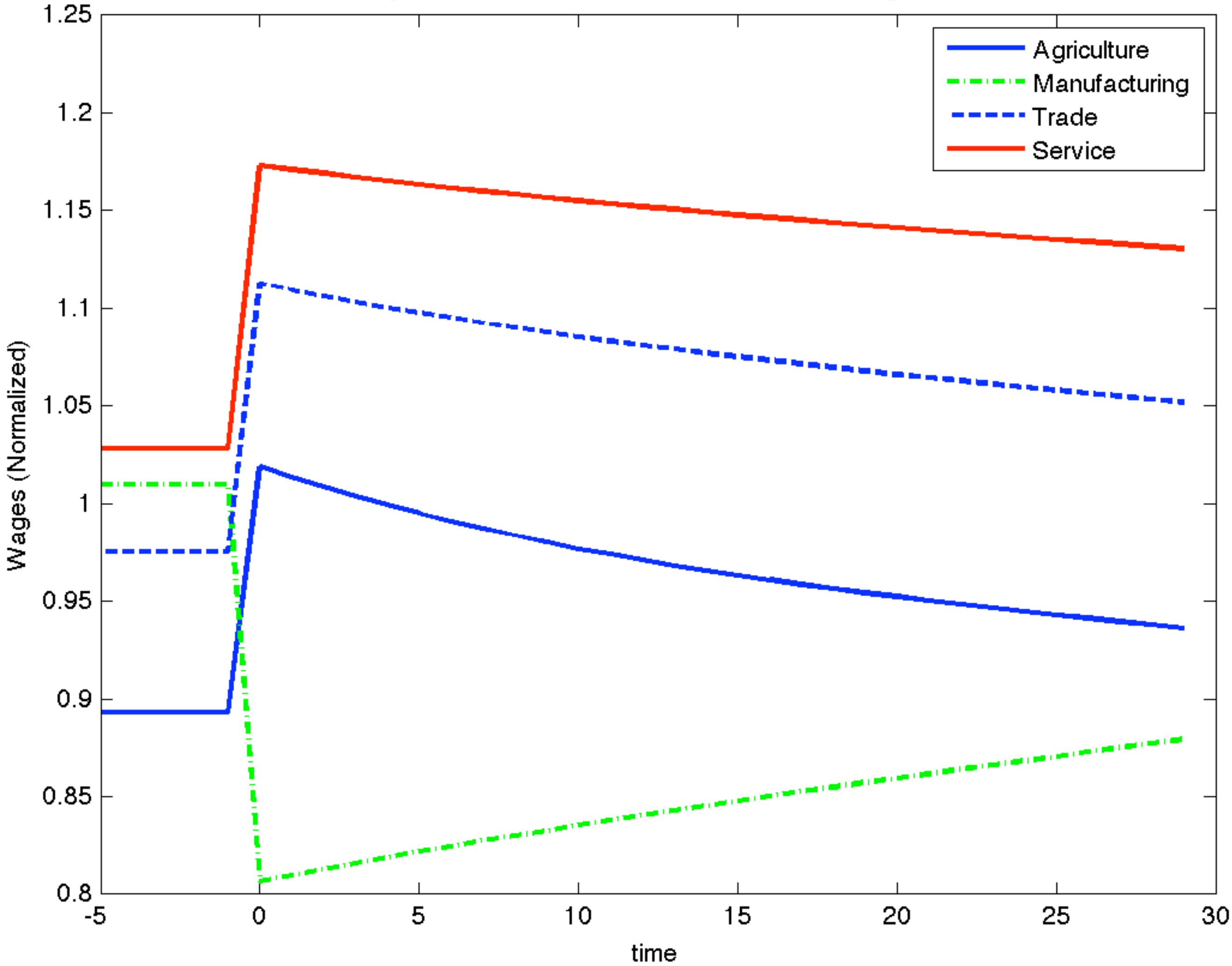
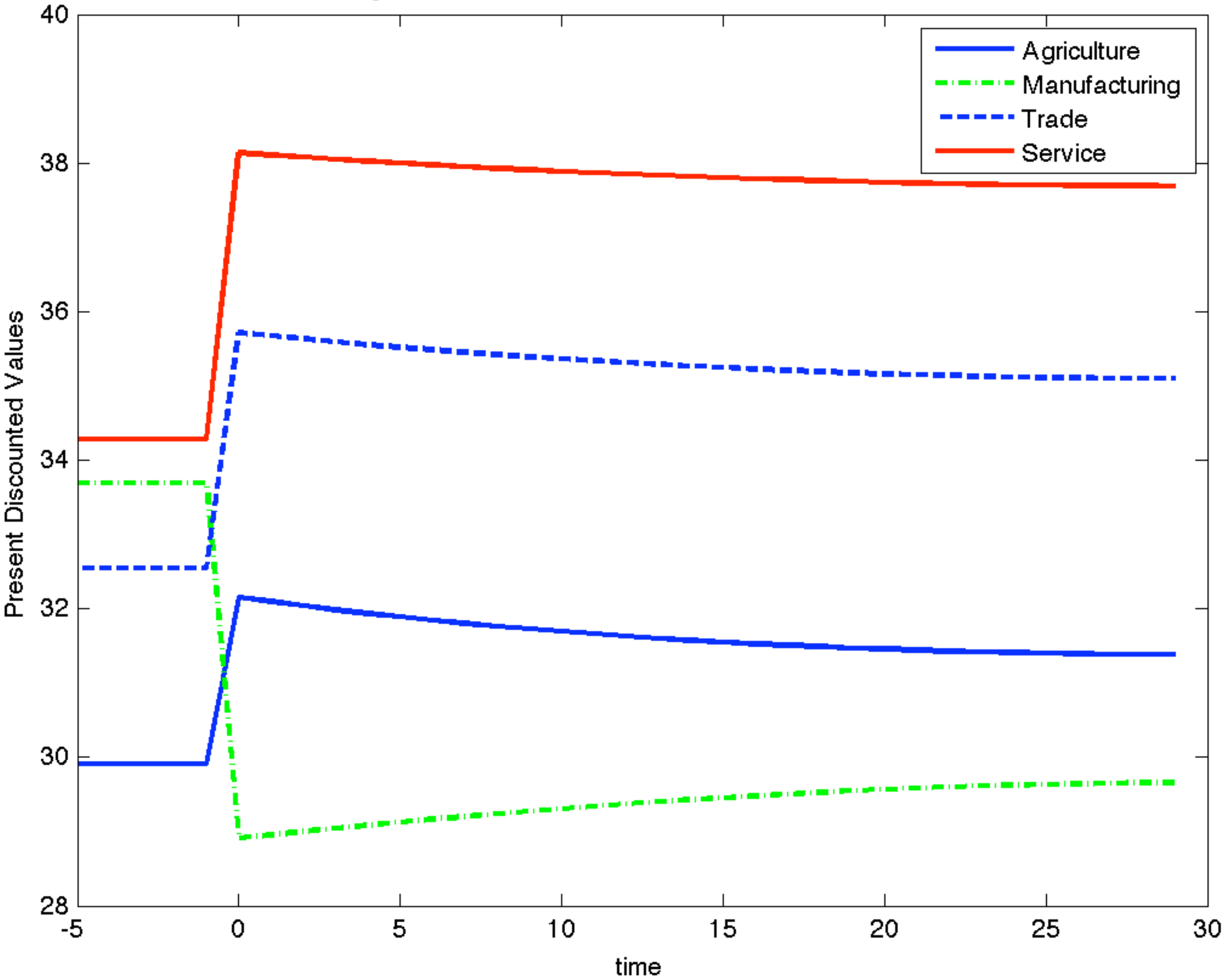


Figure 3: Simulated Trade Liberalization I - Values



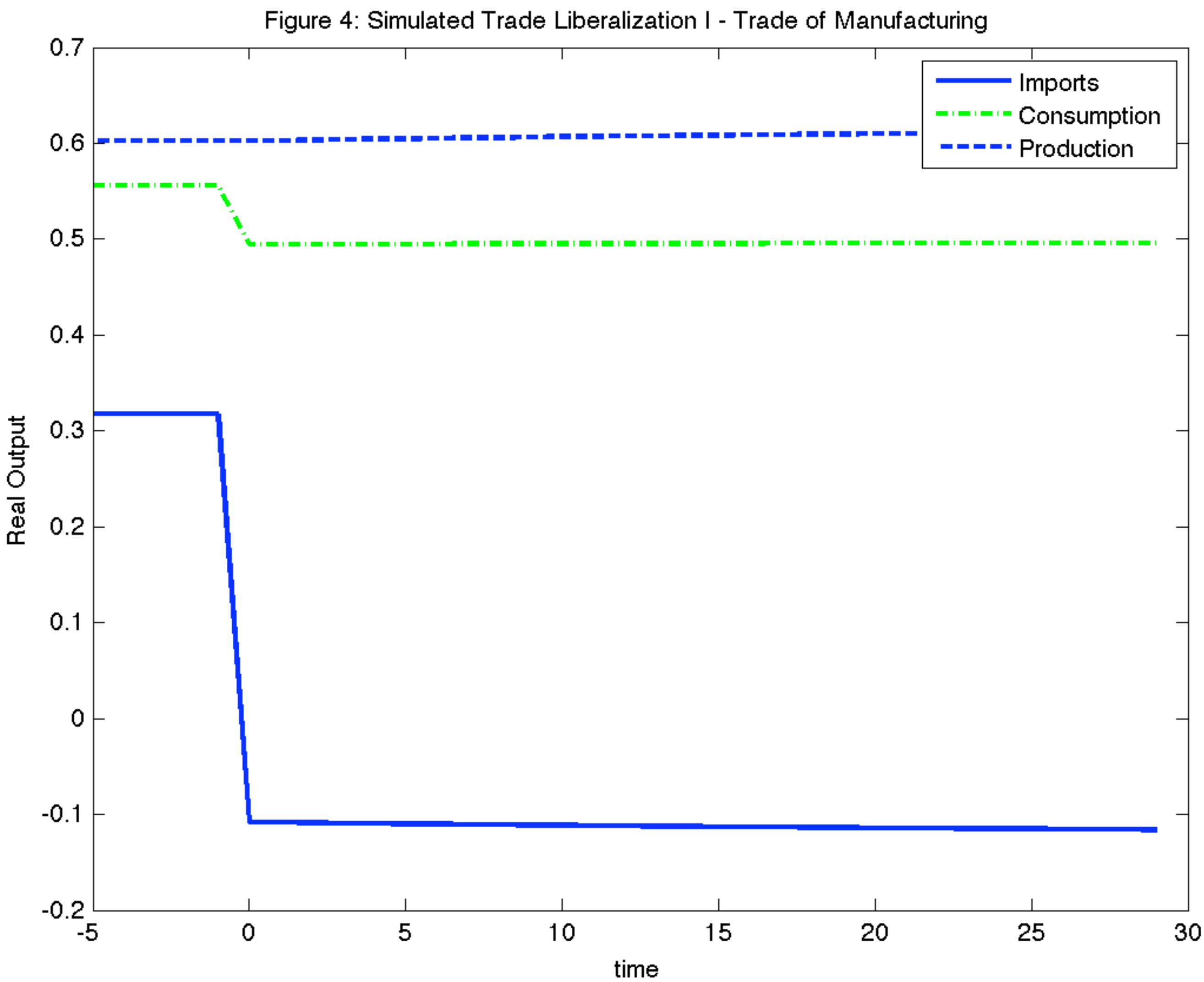


Figure 4: Simulated Trade Liberalization I - Trade of Manufacturing
Imports
Consumption
Production
Real Output
time
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-5
0
5
10
15
20
25
30

Figure 5: Simulated Trade Liberalization I - Prices

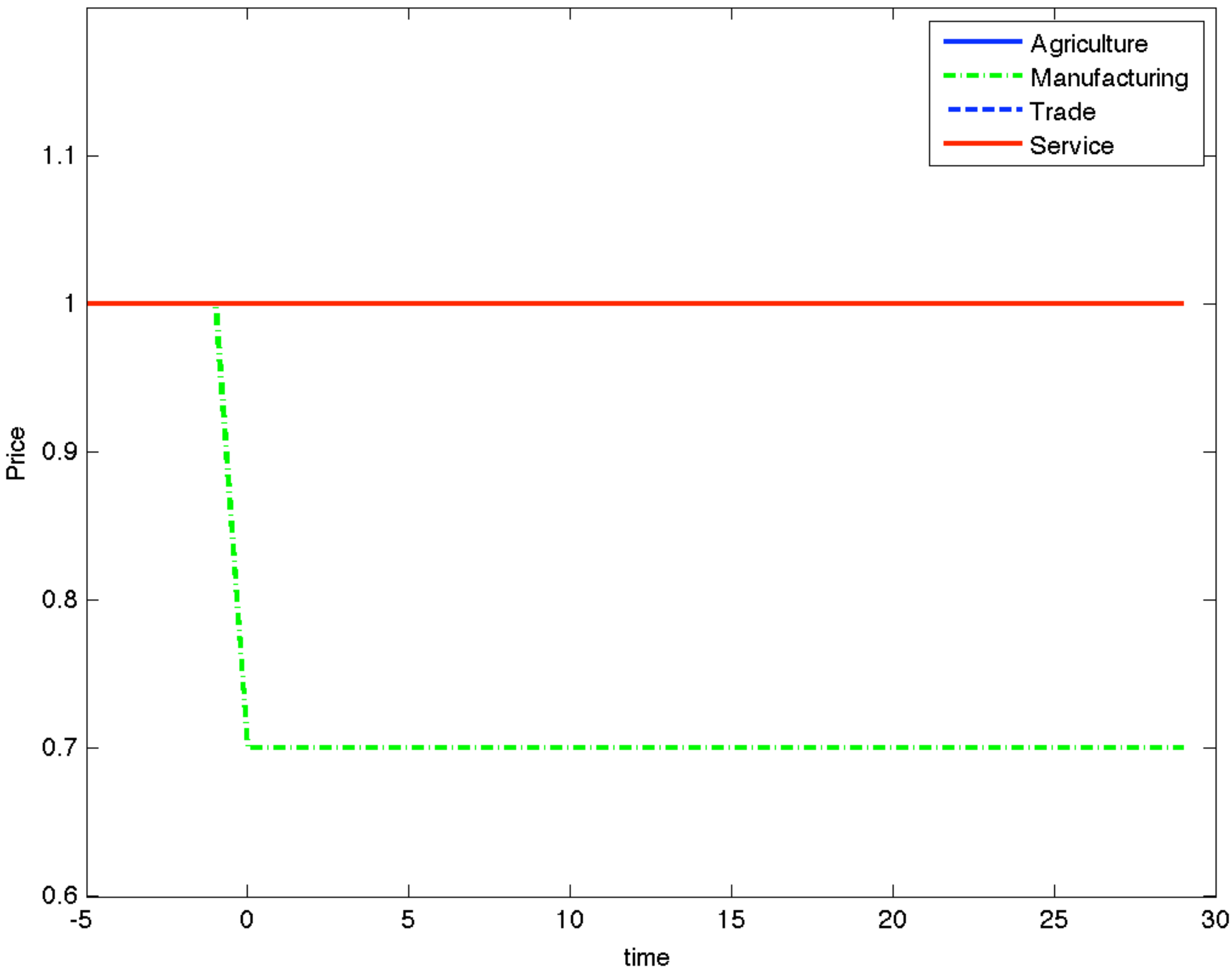
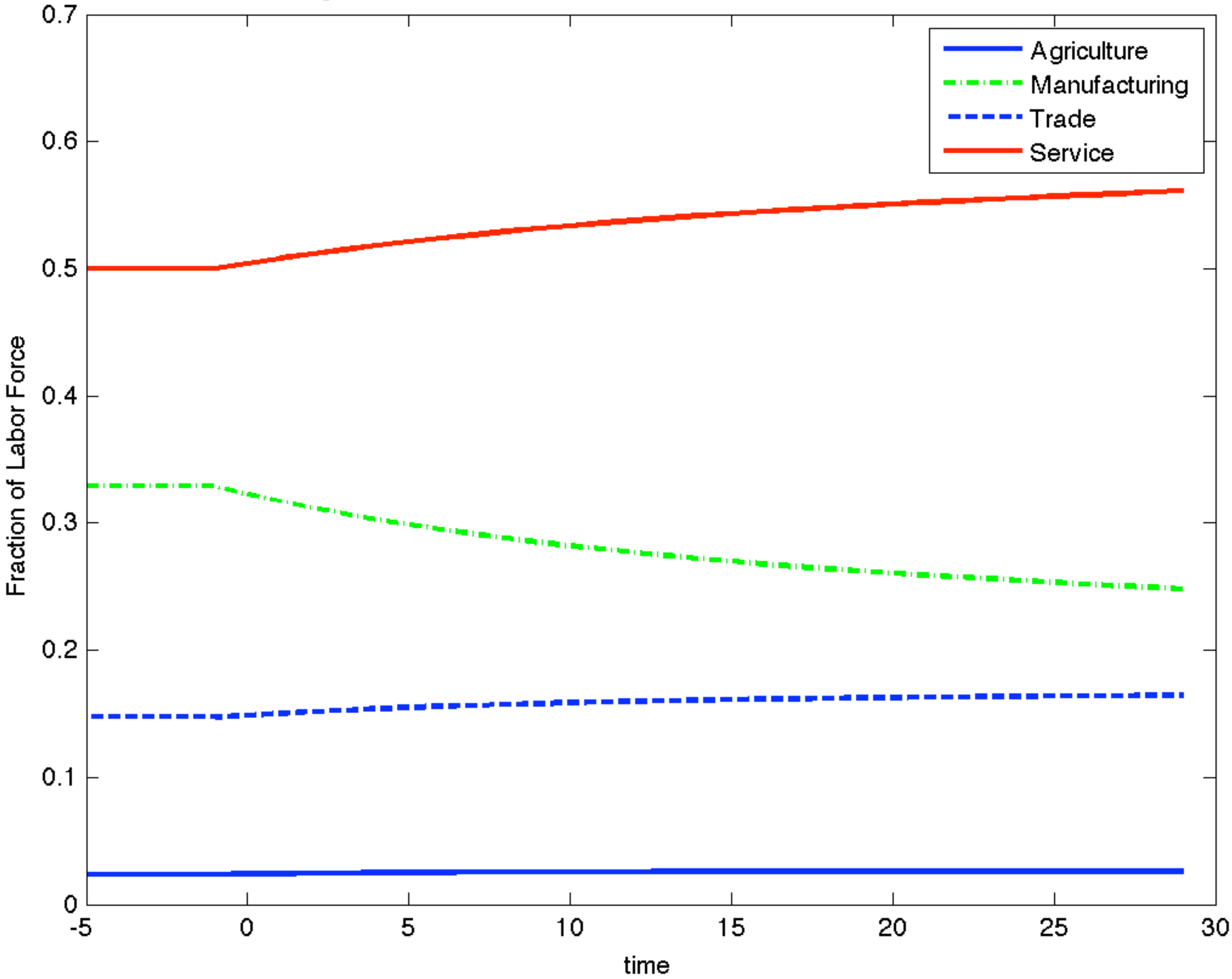


Figure 6: Simulated Trade Liberalization II - Labor Allocation



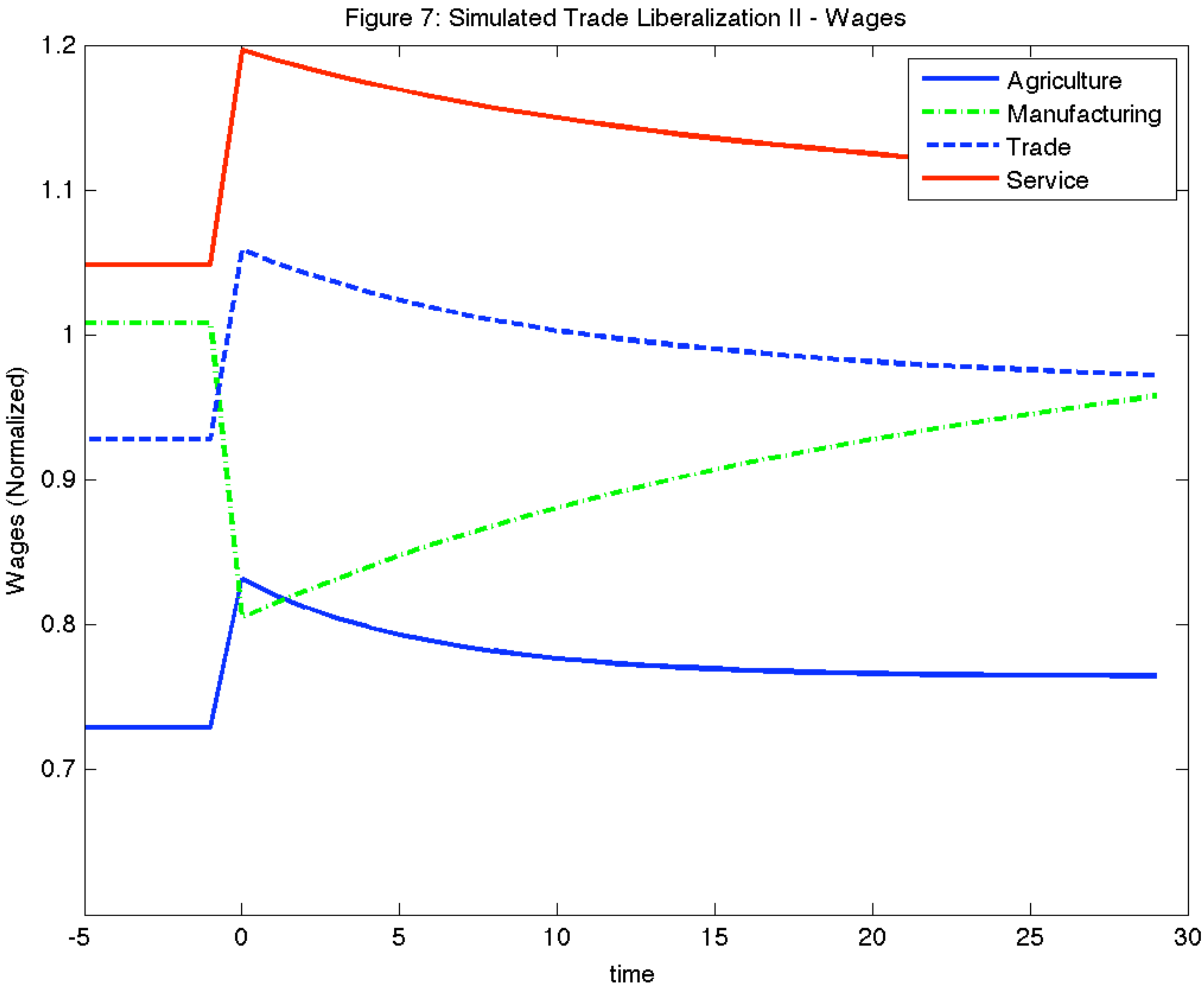


Figure 7: Simulated Trade Liberalization II - Wages
Wages (Normalized)
time
1.2
1.1
1
0.9
0.8
0.7
-5
0
5
10
15
20
25
30
Agriculture
Manufacturing
Trade
Service

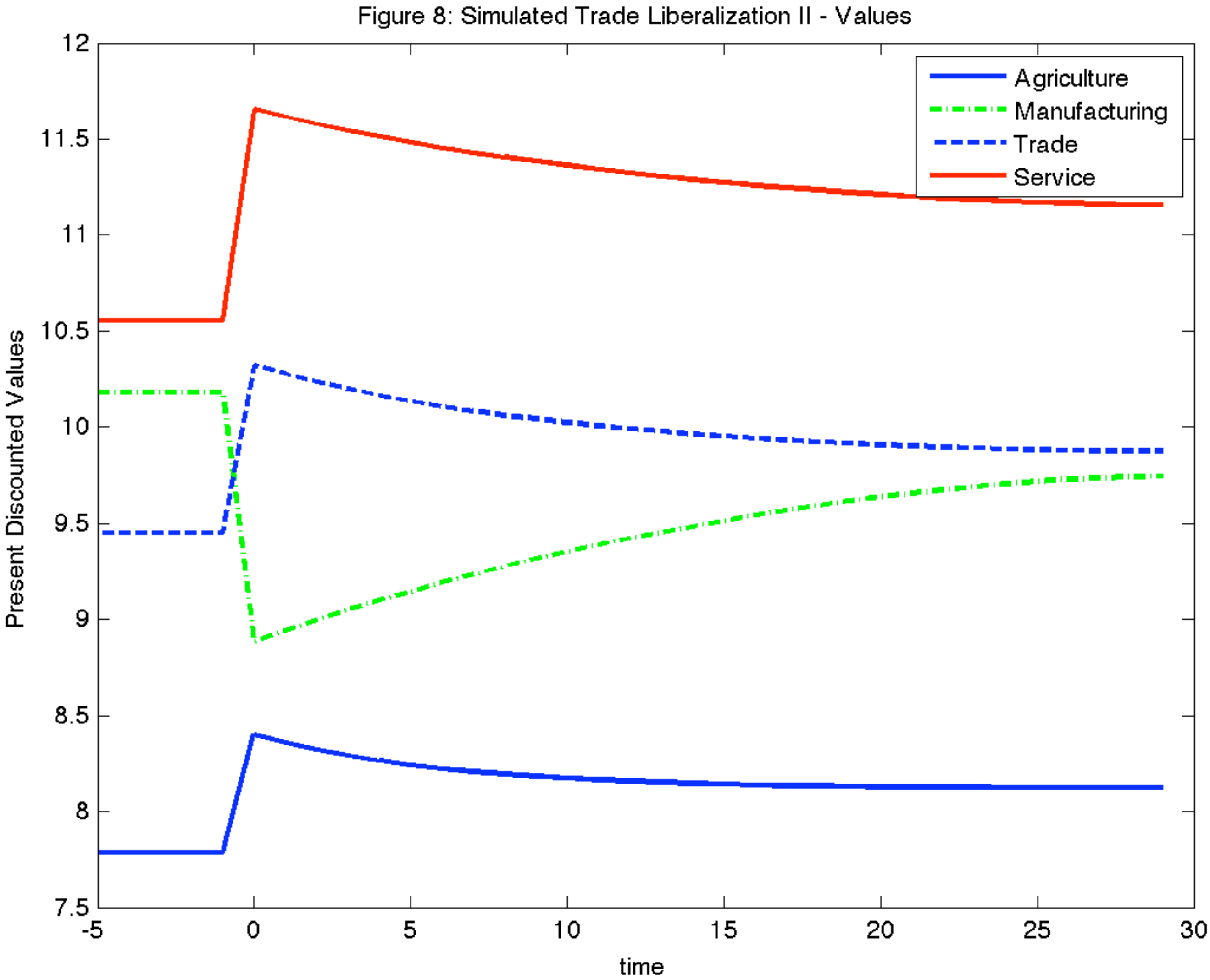


Figure 8: Simulated Trade Liberalization II - Values
Present Discounted Values
time
Agriculture
Manufacturing
Trade
Service
12
11.5
11
10.5
10
9.5
9
8.5
8
7.5
-5
0
5
10
15
20
25
30

Figure 9: Simulated Trade Liberalization II - Trade of Manufacturing

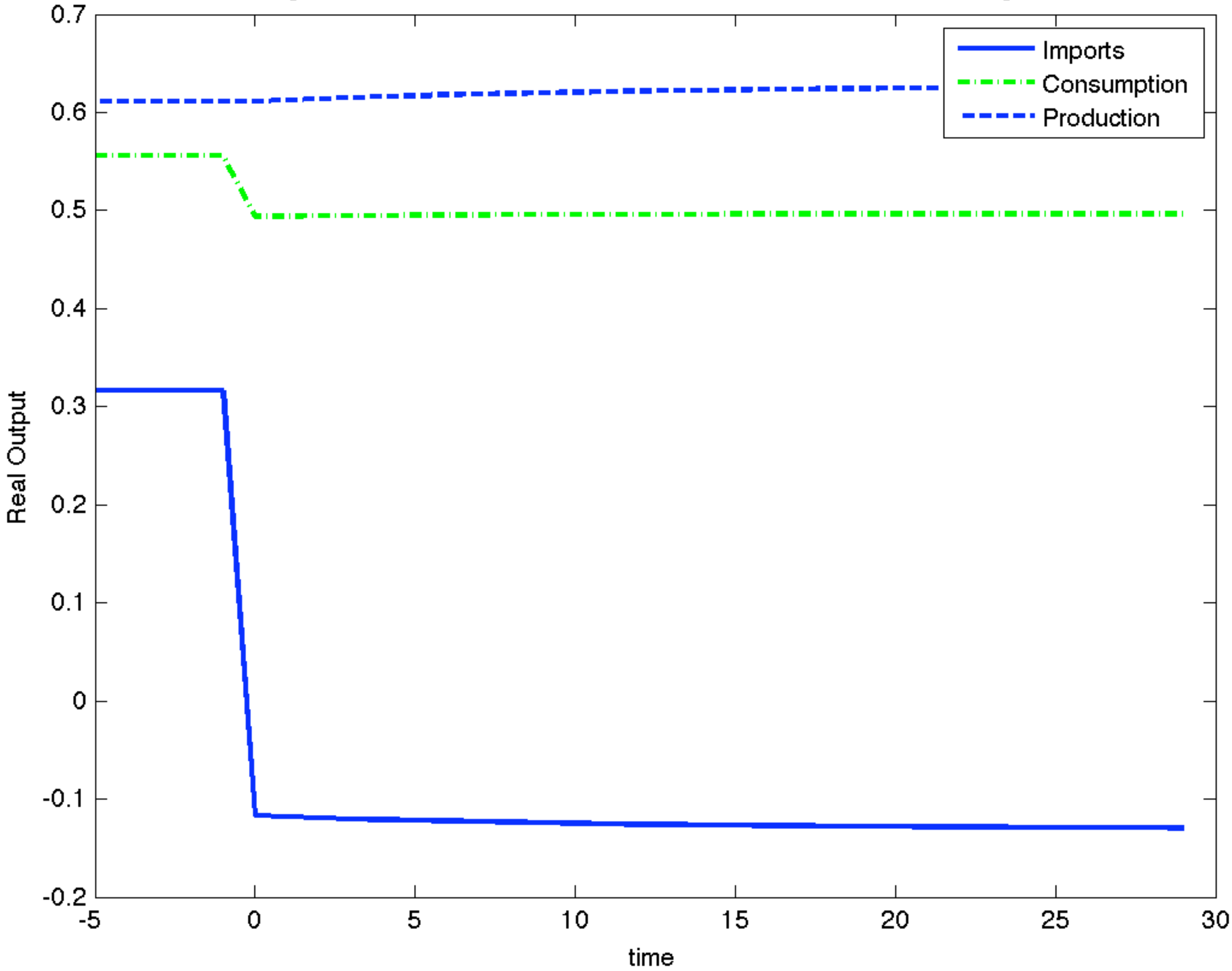


Figure 10: Simulated Trade Liberalization II - Prices

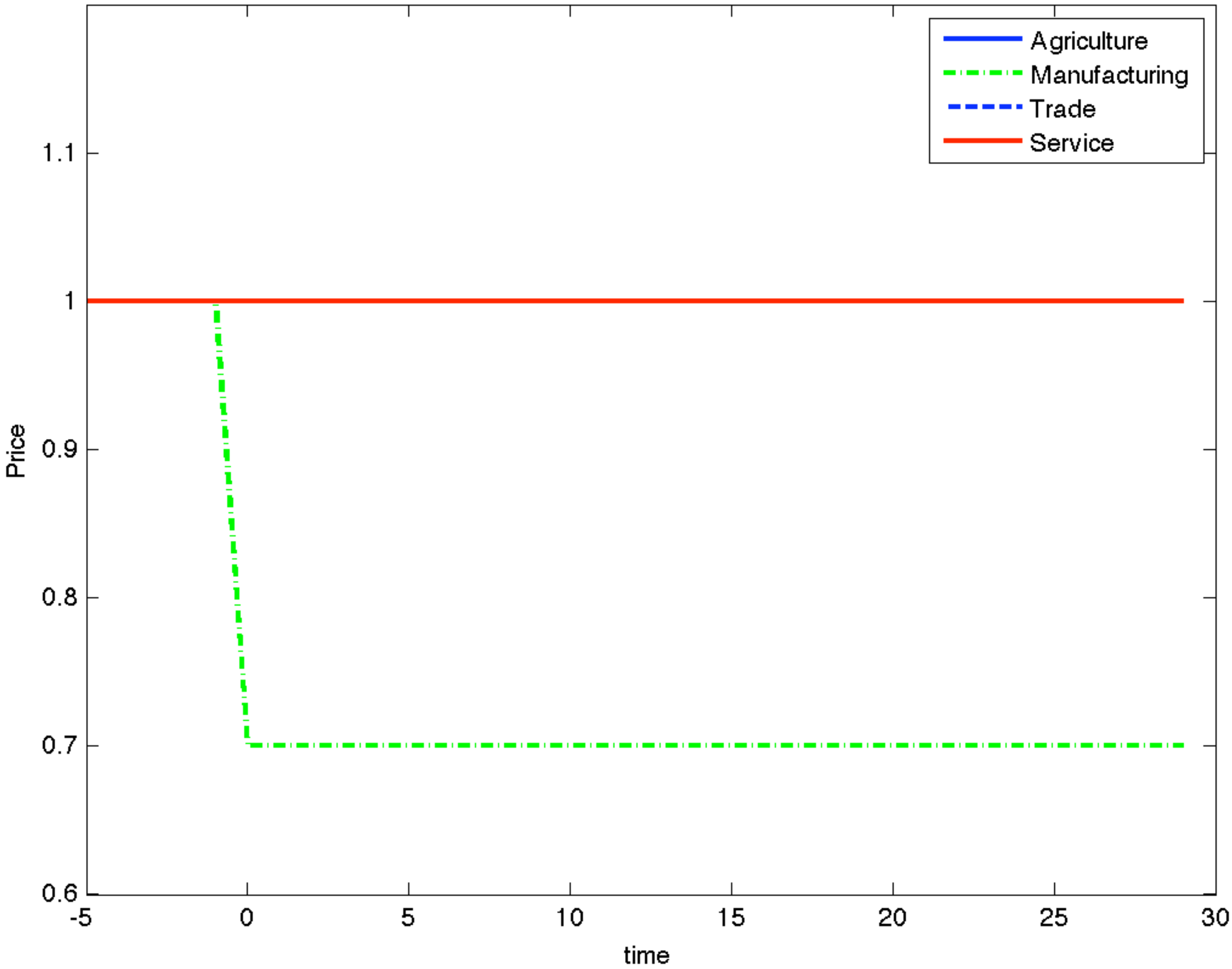


Figure 11: Labor Allocation (β=0.97)

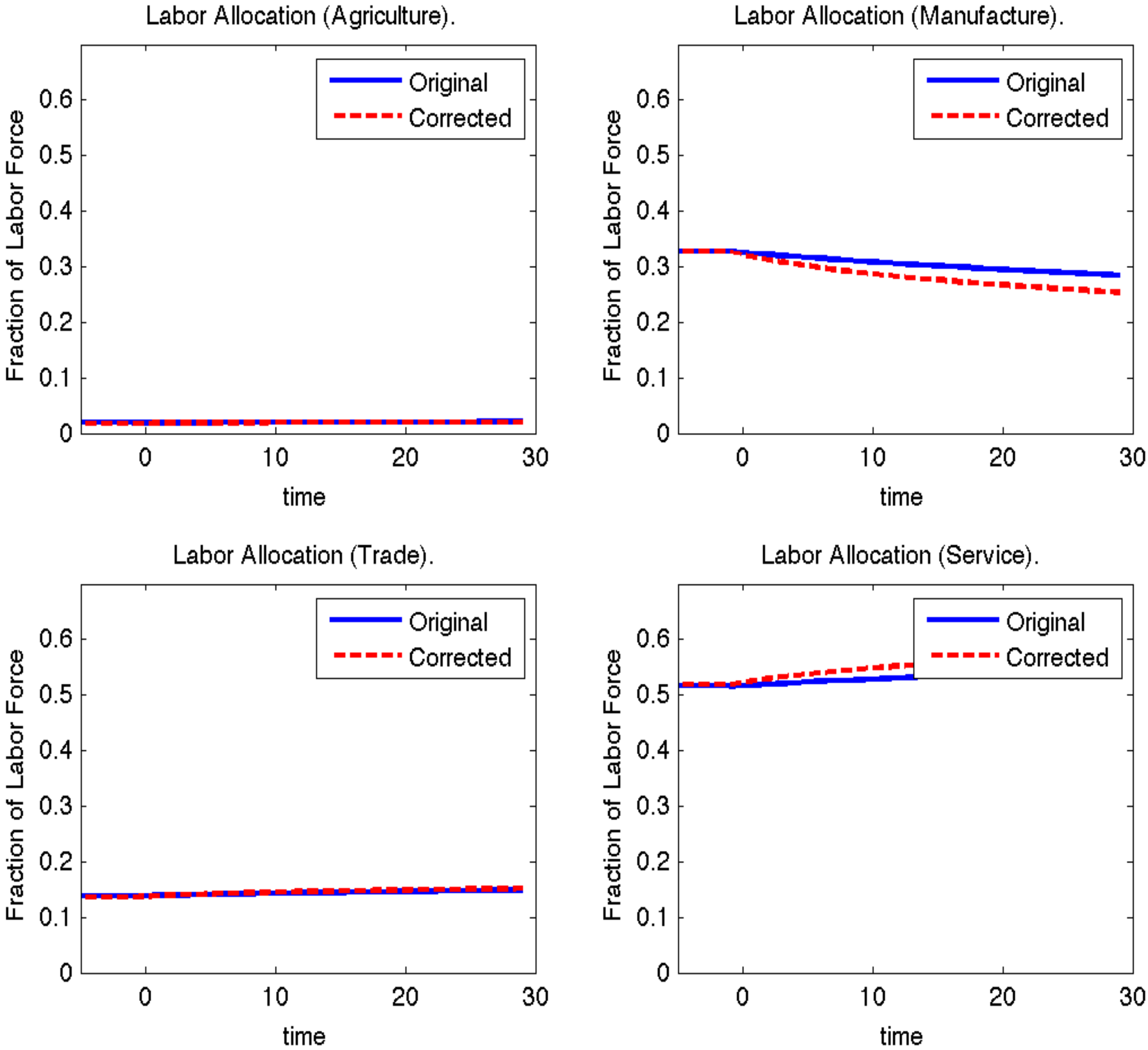


Figure 12: Wages (β=0.97)

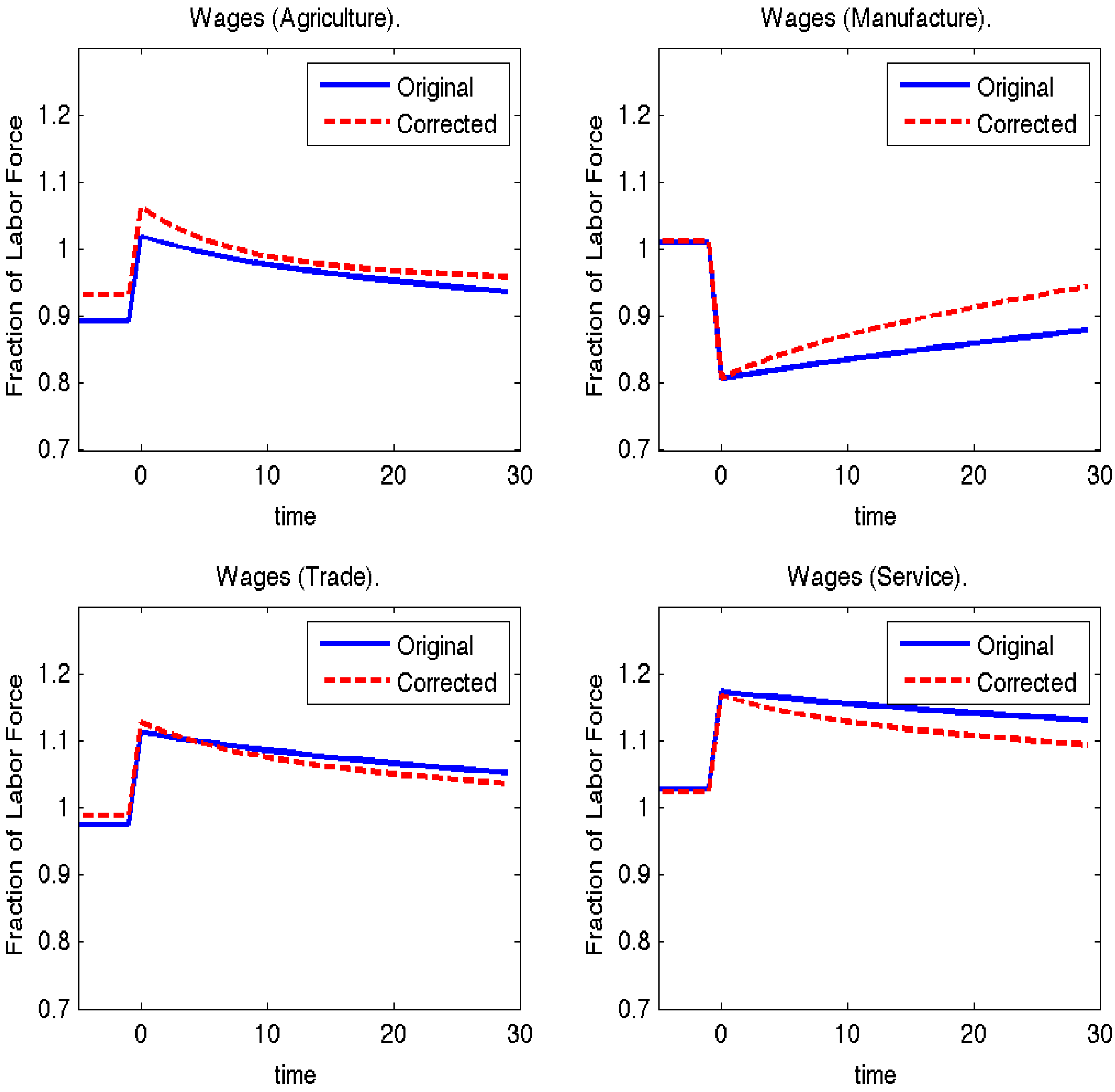


Figure 13: Values (β=0.97)

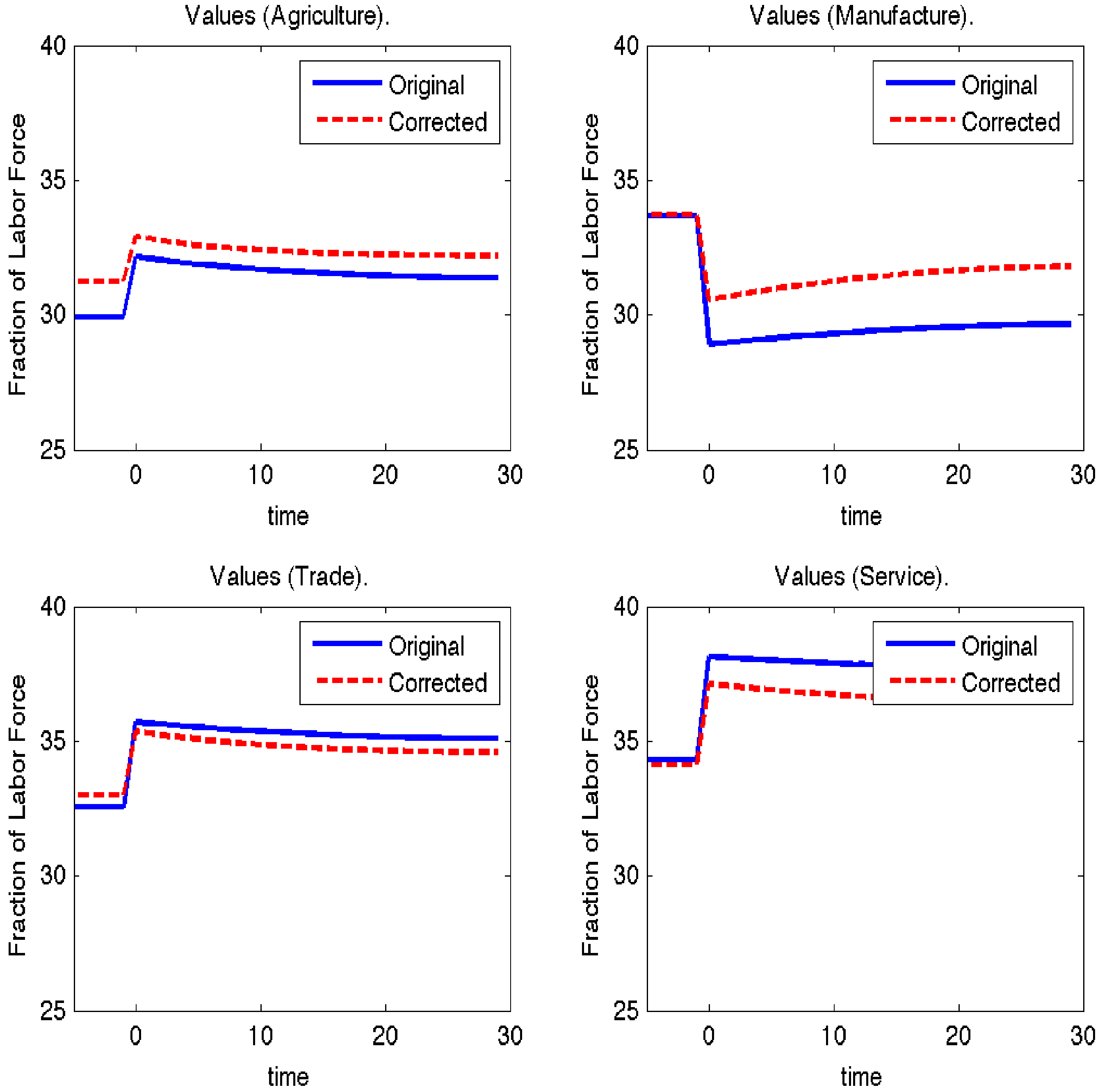


Figure 14: Labor Adjustment (β=0.90)

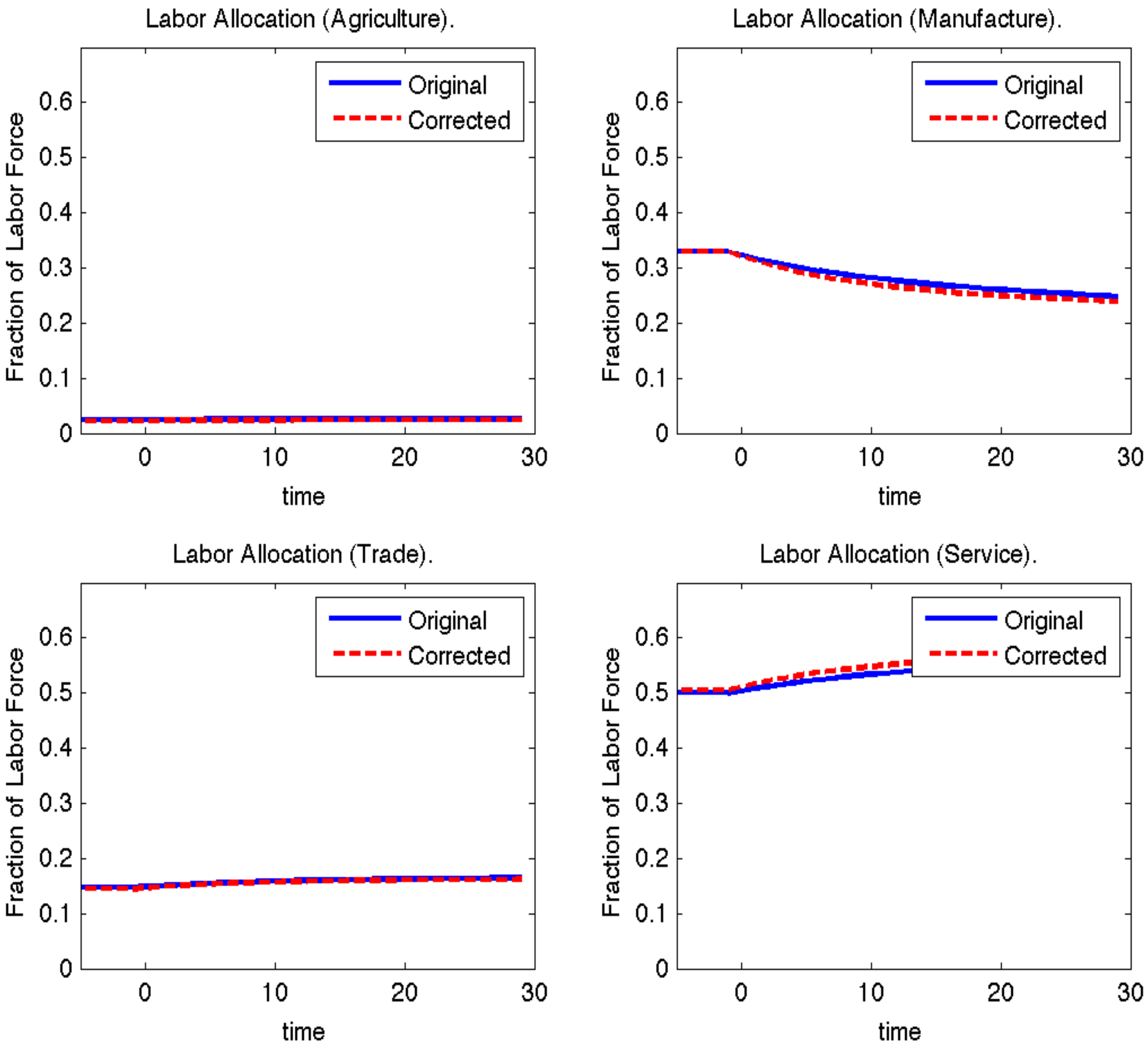


Figure 15: Wages (β=0.90)

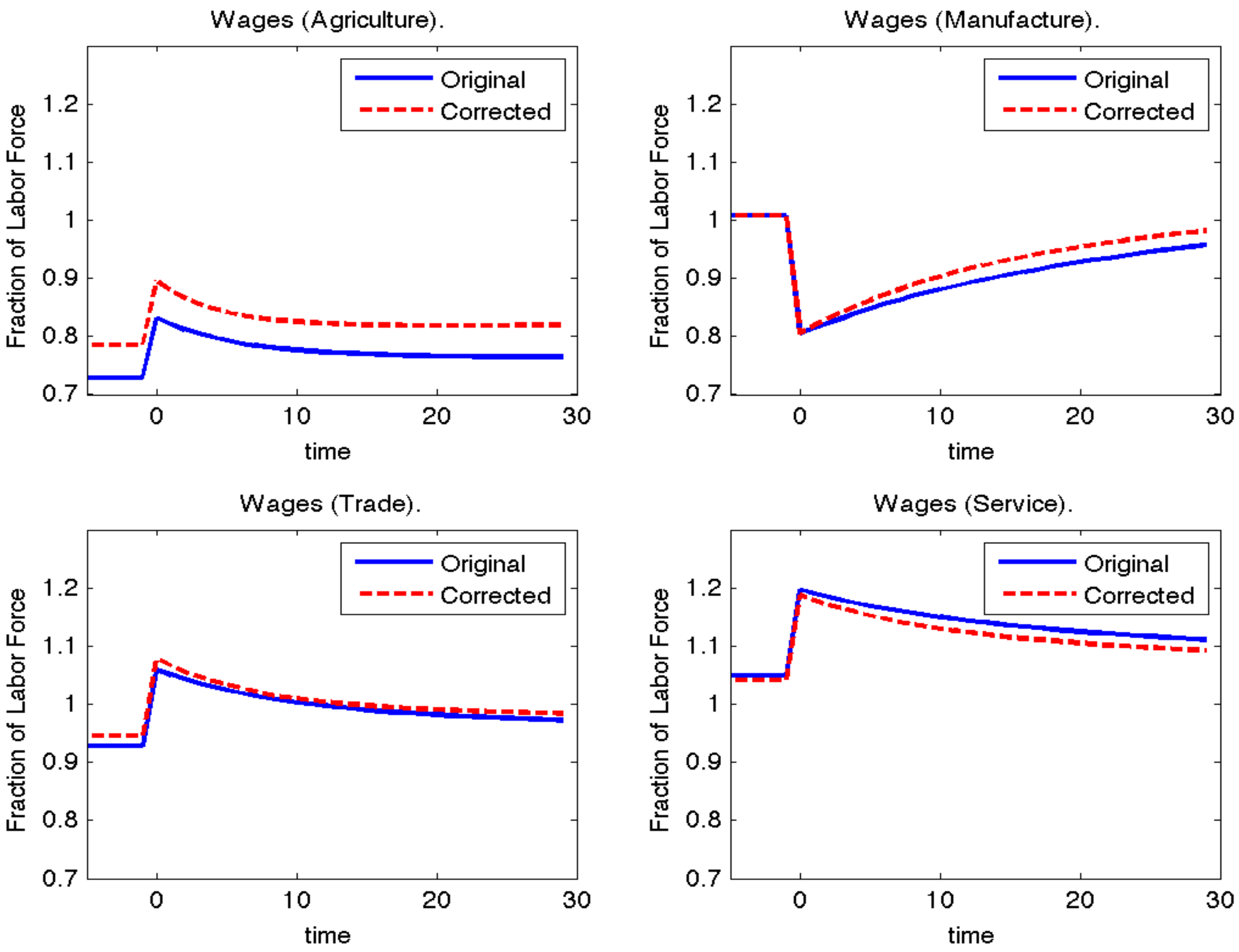


Figure 16: Values (β=0.90)