A Structural Empirical Approach to Trade Shocks and Labor Adjustment: Euler-Equation versus Maximum Likelihood Based Estimators. *

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Abstract

Artuc, Chauhuri and McLaren (forthcoming) propose a new Euler-equation based method for estimating labor mobility to study welfare effects of trade liberalization. In this paper, we compare their method with a more conventional maximum likelihood based estimator to illustrate pros and cons of both methods using simulated data. We find that maximum likelihood based estimator is more efficient but requires value functions to be calculated accurately. However, it is not possible to calculate value functions accurately when sample is short or if future values fluctuate because of an expected policy change or an aggregate shock. The new Euler-equation based method, although less efficient, does not require calculation of value functions and is more reliable. We also show that qualitative results of policy simulations are very robust under different estimation scenarios.

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One of the main concerns of policy makers is to understand how import competing sector workers are affected from trade liberalization. It is very useful to know how much exporting sector workers will benefit and how much import competing sector workers will be hurt, so that it may be possible to design policies that will be popular among workers. If policy makers know how mobile workers are, they can predict how quickly workers will find new jobs in other sectors if they lose their current jobs. The cost of switching sectors directly affect how the gains from trade are distributed. Also when there is a large scale public sector downsizing, mobility cost of workers will affect how much workers, who lose their jobs, will be hurt after the new policy.

A new method was recently introduced 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, forthcoming). 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.

To implement this method, it is possible to estimate parameters of the model using maximum likelihood as an alternative to the Euler equation type equilibrium condition. Artuc (2009) develops a model based on Cameron, Chaudhuri, and McLaren (2007) but uses a very different maximum likelihood based estimation strategy, similar to the structural discrete choice models in labor economics literature, such as Keane and Wolpin (1994). The main advantage of maximum likelihood over Euler-equation approach is its flexibility to allow a richer treatment of worker heterogeneity and its efficiency (smaller standard errors when sample size is small). However, maximum likelihood based methods are more computation intensive and require calculation of future value functions accurately. In order to calculate value functions accurately, the econometrician needs long time series, especially if sector specific value functions fluctuate over time because of economic instability or substantial policy changes. This requirement of value function calculation prevents maximum likelihood based methods from being useful for transition and developing economies, where detailed and long labor force surveys are usually unavailable, or data is contaminated with frequent aggregate shocks.

Euler-equation approach does not require calculation of future value functions, therefore it is robust to introduction of any type of aggregate shocks in the data without strict assumptions about value functions. Thus the methods developed by Cameron, Chaudhuri, and McLaren (2007), Chaudhuri and McLaren (2007) and Artuç, Chaudhuri and McLaren (2007, 2008, forthcoming) can be easily applied to developing countries. Artuc and McLaren (2009) demonstrate this technique on a data set from Turkey. In particular, they 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. They thus show that a well-grounded analysis of the dynamic response to trade shocks can be accomplished quite easily, without much computer power and with very modest data.

In this paper we show how the Euler-equation and maximum likelihood based methods perform using different sub-samples from a simulated data set. Although we do not perform any rigorous econometric tests to compare these two methods, we hope that the example estimations provided in this paper will shed some more light on strengths and shortcomings of these methods. We pick underlying structural parameters to simulate a 200 year long data set. Then we draw sub-samples from this data set, from different years and of different lengths and sizes. Then we estimate the structural parameters from these sub-samples using maximum likelihood and Euler equation based methods. Finally we simulate a trade policy shock using different estimates to check whether the simulation results are robust to different estimation methods using different sub-samples.

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.[1] 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

[1]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.

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,[2] 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 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.[3]

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,

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

[3] 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.

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 $\varepsilon^i_{l,t} - \varepsilon^j_{l,t} + C^{ij}$. The worker knows the values of the $\varepsilon^i_{l,t}$ for all i before making the period-t moving decision.[4] 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.

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^i_t. 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^i_t 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

[4]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 $\varepsilon^j_{l,t}$ in whichever sector j she has landed.

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:[5]

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

where:

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

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:

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

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

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

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

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, $\Omega(\bar{\varepsilon}_t^i)$, derived from having the option to move to another industry should prospects there look better (and which is simply equal to the expectation of $\max_j\{\varepsilon^j + \bar{\varepsilon}_t^{ij}\}$ 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 $\bar{\varepsilon}_t^{ii} \equiv 0$, this is always positive.

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

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

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

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.

1.3 The estimating equations.

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.[6] 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.

Euler-Equation Approach

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 $(\ln m_t^{ij} - \ln m_t^{ii})$) 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

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

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 $C^{ij} = C \forall i, j$.

Maximum Likelihood Approach

Another, more conventional, way of estimating the model is using maximum likelihood. Under the given distributional assumptions, the maximum likelihood estimator is called "Logit" estimator.

The gross flow of workers from i to j at date t, m_t^{ij}, is equal to the probability that a given i-worker will switch to j at date t, or the probability that, for an i-worker, utility $w_t^i + \varepsilon_t^j + \beta E_t[V^j(L_{t+1}, s_{t+1})] - C^{ij}$ will be higher for a move to j than for any of the other $n-1$ options. In other words, from (2),

$$m_t^{ij} = Prob_{\varepsilon_t}\left[\overline{\varepsilon}_t^{ij} + \varepsilon_t^j \geq \overline{\varepsilon}_t^{ik} + \varepsilon_t^k \text{ for } k = 1, \ldots, n\right].$$

Suppressing the time subscript, this can be written:

$$m^{ij} = \int_{-\infty}^{\infty} f(\varepsilon^j) \prod_{k \neq j} F(\varepsilon^j + \overline{\varepsilon}^{ij} - \overline{\varepsilon}^{ik}) d\varepsilon^j.$$

To get logit equation we simply follow steps in the appendix of Artuc Chaudhuri and McLaren (forthcoming). Probability of a worker moving from i to j is expressed as

$$m^{ij} = \frac{\exp(\overline{\varepsilon}^{ij}/\nu)}{\sum_{k=1}^{n} \exp(\overline{\varepsilon}^{ik}/\nu)}.$$

Then maximum likelihood contribution of the worker k who is in sector d_t^k at time t and in sector d_{t+1}^k at time $t+1$ is $m^{d_t^k d_{t+1}^k}$ and the maximum likelihood estimator is

$$\Lambda = argmin \sum_{k=1}^{K} \sum_{t=1}^{T} \log m^{d_t^n d_{t+1}^n},$$

where Λ is the vector of parameters to be estimated such as ν and C^{ij} and K is the total number of workers in data.

2 Simulated Data.

We simulate a data set of 200 years and 6 sectors using exogenous aggregate wage series. The sectors are 1. Agriculture and Mining; 2. Construction; 3. Manufacturing; 4. Transportation, Communication, and Utilities; 5. Trade; and 6. All Other Services including government. We use average wages from Current Population Survey normalized to one similar to Artuc Chaudhuri and McLaren (forthcoming). We add mean zero normally distributed shocks with standard deviation 0.25 to wages, thus we end up with 200x6 normally distributed aggregate wage observations. Finally we allow a time trend for Service wages so that Service wages double by the end of 200 years, which is an average 0.5% real increase per year.

After simulating exogenous wages we calculate value function as given by (3) with structural parameters taken from Artuc Chaudhuri and McLaren's (forthcoming) basic model, where $\beta = 0.97$, $\nu = 1.8$ and $C^{ij} \equiv C = 0.65, \forall i \neq j$. However for the last year ($T = 200$), we assume that values are equal to wages

$$V^i(L_T, s_T) = w_T^i. \tag{10}$$

Thus one needs to start from year $T = 200$ and go backwards recursively in order to calculate value functions accurately. If one starts from a previous year such as $t = 199$, it is not be possible to calculate value functions correctly and the results can be unreliable if one uses a maximum likelihood based method. However, with the Euler-equation based method one can pick any time interval since it does not rely on calculation of values.

3 Results.

Table 1 shows the results from the basic regressions with different sub-samples via Euler-equation and maximum likelihood approaches. We should point out that we do not attempt to estimate β. The 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 and requires very long time series especially with the Euler-equation approach. 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.

The first two columns report results for the Euler-equation method, and the last two report results for the maximum likelihood method. The first row, "I. Actual parameters used in simulations," show the underlying structural parameters used to generate simulated data.

The second row, "II. Last 30 years," provides estimates from a subsample taken between year 171 and 200. In particular we picked an average of 1000 individuals observations per sector per year, thus ended up with 1000x6x30=180,000 observations total. Note that for this subsample value functions can be calculated precisely since for the last year (T=200) $V_T^i = w_T^i$. Thus there is no need to know the value function for t=201, and actually it does not exist. For this sub-sample the maximum-likelihood based method performs extremely well, the parameters are estimated precisely with very tight confidence intervals (it is very efficient). The Euler-equation based method also does a satisfactory job but has much larger standard errors.

The third row, "III. Last 30 year excluding t=200," shows estimates from a sub-sample drawn between years 171 and 199. everything else is the same as the previous case. The

Table 1: Comparison of Estimation Results with Simulated Data.

Euler-Equation Approach.		*Max. Likelihood Approach.*	
I. Actual parameters used in simulations			
ν	C	ν	C
1.800	6.500	1.800	6.500
II. Last 30 years.			
ν	C	ν	C
1.697 (15.6***)	6.853 (3.0***)	1.803 (55.2***)	6.515 (43.8***)
III. Last 30 years excluding t=200.			
ν	C	ν	C
1.685 (15.3***)	6.514 (2.7***)	1.653 (54.4***)	6.047 (43.3***)
IV. Last 5 years.			
ν	C	ν	C
2.062 (2.6***)	12.549 (1.3***)	1.731 (29.5***)	6.217 (23.7***)
V. Mid 30 years.			
ν	C	ν	C
1.813 (9.0**)	6.668 (4.1**)	1.558 (93.0**)	5.699 (76.6**)
VI. Mid 5 years.			
ν	C	ν	C
1.774 (3.5**)	4.995 (0.9**)	0.654 (47.2***)	2.479 (38.7***)
VII. Mid 30 years with small sample.			
ν	C	ν	C
1.921 (4.4***)	3.244 (0.8**)	1.426 (28.9***)	5.128 (23.7***)
VIII. Mid 5 years with small sample.			
ν	C	ν	C
3.700 (0.5***)	-27.20 (-0.3***)	0.655 (14.7***)	2.490 (11.9***)

(T-statistics are in parentheses.

One-tailed significance: 1-percent***, 5-percent**, 10-percent*.)

estimates show that now the maximum-likelihood approach is probably slightly biased. The true values of parameters are outside of 95-percent confidence intervals. The estimates are biased because now it is not possible to calculate value functions accurately and there is no information available to the econometrician about year t=200. The Euler-equation based method performs just as well as the previous case, and it is probably unbiased.

The fourth row, ”IV. Last 5 years,” shows estimates from a sub-sample drawn from the last 5 years. There is again an average of 1000 individual observations per sector per year. Now the maximum likelihood method performs better with much tighter confidence intervals compared to the Euler-equation method.

The fifth row, ”V. Mid 30 years,” shows estimates using a sub-sample between t=71 and t=100. (Needless to say that everything else is same as case II.) Now value functions can not be calculated accurately, similar to case III, and the maximum likelihood method performs poorly compared to the Euler-equation method. Although the confidence interval of maximum likelihood method is tight, it is very obvious that the estimates are biased. The sixth case, ”VI. Mid 5 years,” is very similar but this time estimates are insignificant with the Euler-equation method (but there is no evidence of a bias), and seems terribly biased with the MLE method. Note that MLE method performs better with longer time series not only because of more available observations but also because value functions can be calculated more accurately.

The seventh and ninth cases are very similar to fifth and sixth cases, but this time we have an average of 100 observations per sector per year. Now the aggregate mobility matrices that are used in the Euler-equation method is contaminated with empty cells, and it fails to get reasonable estimates. In the ninth case we find a negative and very large moving cost. This shows that it is not possible to analyze small sectors with the Euler-equation method (such as the metal manufacturing sector studied in Artuc (2009)).

We re-estimate models presented in Artuc and McLaren (2009) (which uses Turkish data) and Artuc Chaudhuri and McLaren (forthcoming) (which uses US data) using maximum likelihood, i.e. ”Logit”. The results are presented in Table 2. We find that for the US data

Table 2: Comparison of Estimation Results with Real Data.

β=0.97.		β=0.90.	
I. US Data with Euler-Eq. Approach			
ν	C	ν	C
1.884 (3.846***)	6.565 (3.381***)	1.217 (5.700***)	4.703 (5.626***)
II. US Data with MLE Approach.			
ν	C	ν	C
1.69 (53.9***)	6.579 (52.6***)	1.182 (54.5***)	4.601 (53.4***)
III. Turkish Data with Euler-Eq. Approach.			
ν	C	ν	C
2.56 (3.5***)	22.89 (3.2***)	1.62 (5.4***)	9.5 (5.4***)
IV. Turkish Data with MLE Approach.			
ν	C	ν	C
0.731 (29.2***)	3.372 (29.6***)	0.657 (29.4***)	3.031 (29.7***)

(T-statistics are in parentheses.

One-tailed significance: 1-percent***, 5-percent**, 10-percent*.)

using MLE or Euler-equation estimation does not really matter, both results are very similar. (Needless to say that Euler-equation method is less efficient because of aggregation). But for the Turkish data the results are very different. This is difference might be partially due to lack of availability of instruments because of short sample size for the Euler equation method. But taking Table 1 seriously one should avoid using MLE when the sample is short. This is especially more relevant for countries like Turkey since value functions might fluctuate more sharply as Turkish economy is not as stable as the US economy.

4 Simulation: A Sudden Trade Liberalization.

After estimating the model presented in the previous sections, the estimates are used to study the effect of a hypothetical trade shock through simulations. In this paper, we use different estimates from Table 1 to illustrate effects of using different sub-samples and methods on simulation results.

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:

$$y_t^i = \psi^i \left(\alpha^i (L_t^i)^{\rho^i} + (1-\alpha^i)(K^i)^{\rho^i} \right)^{\frac{1}{\rho^i}}, \tag{11}$$

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

$$w_t^i = p_t^i \alpha^i \psi^i (L_t^i)^{\rho^i - 1} \left(\alpha^i (L_t^i)^{\rho^i} + (1-\alpha^i) \right)^{\frac{1-\rho^i}{\rho^i}}, \tag{12}$$

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 α^i, ρ^i, and ψ^i to minimize a loss function given our assumptions on prices. 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 (12) and (11) 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 values for calibration are taken directly from Artuc Chaudhuri and McLaren (forthcoming), see their paper for details.

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 (12) 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.

For the simulations we picked case VI (mid 5 years) and case VII (mid 30 years with small sample) estimates as they look very different from the true values of the structural parameters presented in case I (benchmark).

The simulation output is plotted in the Figures. Figures 1 and 2 show the time path of the allocation of workers in the manufacturing and service sectors. We find that small sample MLE performs better than the others and small sample Euler-Eq. approach seems particularly inferior. Figures 3 and 4 show adjustment of wages in manufacturing and service sectors while Figures 5 and 6 show changes in welfare in those two sectors, after the trade shock. Similar to the adjustment of wages small sample MLE performs slightly better, and small sample Euler-equation method performs the worst. Short sample Euler equation approach seems to perform relatively good. This case is particularly important for application of this method to developing countries. Although the numbers used in simulations look different the qualitative implications are very robust. Please note that we particularly picked cases which looked different from the true parameters. If we had picked case V (mid 30 years) and plotted the figures for the Euler-Equation method, they would be indistinguishable from the benchmark case.

5 Conclusion.

We find that maximum likelihood estimators are more efficient compared to the Euler-equation based method introduced in Artuc Chaudhuri McLaren (forthcoming), however they might be biased if the value functions are not calculated accurately. Calculating value functions accurately may not be possible if the data set is short or if there are aggregate shocks. The Euler-equation based method perform very well as long as there are enough observations per sector, so it is more reliable to use with developing country data which are usually short and possibly more contaminated with aggregate shocks. We also showed that although the estimated values are different with alternative sub-samples, the qualitative results of the simulations are robust.

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Figure 1: Manufacturing – Labor Allocation

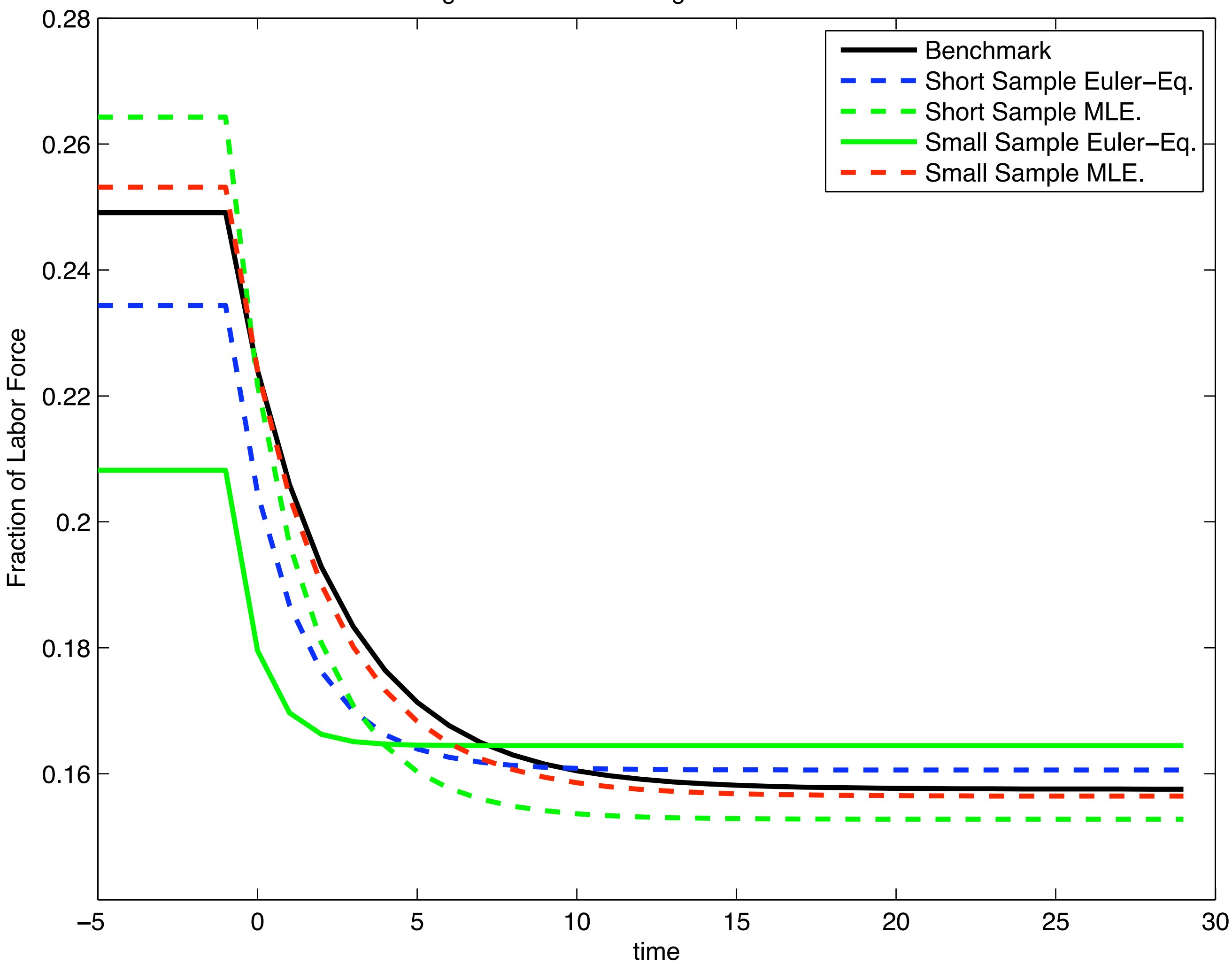
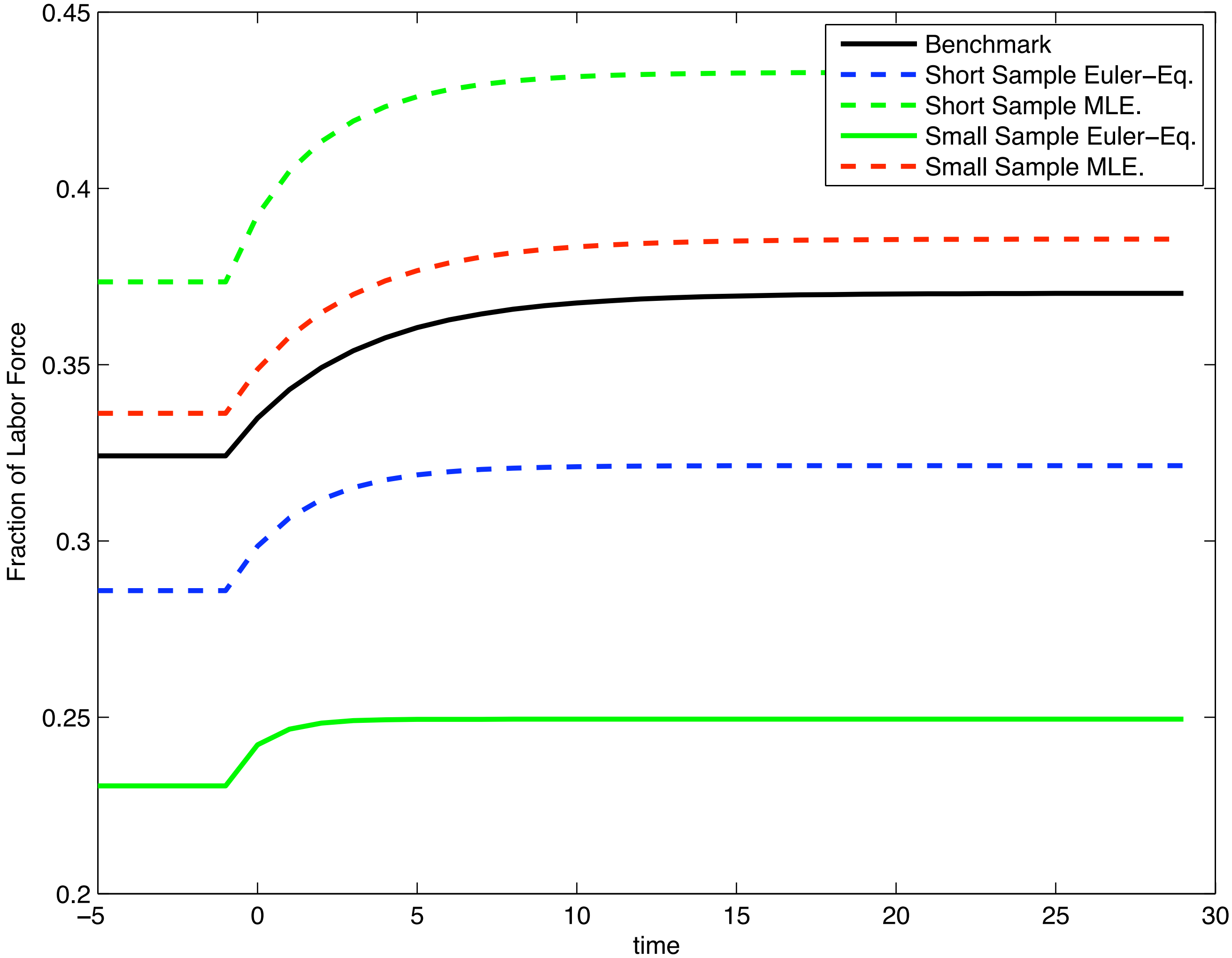


Figure 2: Service − Labor Allocation



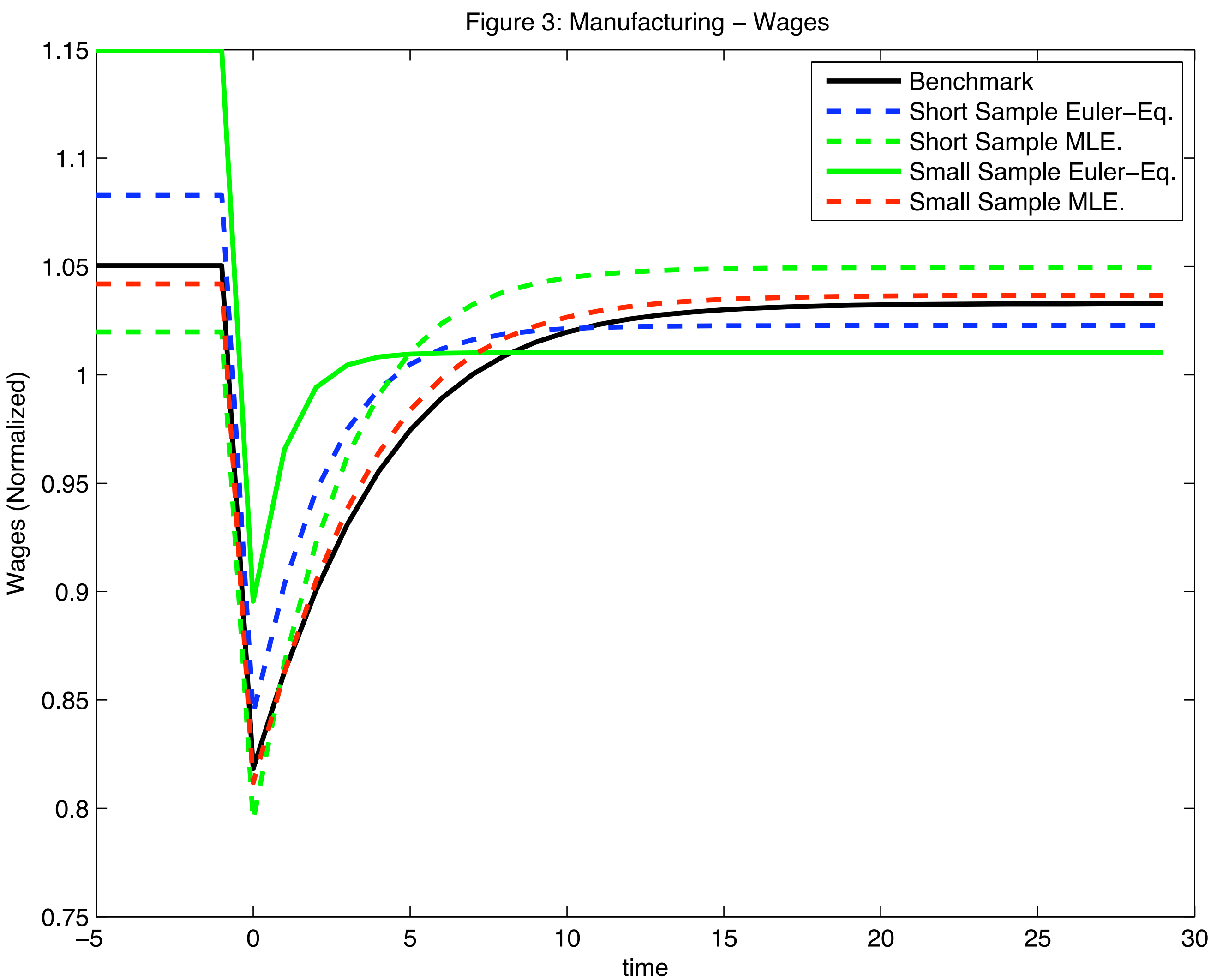


Figure 3: Manufacturing – Wages
Benchmark
Short Sample Euler–Eq.
Short Sample MLE.
Small Sample Euler–Eq.
Small Sample MLE.
Wages (Normalized)
time
1.15
1.1
1.05
1
0.95
0.9
0.85
0.8
0.75
–5
0
5
10
15
20
25
30

Figure 4: Service – Wages

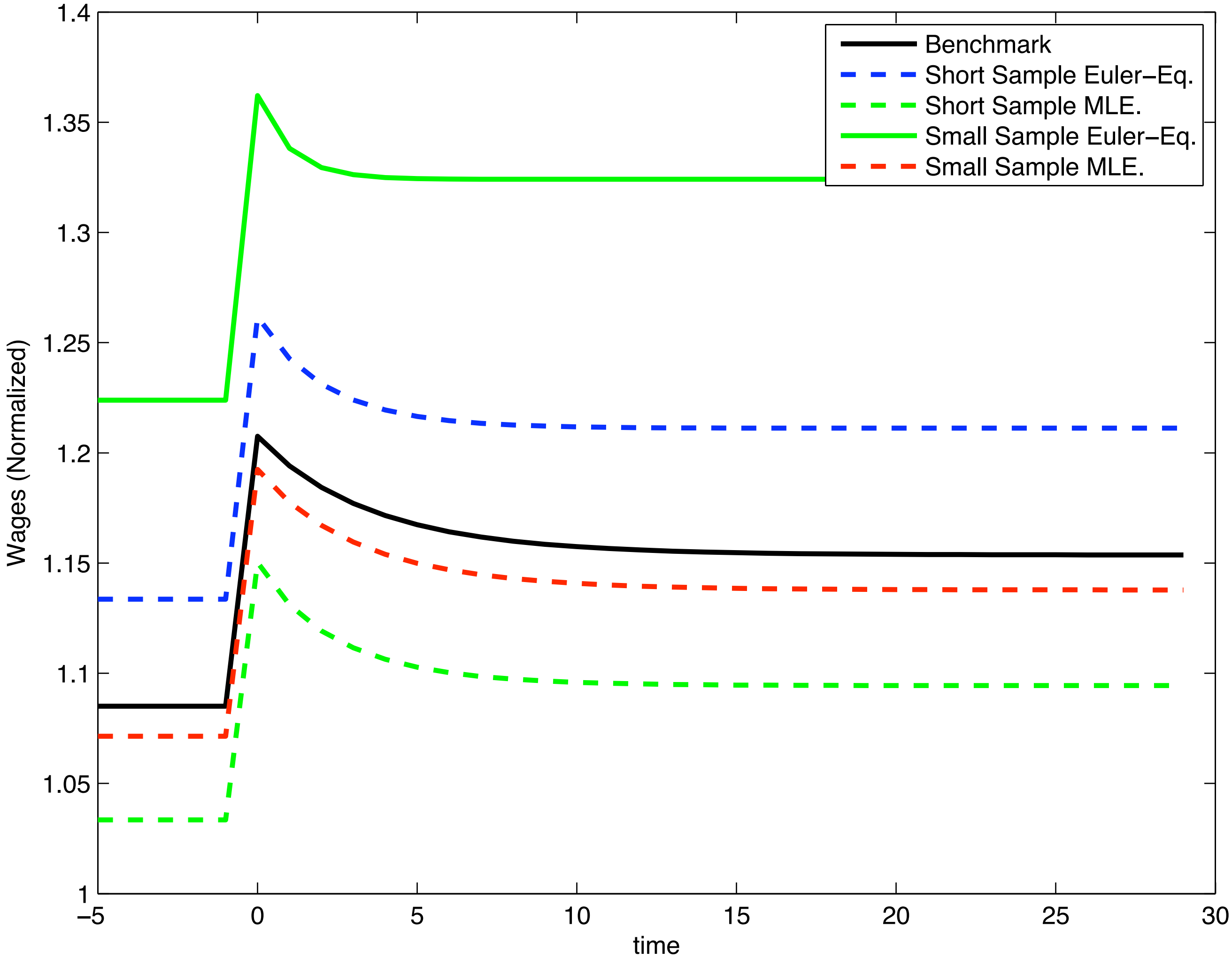


Figure 5: Manufacturing – Change in Welfare

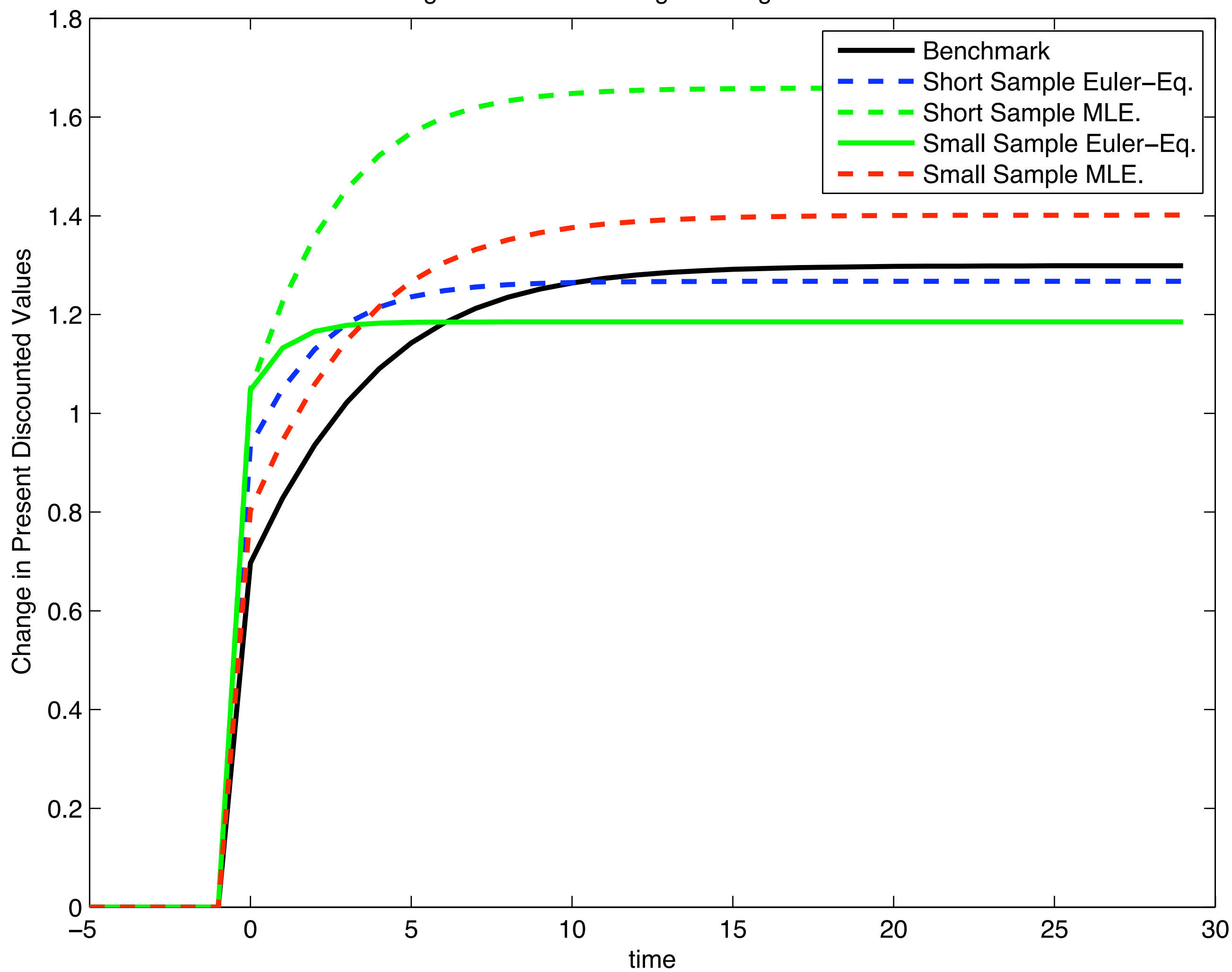


Figure 6: Service – Change in Welfare