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

Erhan Artuç (World Bank) and John McLaren (University of Virginia).

July 20, 2013

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 also specify a novel model of offshoring based on task-by-task comparative advantage that collapses to a very simple form for simulation. We find that the costs of switching industry and occupation are both high, and of similar magnitude. 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, but occupation is crucial in determining who is harmed by an *offshoring* shock.

---

*The views in this paper are the authors' and not those of the World Bank Group or any other institution. McLaren: Department of Economics, University of Virginia, P.O. Box 400182, Charlottesville, VA 22904-4182; jmclaren@virginia.edu. Artuç: World Bank, Development Economics Research Group, 1818 H Street, NW Washington DC, 20433 USA; eartuc@worldbank.org. We are grateful for the financial support of the Scientific and Technological Research Council of Turkey (TUBITAK), Turkish Academy of Sciences (TUBA), and the Bankard Fund for Political Economy at the University of Virginia. We thank seminar participants at the University of Cambridge, Johns Hopkins University (SAIS), Sabanci University, the London School of Economics, University of Oxford, GWU-WAITS, the University of Nottingham, the University of Dundee, the University of Bayreuth, the University of Erlangen-Nuremberg, Penn State and Clemson for helpful comments. Special thanks go to Steven Stern.

> *Matthew Crawford got a PhD in Political Philosophy from the University of Chicago. Then he abandoned academia after a year, abandoned a Washington DC think-tank job after five months, and opened a one-man motorcycle repair shop. He thinks more now than when he worked at think-tank. He's part of a vibrant, intuitive, well-educated community. He's proud of his work, which matters deeply to his customers. His decisions aren't arbitrarily changed by a superior. His job won't suddenly be shipped to India. Of course, most people assume fixing motorcycles was the only job he could get.*

Business Insider, May 24, 2009.

Among the key questions trade economists need to be able to answer is: When a trade shock strikes such as liberalization, trade agreement, expansion of a foreign export power, or the rise of offshoring, 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 (2012)), 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 data from the US Department of Labor that breaks down the 'task' composition of a wide range of occupations in US labor data (the Dictionary of Occupational Titles data or the O*NET data; see Autor, Levy, and Murnane (2003), for example). Authors who exploit these distinctions to look at the differential effects of trade shocks on workers with different types of occupations include Autor and Acemoglu (2011), Ritter (2009), 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, with two innovations. (i) 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.

(ii) We integrate this dynamic structural estimation with a novel specification of the labor-market equilibrium with offshoring, which incorporates features of models by Grossman and Rossi-Hansberg (2008), Autor and Acemoglu (2011), and Eaton and Kortum (2002) and which conveniently allows us to represent a fairly complex labor-market equilibrium as the simple minimization of cost with a CES production function. We use this specification to study the effect of a trade liberalization shock and also a drop in the cost of offshoring jobs, showing that the effects on income distribution are very different, in ways that can be understood only with a dynamic model.

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 is a crucial determinant. Further, it is by no means a given that an industry-level shock such as a trade liberalization will affect workers according to their industry of employment, or that an occupation-level shock such as a rise in offshoring of a particular occupation will affect workers according to their occupation. These outcomes depend crucially on the relative costs of switching industry and switching occupation, which is an empirical matter, and is what we have set out to estimate.

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. Finally, from the simulations, we find: (i) 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. (ii) By stark contrast, who benefits from an *offhshoring shock* in an industry turns crucially on occupation within that industry, and although the shock directly affects only a narrow class of workers in manufacturing, the dynamic general equilibrium welfare effects harm most less-educated workers and benefit most college-educated workers.

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 for some workers and to higher-wage occupations for others. Crucially, if one allows for unobserved heterogeneity in worker productivity the welfare losses to a worker from a trade-induced downward occupational switch are greatly diminished. 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.

In addition, we are adding to the developing literature on dynamic general-equilibrium adjustment to trade shocks. Cosar (2010) studies a model with costly adjustment due to search frictions, calibrated to Brazilian data, and Ritter (2009) calibrates a model to US data that has both search frictions and occupation-specific human capital, which serves as a cost to switching occupation. Dix-Carneiro (2011) estimates a structural model of dynamic labor-market response with costly adjustment and sector-specific human capital, again using Brazilian data. Each of these studies pursues similar themes but emphasizes different aspects of adjustment. Mitra and Ranjan (2010) study the income-distribution and employment effects of offshoring in a model with both search frictions and idiosyncratic moving costs.

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 z in skill class s spends period t working in occupation k in sector i, her instantaneous utility is $w_t^{iks} + \eta_t^{iks} + \epsilon_t^{zik}$, where ϵ_t^{zik} 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 a preference term reflecting 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 the ϵ_t^{zik} as the 'idiosyncratic shock.' The η_t^{iks} term is non-stochastic, but we will allow it to vary over time in a way understood by all and which we will discuss later. 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 $C(i,k,j,l,s)$, where i and k are the worker's initial sector and occupation, and j and l are her final sector and occupation. If a worker does not change her sector or occupation then the moving cost is equal to zero, so $C(i,k,i,k,s) = 0$. 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 make the model impossible to estimate. We will therefore need to parameterize the moving cost function somehow, and we will show later on how we do this.

1.1 Equilibrium relationships.

The optimization problem for worker z can be summarized by the following Bellman equation, in which $U_t^{iks}(\epsilon_t^z)$ 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 idiosyncratic shocks, ϵ_t^z, i.e. $V_t^{iks} = E_\varepsilon U_t^{iks}$.

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

[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).

Taking expectations with respect to all shocks, this yields:

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

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:

$$m_t^{ikjls} = \frac{exp\left[\frac{1}{\nu}\left(\beta E_t\left(V_{t+1}^{jls} - V_{t+1}^{iks}\right) - C_t(i,k,j,l,s)\right)\right]}{\Sigma_{j'=1\ldots I, l'=1\ldots K} exp\left[\frac{1}{\nu}\left(\beta E_t\left(V_{t+1}^{j'l's} - V_{t+1}^{iks}\right) - C_t(i,k,j',l',s)\right)\right]}, \tag{2}$$

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, (2) 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 (2013) and summarized in the Appendix. We need to estimate the parameters of the moving costs, C_t^{ikjls}, as well as the idiosyncratic variance parameter ν. In addition, we need to estimate the non-stochastic common preference parameter η_t^{iks}. We do this in two stages, using the two equations discussed above, the gross-flows equation (2) and the Bellman equation (1).

First stage. The first stage uses (2) with data on actual gross flows to estimate value differences and the moving cost function normalized with ν. Multiplying both sides of equation (2) by L_t^{iks} and gathering together the terms that depend only on the origin cell (i, k) and terms that depend only on the destination cell (j, l), the equation can be represented in a form that can be estimated as follows:

$$y_t^{ikjls} = exp(\lambda_t^{jls} + \alpha_t^{iks} - C_t(i, k.j, l, s)/\nu) + \xi_t^{ikjls}, \tag{3}$$

where y_t^{ikjls} is the measured number of type s workers switching from cell (ik) to cell (jl), λ_t^{jls} is a destination fixed effect, α_t^{iks} is an origin fixed effect, $C_t(i, k.j, l, s)/\nu$ is the moving cost parameter, and ξ_t^{ikjls} is an error term that arises from sampling error, since we compute y_t^{ikjls} from a finite sample. (Put slightly differently, $y_t^{ikjls} = L_t^{iks} m_t^{ikjls} + \xi_t^{ikjls}$: Measured flows equal actual flows plus sampling error.) Note that the λ_t^{jls} and α_t^{iks} terms are not separately identified, so without loss of generality we set $\lambda_t^{11s} = 0$, which is equivalent to defining the destination fixed effects as:

$$\lambda_t^{jls} = \frac{\beta}{\nu} E_t V_{t+1}^{jls} - \frac{\beta}{\nu} E_t V_{t+1}^{11s},$$

and the origin fixed effects as:[2]

$$\begin{aligned} \alpha_t^{iks} &= -\frac{\beta}{\nu} E_t V_{t+1}^{iks} + \log(L_t^{iks}) + \frac{\beta}{\nu} E_t V_{t+1}^{11s} \\ &- \log \Sigma_{j'=1\ldots I, l'=1\ldots K} exp \left[\frac{1}{\nu} \left(\beta E_t \left(V_{t+1}^{j'l's} - V_{t+1}^{iks} \right) - C_t(i, k, j', l', s) \right) \right], \\ &= -\frac{\beta}{\nu} E_t V_{t+1}^{iks} - \frac{1}{\nu} \Omega_t^{iks} + \log(L_t^{iks}) + \frac{\beta}{\nu} E_t V_{t+1}^{11s}. \end{aligned}$$

[2]Here we simplify using (2) and the fact that $\Omega_t^{iks} = -\nu \log(m_t^{ikiks})$, which is proven in Appendix A.3 of Artuç et. al. (2007).

This estimation can be done for each year of the data as a separate cross section. This stage is similar in spirit to Hotz and Miller's (1993) method of Conditional Choice Probabilities (CCP), because it allows us to infer continuation values from observed behavior rather than computing a value function, but it is simpler because we are working with observed gross flows and thus do not need to use non-parametric methods to estimate the choice probabilities. Rather, analogously to Santos Silva and Tenreyro (2006), we use Poisson Pseudo Maximum Likelihood (PPML), which is equivalent to assuming that the variance of ξ_t^{ikjls} is proportional to $L_t^{iks} m_t^{ikjls}$ and running non-linear least squares weighted accordingly. This implies that, if we write the estimating equation (3) in the form $y_t^{ikjls} = \exp(x_t^{ikjls}\gamma_t) + \xi_t^{ikjls}$, where x^{ikjls} is a vector of dummy variables and γ_t is the vector of (year-dependent) parameters to be estimated, then we choose the parameters to solve the first-order condition:

$$\sum_{ikjls} \left[y_t^{ikjls} - \exp(x_t^{ikjls}\gamma_t) \right] x_t^{ikjls} = 0.$$

.

These parameters for the first-stage regression can be identified from gross flows alone. To understand how moving costs are identified separately from the value terms in (3) 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 $L_t^{jls} m_t^{jliks}$ and $L_t^{jls} m_t^{jli'k's}$ 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, $L_t^{iks} m_t^{ikiks}$ is large while $L_t^{i'k's} m_t^{i'k'i'k's}$ is small). Equation (2) 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 $C_t(j, l, i', k', s)/\nu$ 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).

Second stage. The second stage rewrites (1) as an estimating equation using estimated values from the first stage, as follows:

$$\phi_t^{iks} = \zeta_t^s + \frac{\beta}{\nu}\eta_{t+1}^{iks} + \frac{\beta}{\nu} w_{t+1}^{iks} + \xi_t^{iks}, \qquad (4)$$

where ϕ_t^{iks} is the dependent variable constructed from Stage 1 estimates as follows:

$$\phi_t^{iks} = \lambda_t^{iks} + \beta\alpha_{t+1}^{iks} - \beta\log(L_{t+1}^{iks}), \tag{5}$$

and ζ_t^s is the time dummy,[3] $\frac{\beta}{\nu}\eta_{t+1}^{iks}$ is the sector-occupation cell preference term to be estimated,[4], w_{t+1}^{iks} is the expected wage taken from the data, and finally ξ_t^{iks} is the regression residual, which we can interpret as a forecast error. See the Appendix for the derivation of these equations.

In (4), right-hand side variables are the data (namely, the wages w_{t+1}^{iks}) or terms to be estimated (the dummies ζ_t^s and the intercept and time trend for the preference parameters $\frac{\beta}{\nu}\eta_{t+1}^{iks}$). The left hand side variable is constructed using the estimates from Stage 1 with (5). The estimated coefficient of the wage term w_{t+1}^{iks} will be equal to β/ν. We estimate (4) as an IV regression, using two-period lagged values of the right-hand-side variables as instruments similar to ACM.

Interpretation. The identification strategy can be understood 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 β/ν of workers to that future profitability; and (ii) the cost of switching relative to the idiosyncratic variance (the $C_t(i, k.j, l, s)/\nu$ terms). But we need to decompose the 'pull' terms into their separate components, the future relative profitability and the responsiveness. Having, then, a panel of such 'pull' estimates and the cost terms, 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 β/ν and complete the estimation. Essentially, if gross flows of workers do not respond very much to future wage differentials, then the observed 'pull' of any given cell will not respond very much to future wage differentials either, and so in (4) a low value of β/ν will be indicated, otherwise a high value.

A qualification that should be noted is that in principle equation (4) can be used to estimate β as well as ν, but in practice it turns out to be difficult to do so. The reason

[3]Note that the time fixed effect captures $\zeta_t^s = \frac{\beta}{\nu}V_{t+1}^{11s} - \frac{\beta^2}{\nu}V_{t+2}^{11s}$.

[4]Specifically, we assume that $\eta_{t+1}^{iks} = \eta_1^{iks} + \eta_2^{iks}t$ so that η's can have an intercept and a time trend.

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.

This completes our description of our estimation method, which is quick and easy to implement even though it is cumbersome to describe. Aside from computational cost, an advantage of this method over a method based on computing the value function for each worker and applying maximum likelihood is that we need to make no assumption about the distribution of aggregate shocks, or about workers' information about future shocks, other than that the workers have rational expectations. A detailed examination of this estimation method in comparison to alternative methods can be found in Artuç (2013).[5]

2 Data.

2.1 Sector and Occupation Categories.

We use the March Current Population Surveys (CPS) from 1976 to 2010 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 5 occupations. The sectors are: 1. Construction; 2. Manufacturing; 3. Non-traded Service; and 4. Traded Service.[6]

Similarly, we need to aggregate occupations. The occupations we use are:

1. *Managerial and Professional* (Census 2000 codes 001 to 354; SOC categories 11, 13, 15, etc. through 29).

[5]The recent developments in this literature regarding estimating unobserved heterogeneity (as in Arcidiacono and Miller (2011)) are, unfortunately, inapplicable to our estimation problem since we do not have panel data.

[6]"Construction" is composed of Census industries 2-3, respectively "Mining" and "Construction." "Manufacturing" is composed of Census industries 4-5, respectively durables and non-durables manufacturing. "Non-tradable services" is composed of Census industries 8, 10, 14, and 16, respectively "Utilities," "Retail Trade," "Entertainment and Recreational Services," and "Public Administration." "Tradable services" is composed of Census industries 6, 7, 9, 11, 12, 13, and 15, respectively "Transportation, Communication, and Other Public Utilities," "Communications," "Wholesale Trade," "Finance, Insurance, and Real Estate," "Business and Repair Services," and "Personal and Related Services," and "Professional Services." We have dropped agricultural workers from the sample because they form a very small subset; in order to use them, we need to lump them in with another group such as mining and construction, which seems unnatural.

2. *Services and Sales* (Census 2000 codes 360 to 496; SOC categories 31, 33, 35, etc., through 41).

3. *Office* (Census 2000 codes 500 to 593; SOC category 43).

4. *Others, such as extraction, construction, repair* (Census 2000 codes 600 to 762 and 900 to 975; SOC categories 45, 47, 49 and 53).

5. *Production* (Census 2000 codes 770 to 896; SOC category 51).

These categories differ greatly in their potential for offshoring. Using a criterion suggested by Blinder (2009) with O*NET data on the types of task required by each occupation, Ritter (2009, Table 3.1) calculates that 87% of production occupations are potentially offshorable, while only between 0% and 40% of occupations in the other categories is so. Accordingly, in our full model, we assume that production work is potentially offshorable but that the work of the other occupational categories is not.

2.2 The Switching-Cost Function.

We can now show how we implement the switching-cost function $C_t(i, k, j, l, s)$ empirically. 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 and make identification of those parameters impossible. Therefore, we need to parameterize the moving cost function somehow. We have attempted to build a specification that is rich but at the same time parsimonious, and have allowed for four types of effect on switching cost that might or might not turn out to be important in the data. First, we allow for the possibility that some industries or occupations are harder to get into than others. This leads us to estimate an 'entry cost' for each sector and for each occupation. Second, we allow for the possibility that the cost of switching both sector and occupation is different from the sum of the cost of switching sector and the cost of switching occupations – that there may be some non-linearity in the cost of joint switching. Finally, we allow for the possibility of a pecking order in occupations such that it may be more costly to switch to occupation j from more similar occupations than from more distant ones.

More precisely, we specify the function as follows:

$$\begin{aligned}
C_t(i,k,j,l,s) &= 0 \text{ if } i=j,\ k=l; && (6)\\
&= C_t^{1,j,s} \text{ if } i \neq j,\ k=l; && (7)\\
&= C_t^{2} + C_t^{3,k,l,s} \text{ if } i=j,\ k \neq l; && (8)\\
&= C_t^{1,j,s} + C_t^{2,l,s} + C_t^{3,k,l,s} + C_t^{4,s} \text{ if } i \neq j,\ k \neq l, && (9)
\end{aligned}$$

where $C_t^{1,j,s}$, $C_t^{2,l,s}$, $C_t^{3,k,l,s}$, and $C_t^{4,s}$ are parameters common to all workers. The interpretation is as follows. First, the value $C_t^{1,j,s}$ is the 'entry cost' mentioned above for switching sectors, and the cost indicated in line (7) applies when the worker switches sectors ($i \neq j$) but not occupations ($k = l$).

Second, for each educational class s, the value C_t^2 is the basic cost of switching occupations, and the function $C_t^{3,k,l,s}$ captures the possible 'pecking-order' effects discussed above, and can take one of two values: (i) The value $C_t^{To\ High\ Occ,s}$, if $k > 1 = l$, so that the transition takes place into category 1 from 2, 3, 4 or 5; or (ii) The value $C_t^{To\ Med\ Occ,s}$, if $k > 3 \geq l \geq 2$, so the transition takes place from categories 4 or 5 to 2 or 3.[7]

Third, 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 parameter $C_t^{4,s}$ captures this in line (9) where both sector and occupation are changing ($i \neq j$, $k \neq l$), 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.

[7] The 'pecking-order' is constructed roughly based on skill concentration of occupations. In earlier drafts, the $C_t^{3,k,l,s}$ term was absent. We are grateful to many seminar participants who have suggested richer cost structures than the simple one we started with; this specification is a fairly parsimonious way of incorporating some of those ideas. It does not, in the end, change the results dramatically.

2.3 Descriptive Statistics.

We normalize annual real wages so that the average annual real wage across all workers in the sample is unity. Table 1 shows the distribution of normalized wages across occupations and sectors along with the number of observations for each type. The highest average wages are found in White-collar occupations, followed by the Tech/Sales category.

Table 1: Normalized Wages and Number of Observations

		No-College				**College**			
		Wages		Observations		Wages		Observations	
		Mean	*SE*	*Min*	*Max*	*Mean*	*SE*	*Min*	*Max*
Managerial	*Cons*	1.41	*(0.14)*	156	420	1.81	*(0.18)*	188	587
	Manuf	1.40	*(0.07)*	184	526	1.93	*(0.22)*	1013	1710
	Non-traded	1.15	*(0.07)*	375	733	1.54	*(0.14)*	847	1989
	Traded	1.28	*(0.07)*	382	677	1.78	*(0.30)*	2315	5793
Service	*Cons*	0.98	*(0.16)*	7	41	1.45	*(0.27)*	7	46
	Manuf	0.98	*(0.09)*	56	209	1.68	*(0.23)*	116	205
	Non-traded	0.78	*(0.07)*	566	975	1.12	*(0.09)*	358	1314
	Traded	0.80	*(0.05)*	530	843	1.47	*(0.19)*	500	1187
Office	*Cons*	1.13	*(0.22)*	5	40	1.31	*(0.27)*	6	47
	Manuf	0.96	*(0.07)*	89	256	1.16	*(0.09)*	74	145
	Non-traded	0.99	*(0.09)*	123	302	1.13	*(0.04)*	145	380
	Traded	0.91	*(0.07)*	126	263	1.03	*(0.08)*	152	511
Other	*Cons*	0.91	*(0.06)*	875	1896	1.06	*(0.05)*	132	739
	Manuf	0.99	*(0.06)*	420	1175	1.18	*(0.06)*	135	369
	Non-traded	0.90	*(0.03)*	456	862	1.05	*(0.06)*	128	463
	Traded	0.96	*(0.06)*	965	1586	1.15	*(0.06)*	244	959
Production	*Cons*	1.07	*(0.09)*	90	523	1.33	*(0.13)*	23	236
	Manuf	0.94	*(0.06)*	1081	2714	1.16	*(0.04)*	355	832
	Non-traded	0.99	*(0.05)*	150	362	1.20	*(0.06)*	56	211
	Traded	0.89	*(0.07)*	220	429	1.09	*(0.08)*	64	226

2.4 Rates of Mobility: Transition Matrices.

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 95.2% for office occupations to 98.1% for managerial and professional occupations. Clearly, most workers do not switch industry in a given year, which is hardly surprising, but the fraction who do varies from 3.3% to 5% which is significant. In addition, note that the off-diagonal elements are all positive, ranging from the 0.3% of manager/professional workers who move to production jobs each year to the 2% of office workers who move to manager/professional occupations.

Table 2: Occupational Mobility Martix

	Managerial	*Service*	*Office*	*Other*	*Production*
Managerial	0.981	0.008	0.003	0.005	0.003
Service	0.020	0.957	0.005	0.012	0.006
Office	0.020	0.012	0.952	0.010	0.007
Other	0.009	0.008	0.002	0.970	0.010
Production	0.008	0.008	0.003	0.018	0.963

The matrix for sectoral mobility is similar. The rate of switching varies from 2.8% for trade services to 4.7% for non-traded services. The off-diagonal elements range from the 0.5% of manufacturing workers who switch to construction each year to the 3.3% of non-traded services workers who switch to traded services each year. The biggest inflows from any initial sector are into traded services.

Table 3: Sectoral Mobility Matrix

	Cons	*Manuf*	*Non-traded*	*Traded*
Cons	0.958	0.010	0.012	0.020
Manuf	0.005	0.971	0.008	0.016
Non-traded	0.006	0.008	0.953	0.033
Traded	0.005	0.009	0.014	0.972

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 twenty 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 either between the frequency of switching only sector and the frequency of switching only occupation or – more often – 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 $C^{4,s}$. 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 share of each occupation in the corresponding sector's labor force. For example, 43% of manufacturing employees are classed as production workers, higher than any other sector. By contrast, 51% of Traded Services workers are mangers/professional, making it the most white-collar intensive sector. The second column shows the share of each occupation working in each sector. For example, only 7 percent of managers/professional workers are in the "construction" sector. About 40% of office workers are in the traded services sector, and 67% of production workers are in manufacturing. The last column shows the ratio of college graduates in each industry-occupation cell. For example, 88 percent of traded services sector mangers/professional workers are college graduates, while only 24% of manufacturing-sector production workers are.

Table 4: Sector and Occupation Change (Percent)

		No-College				**College**			
		Sec	*Occ*	*Both*	*Stay*	*Sec*	*Occ*	*Both*	*Stay*
Managerial	*Cons*	0.8	1.6	1.6	96.0	2.3	0.8	1.1	95.8
	Manuf	1.1	1.1	1.0	96.8	1.9	0.4	0.6	97.0
	Non-traded	1.3	1.6	2.4	94.7	2.8	1.0	1.4	94.8
	Traded	1.1	1.6	1.6	95.7	1.3	0.8	0.6	97.4
Service	*Cons*	3.7	2.1	2.7	91.6	2.9	1.0	2.7	93.5
	Manuf	1.9	1.2	1.8	95.1	2.8	1.4	2.2	93.6
	Non-traded	1.3	1.2	2.9	94.5	1.7	1.5	3.3	93.5
	Traded	1.4	1.5	2.1	95.0	1.8	2.9	1.8	93.6
Office	*Cons*	1.0	2.6	3.8	92.6	1.5	2.0	3.8	92.7
	Manuf	0.7	2.1	1.9	95.3	1.0	2.5	3.3	93.3
	Non-traded	0.6	1.1	1.6	96.6	0.9	1.5	2.2	95.3
	Traded	0.5	2.2	2.2	95.1	1.1	4.6	2.6	91.6
Other	*Cons*	2.2	0.7	2.1	95.0	2.3	1.2	3.7	92.7
	Manuf	2.2	1.1	1.0	95.7	2.3	1.5	1.8	94.4
	Non-traded	5.9	1.1	1.5	91.5	4.1	1.7	2.2	91.9
	Traded	2.2	1.0	1.4	95.4	2.0	2.1	1.8	94.1
Production	*Cons*	1.5	3.8	2.0	92.7	1.0	3.6	2.5	92.9
	Manuf	0.5	0.7	2.0	96.8	0.5	1.3	2.9	95.3
	Non-traded	3.2	1.5	2.2	93.1	2.4	1.9	2.5	93.2
	Traded	2.0	1.9	2.5	93.6	1.5	3.2	3.2	92.2

Table 5: Ratio of Industry-Occupation Cells

		Share in Sector	*Share in Occupation*	*Ratio of College*
Managerial	*Cons*	0.23	0.07	0.61
	Manuf	0.30	0.19	0.80
	Non-traded	0.37	0.23	0.72
	Traded	0.51	0.52	0.88
Service	*Cons*	0.01	0.01	0.51
	Manuf	0.05	0.08	0.57
	Non-traded	0.29	0.45	0.52
	Traded	0.18	0.46	0.56
Office	*Cons*	0.01	0.03	0.53
	Manuf	0.05	0.21	0.42
	Non-traded	0.09	0.37	0.53
	Traded	0.06	0.40	0.61
Other	*Cons*	0.64	0.32	0.25
	Manuf	0.17	0.18	0.25
	Non-traded	0.17	0.17	0.31
	Traded	0.21	0.34	0.31
Production	*Cons*	0.11	0.08	0.27
	Manuf	0.43	0.67	0.24
	Non-traded	0.07	0.11	0.34
	Traded	0.05	0.14	0.31

3 Results.

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 quite large. For example, the ratio C^{2js}/ν corresponding to the cost of entering a manager/professional occupation for a non-college educated worker is $4.28 + 1.03 = 5.31$, which, given our estimate of $\frac{1}{\nu}$ as 1.62 (from Table 7) and hence $\nu = 0.62$ implies $C^{2js} = 3.28$. In other words, given our normalization of wages, the cost of entering a white-collar occupation for a non-college educated worker is something more than three times an 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 $\nu = 0.62$, given the extreme-value distribution, amounts to a standard deviation for ϵ_t^{nik} of 0.80. In other words, the standard deviation of the idiosyncratic preference shock for non-pecuniary enjoyment of a given sector-occupation cell is four fifths 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, 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 mangerial/professional occupations for a college-educated worker is less than for a non-college educated worker, at $(4.31{+}0.02)(0.62) = 2.68$. 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. For non-college educated workers, the costs of moving up the occupational ladder ('To High Occ' and 'To Med Occ') are one-year's and two-thirds of a year's average earnings respectively, while for college-educated workers the corresponding costs are much smaller. The comparative advantage of the two educational classes is clear: The cost of entering white-collar jobs for a non-college educated worker is substantially higher than the cost of entering a production job, but only slightly more for college-educated workers.

The costs of switching sectors are similar in magnitude to the costs of switching occupation, but unlike for occupations, the patterns of costs are quite similar for the two educational groups. For both, it is much easier to move into the traded services sector than the manufacturing sector, for example.

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^4 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.

Note that although the switching costs we have estimated are sizable, they are an order of magnitude smaller than estimates obtained with a similar model in ACM. The main reason is that here we have allowed for the sector-occupation aggregate preference trends η_t^{iks}, which were absent in ACM. They are not of independent interest, but their estimated values are presented in Table 7.

Table 6: Regression Results - Stage 1

C/ν - Non-college						
	Mean	*Change*	*Min*	*Max*	*Min SE*	*Max SE*
Cons	4.38	0.95	3.81	5.22	*(0.18)*	*(0.28)*
Manuf	4.73	0.02	4.20	5.28	*(0.17)*	*(0.29)*
Non-Traded	3.94	-0.95	3.07	4.51	*(0.17)*	*(0.26)*
Traded	3.44	-1.03	2.67	4.05	*(0.16)*	*(0.25)*
Occ	4.28	0.46	3.85	5.21	*(0.10)*	*(0.22)*
Both	-3.41	0.76	-4.14	-2.94	*(0.13)*	*(0.22)*
To High Occ	1.03	-0.60	0.34	1.97	*(0.25)*	*(0.52)*
To Med Occ	0.64	-1.01	-0.41	1.33	*(0.20)*	*(0.39)*

C/ν - College						
	Mean	*Change*	*Min*	*Max*	*Min SE*	*Max SE*
Cons	4.97	1.12	4.27	5.93	*(0.21)*	*(0.35)*
Manuf	4.85	0.90	4.26	5.78	*(0.18)*	*(0.26)*
Non-Traded	3.93	-0.42	3.52	4.29	*(0.16)*	*(0.25)*
Traded	3.10	-0.58	2.46	3.53	*(0.15)*	*(0.24)*
Occ	4.31	0.39	4.01	4.98	*(0.13)*	*(0.21)*
Both	-3.15	0.42	-3.69	-2.75	*(0.12)*	*(0.19)*
To High Occ	0.02	0.23	-0.72	0.89	*(0.27)*	*(0.43)*
To Med Occ	0.30	-0.15	-0.46	0.79	*(0.23)*	*(0.39)*

Table 7: Regression Results - Stage 2

$\beta = 0.97$		$\beta = 0.90$	
$1/\nu$	SE	$1/\nu$	SE
1.62	*(0.36)*	1.80	*(0.37)*

4 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 aggregate preference terms η_t^{iks} (see (1)), since they are a distraction from our interest in the effects of a trade shock. We also take the mean value of the parameters (C_t^{1is})'s, (C_t^{2ls})'s, $C_t^{3,k,l,s}$'s, and (C_t^{4s})'s and hold them constant for the simulation.

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 (2). 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 (1), 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).

Production in each sector i is given by the following production function:

$$Y^i = \left(K^i\right)^{\theta_i} \left(\sum_{k=1}^{K} \left\{y^{i,k}\right\}^{\rho_2}\right)^{\frac{1-\theta_i}{\rho_2}}, \tag{10}$$

where K^i is fixed capital for sector i and $y^{i,k}$ denotes the input provided by occupation k in sector i. To discuss the equilibrium level of offshoring, it is useful to be able to think of $y^{i,k}$ as the output of a set of tasks, some of which may be allocatable to foreign workers.

We formulate this idea in a model of comparative advantage across tasks for different types of workers, as in Grossman and Rossi-Hansberg (2008) and Acemoglu and Autor (2011), but that borrows the mathematical specification of comparative advantage from Eaton and Kortum (2002). We will show how it collapses to a simple form.[8] To make things simple and realistic, we assume that only production-occupation tasks in manufacturing can be done by foreigners, so for the moment let $k = 5$ (the production occupation) and $i = 2$ (the manufacturing sector). In this light, suppose that to produce 1 unit of composite input k for sector i, a continuum of tasks $z \in [0, 1]$ has to be performed.

Now, suppose that for task z, the labor requirement is $\phi_s^{i,k} a_s^{i,k}(z)$ units of type s worker, where s can be a foreign (f), domestic college (c) or domestic non-college (n) worker. The $\phi_s^{i,k}$ term is a cost shifter that applies to all tasks equally for labor type s, but the $a_s^{i,k}(z)$ terms vary by task. These are fixed parameters for each z, but we can think of their values as having been drawn from a random distribution once and for all at some point in the past.

Task z will be performed by factor s if and only if:

$$w_s^k \phi_s^{i,k} a_s^{i,k}(z) \leq w_j^k \phi_j^{i,k} a_j^{i,k}(z), \forall j \in f, c, n.$$

Now, suppose that we assume that $a_s^{i,k}(z)$ is distributed $Weibull(\nu_1, 1)$, with shape parameter ν_1 and scale parameter 1. It is shown in the Appendix that the cost-minimizing allocation of tasks to the three types of workers is equivalent to minimizing the cost of producing a unit of $y^{i,k}$ output, where:

$$y^{i,k} = \left\{ \alpha_f^{i,k} (L_{i,k}^f)^{\rho_1} + \alpha_c^{i,k} (L_{i,k}^c)^{\rho_1} + \alpha_n^{i,k} (L_{i,k}^n)^{\rho_1} \right\}^{\frac{1}{\rho_1}}, i = 2, k = 5 \tag{11}$$

with $\rho_1 = \nu_1/(1 + \nu_1)$ and $\alpha_s^{i,k} = \left(\Gamma(1 + 1/\nu_1)\phi_s^{i,k}\right)^{-\rho_1}$. Thus, the offshoring equilibrium is equivalent to cost minimization with a Cobb-Douglas production function. For cells with $i \neq 2$ or $k \neq 5$, the set-up is the same except that foreign workers are not available, so the

[8] Our approach here is analogous to Anderson et. al. (1987). They study a model with a large number of consumers, each facing a discrete multinomial choice problem with idiosyncratic taste shocks driven by a Gumbel distribution. They show that it produces a demand system that is identical to that produced by a CES utility function.

aggregator is the same as (11) with no foreign-worker term:

$$y^{i,k} = \left\{\alpha_c^{i,k}(L_{i,k}^c)^{\rho_1} + \alpha_n^{i,k}(L_{i,k}^n)^{\rho_1}\right\}^{\frac{1}{\rho_1}}, i \neq 2 \text{ or } k \neq 5. \tag{12}$$

Equation (10) together with (11) and (12) then give a production function for each sector.

In all simulations, we assume that the foreign wage $w_f^{i,k}$ is fixed at world prices, which in practice means that it is fixed in terms of the price of tradable services, sector 4. All of the other wages are endogenous, and take a value equal to the marginal value product of labor of type s in cell i, k at each date. In addition, the prices of non-tradeable services, sector 3, and of construction are endogenous, and adjust so that the domestic supply equals the domestic demand.

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 (10) and its derivatives together with empirical employment levels for each sector. 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 elasticity of substitution between labor types within an occupation is set at $\sigma_1 = 2$, which is in the range of estimates summarized by Acemoglu and Autor (2011) for the elasticity of substitution between high- and low-skill workers, and the elasticity of substitution across occupations is set at the value $\sigma_2 = 0.5$, which is the value Ritter (2009) uses for a similar elasticity, based on an empirical estimate. Note that this implies that the different occupations are gross complements. The calibration results are presented in Table 8.

Table 8: Parameters for Simulation

Common Parameters				
	Cons	*Manuf*	*Non-Traded*	*Traded*
θ	0.37	0.30	0.10	0.23
A	0.31	0.32	0.10	0.16
α_K	0.35	0.45	0.35	0.55
σ_1	2.00	2.00	2.00	2.00
σ_2	0.50	0.50	0.50	0.50

α - *No-College*				
	Cons	*Manuf*	*Non-Traded*	*Traded*
Managerial	2.22	1.89	1.37	1.51
Service	42.03	17.17	2.87	8.72
Office	48.66	29.09	9.82	37.44
Other	1.52	9.47	6.23	12.89
Production	8.04	2.72	13.89	49.82

α - *College*				
	Cons	*Manuf*	*Non-Traded*	*Traded*
Managerial	3.31	4.96	2.76	5.25
Service	57.32	32.55	3.86	16.62
Office	58.12	28.72	11.09	48.86
Other	0.92	6.11	4.50	9.53
Production	5.33	1.75	11.13	37.64

We treat manufacturing and traded services as goods whose prices are determined on world markets, 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, we study simulations of two globalization shocks: a trade liberalization and an increase in offshoring. These are set up as follows.

(i) *The liberalization experiment.* The world prices of manufactures and traded services are 0.8 and 1 respectively. Initially, there is a 50% tariff on manufactures, so the domestic price is 1.2, 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. Thus, the domestic price of manufactures falls by a third.[9] 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 $\beta = 0.97$.

(ii) *The offshoring experiment.* The cost parameter for foreign production labor in manufacturing, $\phi_f^{2,5}$, unexpectedly drops by 50% at date $t = 0$. This figure was chosen because it results in a time path that roughly mimics the rise in offshoring in manufacturing of recent years.[10] The foreign wage w^*, is unchanged (in terms of tradable services). Again, the simulation begins at the old steady state with the higher value of $\phi_f^{2,5}$ expected to continue permanently, and once the parameter change occurs, it is expect to be permanent.

Consider the simulation results for the two shocks in turn.

4.1 The trade shock.

The results for the trade shock are shown in Figures 1-11 and in Table 9. On the day of the surprise liberalization, the real marginal value product of labor and hence the wage for all workers in manufacturing drops by 27.35%, as seen in the second column of the first two panels of Table 9. The reason the drop is less than 33% is that the domestic

[9] Since the A_i factor includes the price, we operationalize this by reducing A_i, holding all other parameters constant. The non-traded sectors' prices, thus A_i's, are re-calculated for each time period during the transition.

[10] For example, Harrison and McMillan (2011) report that from 1982 to 1999, the foreign share of US multinational employment rose from 26% to 39%, a 50% increase, a similar order of magnitude to what is observed in the simulation.

consumer price of manufactures falls, which 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. The exception to the 27.35% wage drop is production workers in that sector, whose wage falls much less because they are in competition with foreign workers. From (11), any drop in the wages of domestic manufacturing production workers induces a substitution away from foreign workers – 'onshoring' – which puts a brake on the fall in the domestic workers' wages.

Figure 1 shows non-college workers' wages over time, averaged by occupation. Average production-worker wages fall initially, with a substantial drop in manufacturing and a modest rise elsewhere due to the drop in consumer prices. Over time, the production wages recover as workers edge out of that occupational category, as shown in Figure 10. The opposite pattern is observed in the other occupations. Figure 2 shows the same pattern for college-educated workers' wages by occupation, and Figure 11 the same pattern for workers leaving the occupation and causing the wages to recover. The great difference between Figures 10 and 11 is that the production occupation is much more important for non-college educated workers than for college-educated workers.

All of these subtle movements in wages stand in contrast to the dramatic effects of Figures 3 and 4, which plot average wages by sector. At the date of the liberalization, manufacturing wages drop abruptly due to the abrupt drop in the domestic price of manufactures. Real marginal value products of labor in tradeable services jump up, due to the drop in consumer prices for manufactures and non-tradables; since the prices of output in construction and in non-traded services have been forced down, the wage increases in those sectors are much smaller. Figures 3 and 4 make 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. Figures 5 and 6 show how workers in every occupation leave manufacturing, and Figures 8 and 9 show the movement of those workers into the other sectors. As workers leave the manufacturing sector, the marginal product of manufacturing labor in the various occupations rises, gradually raising manufacturing wages, and *vice versa* for the other sectors.

Because of these movements of workers out of manufacturing, the long-run drop in man-

Table 9: Simulation Results - Trade Shock ($\beta = 0.97$)

Changes in Wages: No-College								
	Short-Run				Long-Run			
	Cons	*Manuf*	*Non-Tra*	*Traded*	*Cons*	*Manuf*	*Non-Tra*	*Traded*
Managerial	8.51	-27.39	8.51	17.01	0.46	-1.62	0.54	1.07
Service	8.51	-27.39	8.51	17.01	1.26	-3.78	0.71	1.54
Office	8.51	-27.39	8.51	17.01	1.35	-3.15	0.79	2.18
Other	8.51	-27.39	8.51	17.01	0.53	-2.16	0.67	1.22
Production	8.51	-14.39	8.51	17.01	0.79	-1.24	0.98	2.18

Changes in Wages: College								
	Short-Run				Long-Run			
	Cons	*Manuf*	*Non-Tra*	*Traded*	*Cons*	*Manuf*	*Non-Tra*	*Traded*
Managerial	8.51	-27.39	8.51	17.01	4.60	3.06	5.40	5.00
Service	8.51	-27.39	8.51	17.01	6.02	2.41	7.28	6.23
Office	8.51	-27.39	8.51	17.01	6.45	3.22	7.33	9.12
Other	8.51	-27.39	8.51	17.01	7.52	3.82	7.68	7.87
Production	8.51	-14.39	8.51	17.01	6.03	5.14	6.98	9.03

Changes in Values: No-College								
	Short-Run				Long-Run			
	Cons	*Manuf*	*Non-Tra*	*Traded*	*Cons*	*Manuf*	*Non-Tra*	*Traded*
Managerial	0.73	-1.47	0.71	1.12	0.21	-0.22	0.21	0.29
Service	0.58	-0.94	0.64	0.91	0.22	-0.24	0.21	0.28
Office	0.56	-1.10	0.59	0.82	0.22	-0.24	0.21	0.30
Other	0.66	-1.34	0.58	0.97	0.20	-0.25	0.20	0.27
Production	0.48	-1.31	0.44	0.67	0.20	-0.21	0.20	0.28

Changes in Values: College								
	Short-Run				Long-Run			
	Cons	*Manuf*	*Non-Tra*	*Traded*	*Cons*	*Manuf*	*Non-Tra*	*Traded*
Managerial	4.47	2.20	4.43	4.95	4.26	3.88	4.25	4.31
Service	4.43	2.65	4.35	4.78	4.32	3.89	4.24	4.33
Office	4.39	2.86	4.32	4.54	4.32	3.89	4.26	4.34
Other	4.29	2.72	4.29	4.59	4.22	3.87	4.25	4.32
Production	4.31	2.78	4.28	4.47	4.28	3.88	4.28	4.35

ufacturing wages is modest, as shown in the sixth column of the first panel of Table 9, and long-run wages for college-educated manufacturing wages are *higher* than in the original steady state. Reviewing Figures 8 and 9, it is clear that the non-manufacturing sectors more easily absorb the exodus of college-educated workers from manufacturing compared with the corresponding flow of non-college-educated workers, because the initial share of manufacturing in the non-college workforce is much larger than for the college-educated workforce.

The most relevant indicator of welfare changes is in the first four columns of the bottom two panels of Table 9, which record the change in lifetime expected utility as of the day the surprise shock occurs. The welfare effect on manufacturing workers depends on a trade-off between the large short-run drop in their wages, which is mostly attenuated or even reversed over an eight-year span, and a rise in option value due to an increase in real wages in other sectors to which a worker might choose to move. For non-college-educated workers, the trade-off winds up negative, as shown in the second column of the third panel of Table 9, with a welfare loss of around one percent for all occupations. For college-educated workers, with bigger long-run increases in long-run non-manufacturing wages compared with non-college-educated workers (second panel of Table 9), the trade-off is positive, with a rise in welfare of 2-3% for manufacturing workers and 4-5% for other sectors (first four columns of bottom panel of Table 9).

There are three important messages here. First, a reduced-form wage regression that looked at wage changes just after the policy change compared to just before would be very misleading. From the first four columns of the first two panels of Table 9, *the short-run wage effects for the two educational classes of workers are identical*, but from the first four colums of the last two panels, the effects on lifetime utility are (i) much smaller in magnitude, and (ii) in the opposite direction for the two educational classes. This is because of the importance of anticipated future wages and of option value.

Second, studying the last two panels of Table 9, *once we have identified the workers' industry of employment, the occupation of employment is irrelevant for determining the welfare effect of the trade shock*. This is at base because the estimated moving costs for sector switches are similar in magnitude to those for occupational switches (see Table 6), which ultimately springs from the similarity in mobility across sectoral and occupational lines (see Table 4). Since the trade shock is a sectoral shock, this means that its main effects

Table 10: Simulation Results - Offshoring Shock ($\beta = 0.97$)

Changes in Wages: No-College								
	Short-Run				Long-Run			
	Cons	*Manuf*	*Non-Tra*	*Traded*	*Cons*	*Manuf*	*Non-Tra*	*Traded*
Managerial	0.55	14.11	0.55	-0.48	-0.45	-0.10	-0.54	-0.58
Service	0.55	14.11	0.55	-0.48	-0.54	0.19	-0.78	-0.89
Office	0.55	14.11	0.55	-0.48	-0.49	0.05	-0.62	-0.82
Other	0.55	14.11	0.55	-0.48	-0.69	-0.17	-0.69	-0.77
Production	0.55	-19.45	0.55	-0.48	-0.45	-1.15	-0.48	-0.69

Changes in Wages: College								
	Short-Run				Long-Run			
	Cons	*Manuf*	*Non-Tra*	*Traded*	*Cons*	*Manuf*	*Non-Tra*	*Traded*
Managerial	0.55	14.11	0.55	-0.48	0.76	0.90	0.89	0.73
Service	0.55	14.11	0.55	-0.48	0.99	1.22	1.20	0.86
Office	0.55	14.11	0.55	-0.48	1.04	1.69	1.19	1.14
Other	0.55	14.11	0.55	-0.48	1.23	1.55	1.23	1.02
Production	0.55	-19.45	0.55	-0.48	1.03	0.50	1.19	1.12

Changes in Values: No-College								
	Short-Run				Long-Run			
	Cons	*Manuf*	*Non-Tra*	*Traded*	*Cons*	*Manuf*	*Non-Tra*	*Traded*
Managerial	-0.32	0.33	-0.32	-0.38	-0.42	-0.35	-0.42	-0.43
Service	-0.37	0.06	-0.34	-0.39	-0.43	-0.36	-0.42	-0.43
Office	-0.36	0.09	-0.35	-0.39	-0.43	-0.36	-0.43	-0.44
Other	-0.34	0.18	-0.35	-0.40	-0.42	-0.36	-0.43	-0.44
Production	-0.42	-1.26	-0.42	-0.47	-0.43	-0.52	-0.43	-0.44

Changes in Values: College								
	Short-Run				Long-Run			
	Cons	*Manuf*	*Non-Tra*	*Traded*	*Cons*	*Manuf*	*Non-Tra*	*Traded*
Managerial	0.72	1.45	0.71	0.66	0.71	0.76	0.71	0.70
Service	0.71	1.26	0.69	0.65	0.72	0.77	0.71	0.70
Office	0.71	1.13	0.70	0.67	0.72	0.76	0.71	0.70
Other	0.68	1.16	0.69	0.66	0.70	0.76	0.71	0.70
Production	0.67	-0.02	0.67	0.64	0.71	0.62	0.71	0.70

cut across sectoral, rather than occupational, lines.[11]

Third, the presence of offshoring partially cushions US manufacturing production workers against the trade shock, as shown by the fact that the sole offshorable group of workers, the production workers in manufacturing, have a smaller wage drop than the other manufacturing workers. The incipient drop in US production-worker wages results in a substitution toward those workers away from foreign workers, as shown by the dramatic drop in foreign employment displayed in Figure 7, resulting in a limited drop in wages for those US workers. Since in the public discourse both import competition for manufactures and offshoring of manufacturing jobs are often portrayed as threats to the incomes of US workers, it may be viewed as paradoxical that in this model one of those phenomena cushions some of the impact of the other.

4.2 The offshoring shock.

The effects of the offshoring shock are portrayed in Figures 12 to 22 and in Table 10. On the day of the shock, suddenly the cost of hiring foreign production workers in manufacturing drops, and as a result manufacturing employers shift toward foreign workers for production hiring. This results in a sharp drop in wages for production workers in manufacturing, both college-educated and non-college-educated (second column of the first two panels of Table 10). All other wages in manufacturing *rise* sharply, since the influx of cheap new production workers increases the marginal physical product of labor for all other occupations (recall that we are assuming an elasticity of substitution between occupations equal to 0.5, so that the different occupations are complementary to each other.) There is a small increase in wages for the two non-traded sectors (first and third columns of first two panels of Table 10), for a subtle reason: The increase in GDP resulting from the drop in offshoring costs results in more spending on non-tradeables, increasing their prices slightly. Real wages in traded services fall (fourth column), for the same reason: The prices of non-tradables have risen, raising the CPI, while the prices of traded services have not changed.

[11] It should be underlined that this is by no means a given. Recalling the thought experiment in the introduction, we could have found that this sectoral shock affects workers according to their occupation or according to their skill class; a worker's industry of employment can be irrelevant to the effect of a trade shock on the worker's income – or it can be the prime determinant – depending on the pattern of switching costs. One cannot know what that pattern will be without estimating those costs, as we have done here.

Although the short-run change in wages for college and non-college workers are identical, the long-run changes are very different (last four columns of the first two panels of Table 10). In the long run, almost every cell sees a small drop in real wages for non-college-educated workers, while every cell sees a rise in real wage for college-educated workers. The reason can be seen at a glance from Figures 16 and 17, which show the occupational breakdown of workers in manufacturing for non-college-educated and college-educated workers respectively. Both types of worker leave the manufacturing-production cell following the shock because of the sharp drop in wages, but there are many more non-college-educated workers in that cell to begin with, so they push down wages elsewhere when they leave. By contrast, there are just not enough dislocated college-educated workers to push down wages in the other cells. These movements in workers result in the behavior in occupational wages shown in Figures 12 and 13, with an initial drop in the production wages followed by gradual increases as workers leave the occupation, and a small opposite movement in the other occupations.

The magnitude of the rise in foreign hiring is depicted in Figure 18. Over the space of five years, foreign workers employed by US manufactures almost doubles. (Notice that we have not imposed moving costs on the foreign workers, implying that US employers can adjust their foreign labor force much more flexibly than their domestic labor force. This is in line with available evidence on the volatility of employment in US manufacturing operations abroad; see Bergin et. al. (2009).)

There are two important messages here. First, once again, a reduced-form wage regression would be a very misleading guide to welfare effects. The welfare effects shown in the first four columns of the bottom two panels of Table 10 are much smaller in magnitude than the impact wage changes shown in the top two panels. The reason is, again, that workers understand that wages in the wake of the shock overshoot their long-run values, and also consider option value. In addition, college-educated workers do well in almost every cell, and even in the directly affected production-manufacturing cell lose only 0.02% of their lifetime expected utility, while non-college-educated workers in most cells see a drop in lifetime utility. Thus, not only the magnitudes, but the pattern of welfare changes is very different from the pattern of impact wage effects.

Second, because this is a shock that is specific to an occupation (within one sector), occupation now does have some explanatory power for welfare effects. Within manufacturing, occupation is everything: for both educational classes, the production workers see a small drop in welfare while the other occupations see a small rise. However, in the other sectors, the only criterion for the sign of the welfare effect is educational class: All non-college-educated workers are harmed, while all college-educated workers benefit.

Third, note that the welfare effects contrast with those of a number of approaches in the literature. Grossman and Rossi-Hansberg (2008) and Mitra and Ranjan (2010) show that under some circumstances offshoring of a class of jobs can benefit all workers, including those whose jobs are being offshored, because offshoring creates a kind of productivity improvement that under some conditions is passed on to the workers themselves through higher wages (and, in the latter paper, lower unemployment rates). In our simulations, that does not occur, because both intersectoral and occupational moving costs are large enough to prevent the offshorable workers from benefitting. In addition, our results contrast with the findings of Ritter (2009), who finds that workers employed in offshorable occupations benefit. It seems that our estimated portmanteau switching costs are more formidable than the calibrated job-search frictions and occupational human-capital-costs of his model.

5 Conclusion.

We present a dynamic structural econometric model of workers' adjustment to international shocks, allowing for workers to switch sector and occupation over time. We estimate both the average switching costs and the variance of idiosyncratic switching costs, and simulate a trade liberalization and an offshoring shock in a model that incorporates task-by-task comparative advantage for domestic vis a vis foreign workers in a novel and simple way. We find that switching costs are substantial, but similar in magnitude for sectoral and occupational switching, and switching in both dimensions is about as costly as switching in only one dimension.

Simulating a trade shock, we find that wages in the import-competing sector drop sharply as a result of the shock, but recover within a decade. This results in a modest welfare loss for workers in that industry, regardless of occupation or educational status. Simulating an offshoring shock, we find that wages for the offshorable occupation/sectoral cell drop sharply, but recover within a decade. This results in a modest welfare loss for the offshorable workers in that industry, but a welfare gain for non-offshorable workers within that industry, in contrast to the predictions of some well-known theoretical models. In addition, welfare of less-educated workers in other industries is modestly reduced by the exodus of workers from the offshoring sector, with a corresponding welfare gain for college-educated workers in those other industries.

All of these results underscore the crucial role for *dynamic* analysis of trade and offshoring shocks.

6 Appendix I: Derivation of equation (11)

Time and industry superscripts are omitted for notational convenience. Assume that to produce 1 unit of composite input k, a continuum of tasks $z \in [0, 1]$ has to be performed.

Now, suppose that for task z, the labor requirement is $\phi_s^k a_s^k(z)$ units of type s worker. Where s can be foreign, domestic college or domestic non-college worker. These are fixed parameters for each z, but we can think of their values as having been drawn from a random distribution once and for all at some point in the past.

Task z will be performed by factor s if and only if:

$$w_s^k \phi_s^k a_s^k(z) \leq w_j^k \phi_j^k a_j^k(z), \forall j \in 1, 2, .., S.$$

Now, suppose that we assume that $a_s(z)$ is distributed $Weibull(\nu_1, 1)$, with the shape parameter ν_1 and the scale parameter 1 . Then the amount of tasks done by factor s to produce one unit of input k is equal to

$$N_s^k = \frac{\left(\phi_s^k w_s^k\right)^{-\nu_1}}{\sum_j \left(\phi_j^k w_j^k\right)^{-\nu_1}}.$$

Then the ratio of tasks performed by type s versus type s' workers are

$$\frac{N_s^k}{N_{s'}^k} = \left(\frac{\phi_{s'}^k w_{s'}^k}{\phi_s^k w_s^k}\right)^{\nu_1}.$$

The number of type s workers required to do N_s tasks (conditional on optimality) is equal to

$$L_s^k = N_s^k \frac{1}{w_s^k} \left(\sum_j \left(\phi_j^k w_j^k \right)^{-\nu_1} \right)^{-\frac{1}{\nu_1}} \Gamma(1 + 1/\nu_1),$$

where $\Gamma(.)$ is the statistical gamma function. Then, the ratio of type s workers to type s' workers is equal to:

$$\frac{L_s^k}{L_{s'}^k} = \left(\frac{w_{s'}^k}{w_s^k} \right)^{1+\nu_1} \left(\frac{\phi_{s'}^k}{\phi_{s'}^k} \right)^{\nu_1}. \tag{13}$$

This means the elasticity of substitution is constant and equal to $\sigma_1 = 1 + \nu_1$, hence we can use a CES aggregator to calculate the amount of intermediate input y_k produced with the optimal composition of factors

$$y_k = \left(\sum_{s=1}^{S} \alpha_s^k \left(L_s^k \right)^{\rho_1} \right)^{\frac{1}{\rho_1}}, \tag{14}$$

where $\rho_1 = \nu_1/(1 + \nu_1)$ or $\nu_1 = \rho_1/(1 - \rho_1)$ and

$$\alpha_s^k = \left(\Gamma(1 + 1/\nu_1) \phi_s^k \right)^{-\rho_1}.$$

Proof. Note that (13) can be rearranged as

$$\frac{w_s^k}{w_{s'}^k} = \left(\frac{L_s^k}{L_{s'}^k} \right)^{\rho_1 - 1} \left(\frac{\phi_s^k}{\phi_{s'}^k} \right)^{-\rho_1},$$

which should be equal to the relative marginal product of labor from equation (14)

$$\frac{\partial y_k / \partial L_s^k}{\partial y_k / \partial L_{s'}^k} = \left(\frac{L_s^k}{L_{s'}^k} \right)^{\rho_1 - 1} \left(\frac{\alpha_s^k}{\alpha_{s'}^k} \right).$$

Thus

$$\frac{\alpha_s^k}{\alpha_{s'}^k} = \left(\frac{\phi_s^k}{\phi_{s'}^k} \right)^{-\rho_1}.$$

Now, assume that $L_s^k = 1$ and $L_{s'}^k = 0$ for $s' \neq s$. Thus, we assume that there is only one input available for production. Then the output should be

$$\begin{aligned} y_k &= \left(\alpha_s^k\right)^{\frac{1}{\rho_1}}, \\ &= \frac{1}{E\phi_s^k a_s^k(z)}, \\ &= \left(\Gamma(1+1/\nu_1)\phi_s^k\right)^{-1}. \end{aligned}$$

Hence, $\alpha_s^k = \left(\Gamma(1+1/\nu_1)\phi_s^k\right)^{-\rho_1}$.

7 Appendix II: Estimation Details.

Our method has two stages: First, the Poisson regression stage, where we estimate the moving cost parameter and the expected values associated with each choice for every time period. Second, the Bellman equation stage, where we plug the estimated expected values in a Bellman equation and construct a linear regression in order to retrieve the remaining structural parameters of the model.

Stage 1: Poisson Regression

In this stage, our goal is to estimate expected values $V_t^{ik,s}$ and bilateral resistance parameters $C_t^{ikjl,s}$. We construct a log-linear expression for flows, $m_t^{ikjl,s}$, which can be estimated with Poisson pseudo maximum likelihood using standard statistical software.

Asymptotically, the total number of agents with state (i, k, s) who choose (j, l) is equal to $y_t^{ikjl,s} = L_t^{ik,s} m_t^{ikjl,s}$. Hence, after multiplying (2) with L_t^{ik}, we get

$$y_t^{ik,s} = \exp\left\{\frac{\beta}{\nu}\tilde{V}_{t+1}^{jl,s} - \frac{\beta}{\nu}\tilde{V}_{t+1}^{ik,s} - \frac{1}{\nu}C_t^{ikjl,s} + \log\left(L_t^{ik,s}\right) - \frac{1}{\nu}\Omega_t^{ik,s}\right\}. \tag{15}$$

We interpret the equation above as Poisson pseudo-maximum likelihood.[12] Then, the equation (15) becomes the first stage regression equation

[12] See Gourieroux, Monfort and Trognon (1984) and Cameron and Trivedi (1998) for properties of the Poisson regression.

$$y_t^{ikjl,s} = \exp\left[\lambda_t^{jl,s} + \alpha_t^{ik,s} + \Psi_t^{ikjl,s}\right] + \xi_t^{1,ikjl,s}, \tag{16}$$

where the destination fixed effect is:

$$\lambda_t^{jl,s} = \frac{\beta}{\nu} E_t V_{t+1}^{jl,s} - \frac{\beta}{\nu} E_t V_{t+1}^{11,s},$$

the switching cost term is:

$$\Psi_t^{ikjl,s} = -\frac{1}{\nu} C_t^{ikjl,s},$$

and the origin fixed effect is:

$$\alpha_t^{ik,s} = -\frac{\beta}{\nu} E_t V_{t+1}^{ik,s} - \frac{1}{\nu}\Omega_t^{ik,s} + \log(L_t^{ik,s}) + \frac{\beta}{\nu} E_t V_{t+1}^{11,s}.$$

Note that the option value term $\Omega_t^{i,s}$ can be written as:

$$\frac{1}{\nu}\Omega_t^{ik,s} = -\lambda_t^{ik,s} - \alpha_t^{ik,s} + \log(L_t^{ik,s}). \tag{17}$$

Stage 2: Bellman Equation

From Stage 1, we have estimated the expected values, $\lambda_t^{jk,s}$, and moving cost parameters, $\Psi_t^{ikjl,s}$. In Stage 2, the goal is to construct the Bellman equation using the estimated parameters from Stage 1 and estimate the remaining parameters, most importantly $1/\nu$.

After multiplying (1) with β/ν, we get

$$\frac{\beta}{\nu} V_{t+1}^{ik,s} = \frac{\beta}{\nu}\left(w_{t+1}^{ik,s} + \eta_{t+1}^{ik,s} + \beta E_t V_{t+2}^{ik,s} + \Omega_{t+1}^{ik,s}\right). \tag{18}$$

Using (17) yields: Then we write (18) as

$$\lambda_t^{ik,s} + \frac{\beta}{\nu} V_{t+1}^{11,s} = E_t\left\{\frac{\beta}{\nu} w_{t+1}^{ik,s} + \frac{\beta}{\nu}\eta_{t+1}^{ik,s} - \beta\alpha_{t+1}^{ik,s} + \beta\log(L_{t+1}^{ik,s}) + \frac{\beta^2}{\nu} V_{t+2}^{11,s}\right\}, \tag{19}$$

Now define

$$\phi_t^{ik,s} = \lambda_t^{ik,s} + \beta\alpha_{t+1}^{ik,s} - \log(L_{t+1}^{ik,s}), \tag{20}$$

and

$$\zeta_t^s = \frac{\beta}{\nu}V_{t+1}^{11,s} - \frac{\beta^2}{\nu}V_{t+2}^{11,s},$$

The second stage regression equation is

$$\phi_t^{ik,s} = \zeta_t^s + \frac{\beta}{\nu}\eta_{t+1}^{ik,s} + \frac{\beta}{\nu}w_{t+1}^{ik,s} + \xi_t^{ik,s}, \tag{21}$$

where $\phi_t^{ik,s}$ is the dependent variable constructed from Stage 1 estimates using equation (20), ζ_t^s is the time dummy specific to type s, $\frac{\beta}{\nu}\eta_{t+1}^{ik,s}$ is the sector-occupation cell dummy (specifically, we assume that $\eta_{t+1}^{ik,s} = \eta_1^{ik,s} + \eta_2^{ik,s}t$ so that η's can have an intercept and a time trend), $w_{t+1}^{ik,s}$ is the wage taken from the data, and finally $\xi_t^{ik,s}$ is the regression residual. Note that the estimated coefficient of the wages will be equal to $\frac{\beta}{\nu}$.

It is possible to use Generalized Method of Moments or Instrumental Variables method for the regression. We use IV regression with lags and cluster the standard errors across sector-occupation cells .

See Artuc (2013) for the Monte-Carlo simulations and further details.

References

[1] **Acemoglu, Daron and David Autor** (2011). "Skills, Tasks and Technologies: Implications for Employment and Earnings." In Orley Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Volume 4, Amsterdam: Elsevier North Holland, 2011, pp. 1043-1171.

[2] **Anderson, Simon P., André De Palma, and Jacques-François Thisse.** 1987. "The CES is a discrete choice model?" *Economics Letters*, 24:2, pp. 139-40.

[3] **Artuç, Erhan.** 2012. "Workers' Age and the Impact of Trade Shocks." World Bank Working Paper.

[4] **Artuç, Erhan.** 2013. "PPML estimation of dynamic discrete choice models with aggregate shocks," World Bank Policy Research working paper series # 6480.

[5] **Artuç, Erhan, Shubham Chaudhuri, and John McLaren.** 2007. "Trade Shocks And Labor Adjustment: A Structural Empirical Approach." NBER Working Paper #13465 (October).

[6] **Artuç, Erhan, Shubham Chaudhuri, and John McLaren.** 2008. "Delay and Dynamics in Labor Market Adjustment: Simulation Results." *Journal of International Economics,* 75(1): 1-13.

[7] **Artuç, Erhan, Shubham Chaudhuri, and John McLaren.** 2010. "Trade Shocks and Labor Adjustment: A Structural Empirical Approach." *American Economic Review,* 100(3).

[8] **Autor, David H., Frank Levy and Richard J. Murnane. 2003.** "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics*, 116:4.

[9] **Bergin, Paul R., Robert C. Feenstra, and Gordon H. Hanson.** 2009. "Offshoring and volatility: evidence from Mexico's maquiladora industry." *The American Economic Review* 99:4, pp.1664-71.

[10] **Blinder, Alan** 2009. "How Many U.S. Jobs Might Be Offshorable." *World Economics* 10:2, pp. 41-78.

[11] **Borjas, George J., Richard B. Freeman and Lawrence F. Katz.** 1992. "Richard B. Freeman, Lawrence F. Katz." In *Immigration and the Workforce: Economic Consequences for the United States and Source Areas,*, ed. George J. Borjas and Lawrance Katz, University of Chicago Press, Chicago

[12] **Burstein, Ariel and Johnathan Vogel.** 2009. "Globalization, Technology, and the Skill Premium ." *Mimeo: Columbia University.*

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

[14] **Chaudhuri, Shubham and John McLaren.** 2007. "Some Simple Analytics of Trade and Labor Mobility." NBER Working Paper 13464.

[15] **Cosar, A. Kerem.** 2010. "Adjusting to Trade Liberalization: Reallocation and Labor Market Policies." Working Paper, University of Chicago Booth School of Business.

[16] **Dix-Carneiro, Rafael.** 2011. "Trade Liberalization and Labor Market Dynamics." Working Paper, University of Maryland.

[17] **Eaton, Jonathan and Samuel Kortum.** 2002. "Technology, Geography, and Trade." *Econometrica* 70:5 (September), pp. 1741-79.

[18] **Ebenstein, Avraham, Ann Harrison, Margaret McMillan, and Shannon Phillips.** 2009. "Estimating the impact of trade and offshoring on American workers using the current population surveys." Working Paper #15107. National Bureau of Economic Research.

[19] **Feenstra, Robert C. and Gordon H. Hanson.** 1996. "Foreign Investment, Outsourcing and Relative Wages." In R.C. Feenstra, G.M. Grossman and D.A. Irwin, eds., *The Political Economy of Trade Policy: Papers in Honor of Jagdish Bhagwati*, Cambridge, MA: MIT Press, pp. 89-127.

[20] **Grossman, Gene M., and Esteban Rossi-Hansberg.** 2008. "Trading Tasks: A Simple Theory of Offshoring." *American Economic Review*, 98:5, pp. 197817.

[21] **Hakobyan, Shushanik and John McLaren.** 2010. "Looking For Local Labor Market Effects Of Nafta." NBER Working Paper #16535 (November).

[22] **Harrison, Ann, and Margaret McMillan.** 2011. "Offshoring jobs? Multinationals and US manufacturing employment." *Review of Economics and Statistics* 93.3. pp. 857-75.

[23] **Helpman, Elhanan., Oleg Itskhoki and Stephen Redding.** 2010. "Inequality and Unemployment in a Global Economy." *Mimeo: Princeton University.*

[24] **Kambourov, G., and I. Manovskii.** 2009. "Occupational Specificity of Human Capital," International Economic Review, 50(1), pp. 63-115.

[25] **Keane, Michael P., and Wolpin, Kenneth I.** 1997. "The Career Decisions of Young Men." *Journal of Political Economy*, 105(3): 473-522.

[26] **Kovak, Brian K.** 2010. "Regional Labor Market Effects of Trade Policy: Evidence from Brazilian Liberalization." Working Paper, Carnegie Mellon University.

[27] **Krugman, Paul.** 1995. "Growing World Trade: Causes and Consequences." *Brookings Papers on Economic Activity, Volume 1.*

[28] **Krugman, Paul.** 2008. "Trade and Wages, Reconsidered." *Mimeo: Princeton University.*

[29] **Lawrence, Robert Z.** 2008. "Blue-Collar Blues: Is Trade to Blame?." *Institute for International Economics.*

[30] **Mitra, Devashish and Priya Ranjan.** 2010. "Offshoring and Unemployment: The Role of Search Frictions and Labor Mobility." *Journal of International Economics*, 81:2, (July).

[31] **Patel, Jagdish, C. H. Kapadia, and D. B. Owen.** 1976. *Handbook of Statistical Distributions*, New York: Marcel Dekker, Inc.

[32] **Pavcnik, Nina, Orazio Attanasio and Pinelopi Goldberg.** 2004. "Trade Reforms and Income Inequality in Colombia." *Journal of Development Economics*, 74 (August), pp. 331-366.

[33] **Liu, Runjuan and Daniel Trefler.** 2011. "A Sorted Tale Of Globalization: White Collar Jobs And The Rise Of Service Offshoring." NBER Working Paper #17559 (November).

[34] **Ottaviano, Gianmarco I.P. and Giovanni Peri.** (2012). "Rethinking the Effects of Immigration on Wages." *Journal of the European Economic Association* 10:1, pp. 152-197.

[35] **Revenga, Ana L.** 1992. "Exporting Jobs?: The Impact of Import Competition on Employment and Wages in U.S. Manufacturing," *The Quarterly Journal of Economics* 107:1. (February), pp. 255-284.

[36] **Reshef, Ariell.** 2007. "Heckscher-Ohlin and the global increase of skill premia: factor intensity reversals to the rescue " *Mimeo: University of Virginia*

[37] **Ritter, Moritz** 2009. "Offshoring and Occupational Specificity of Human Capital." MPRA Paper No. 19671 (December), http://mpra.ub.uni-muenchen.de/19671/.

[38] **Santos Silva, J. M. C. and Silvana Tenreyro.** 2006. "The Log Of Gravity." *The Review of Economics and Statistics*, November 88:4, pp. 64117.

[39] **Topalova, Petia.** 2007. "Trade Liberalization, Poverty and Inequality: Evidence from Indian Districts." Chapter 7 in Ann Harrison (ed.) *Globalization and Poverty*. Chicago: University of Chicago Press, pp. 291-336.

Figure1:Trade Shock –Average Low Skill Wages in each Occupation(σ_1=2, σ_2=0.5)

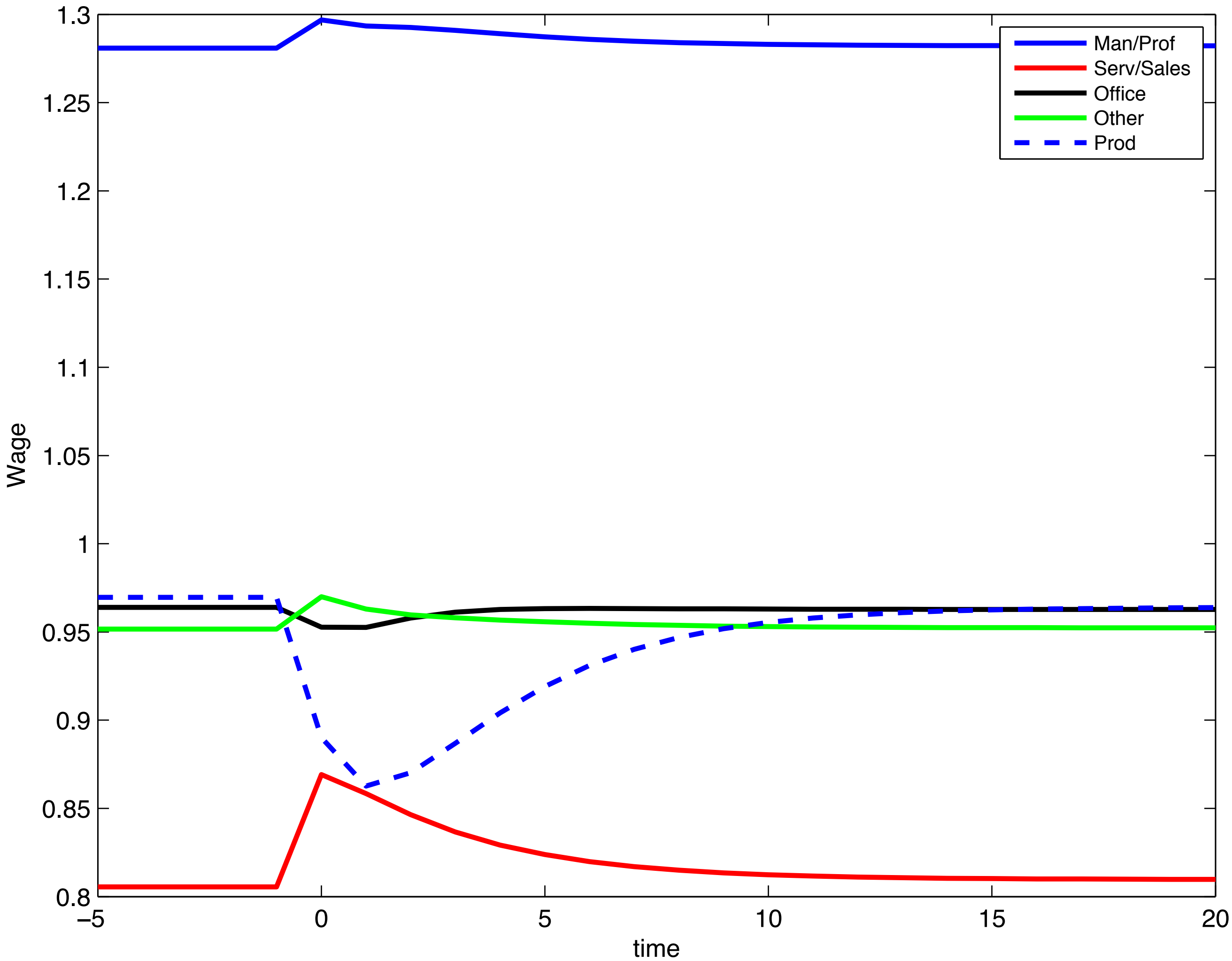


Figure2:Trade Shock −Average High Skill Wages in each Occupation(σ_1=2, σ_2=0.5)

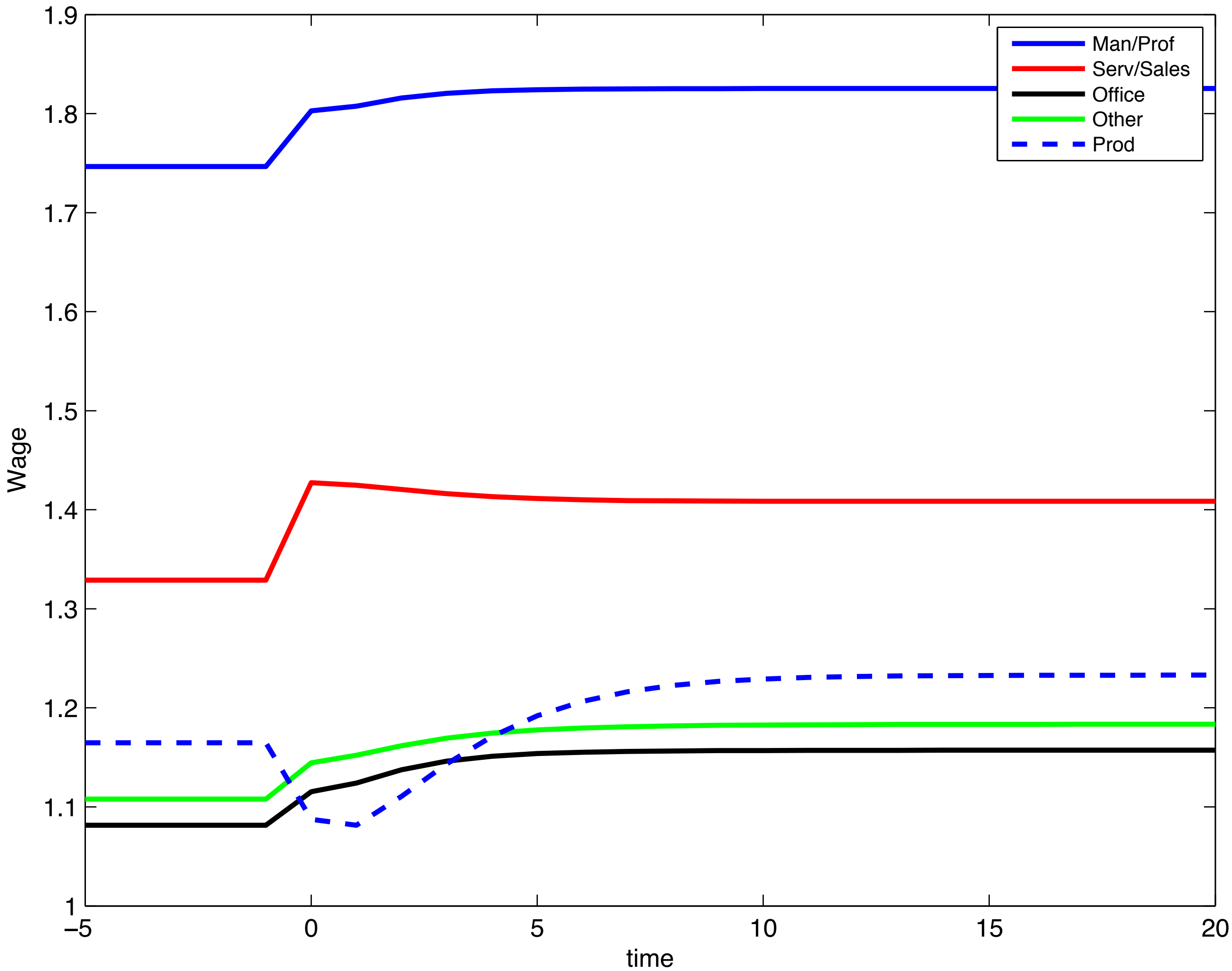
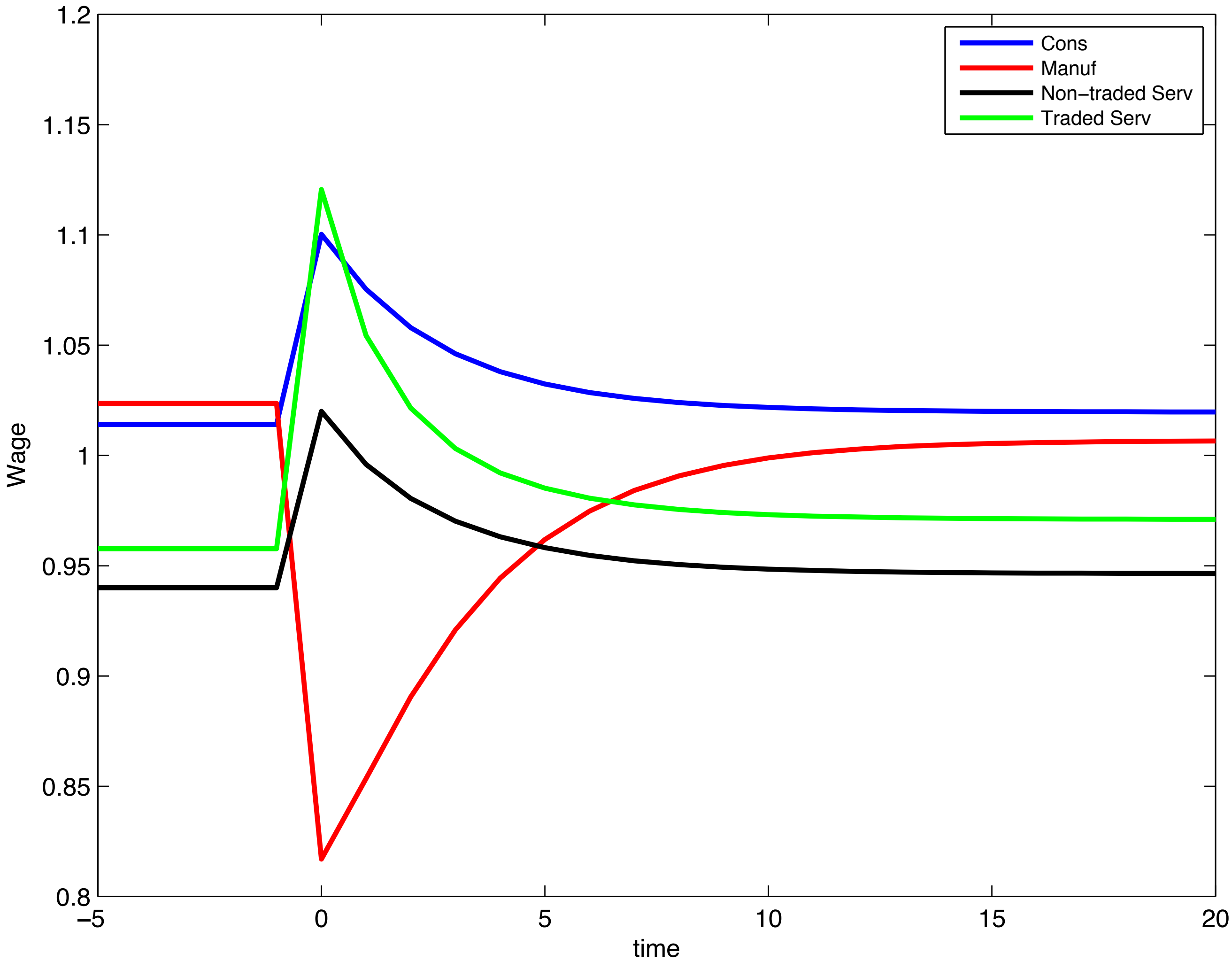


Figure3:Trade Shock –Average Low Skill Wages in each Sector(σ_1=2, σ_2=0.5)



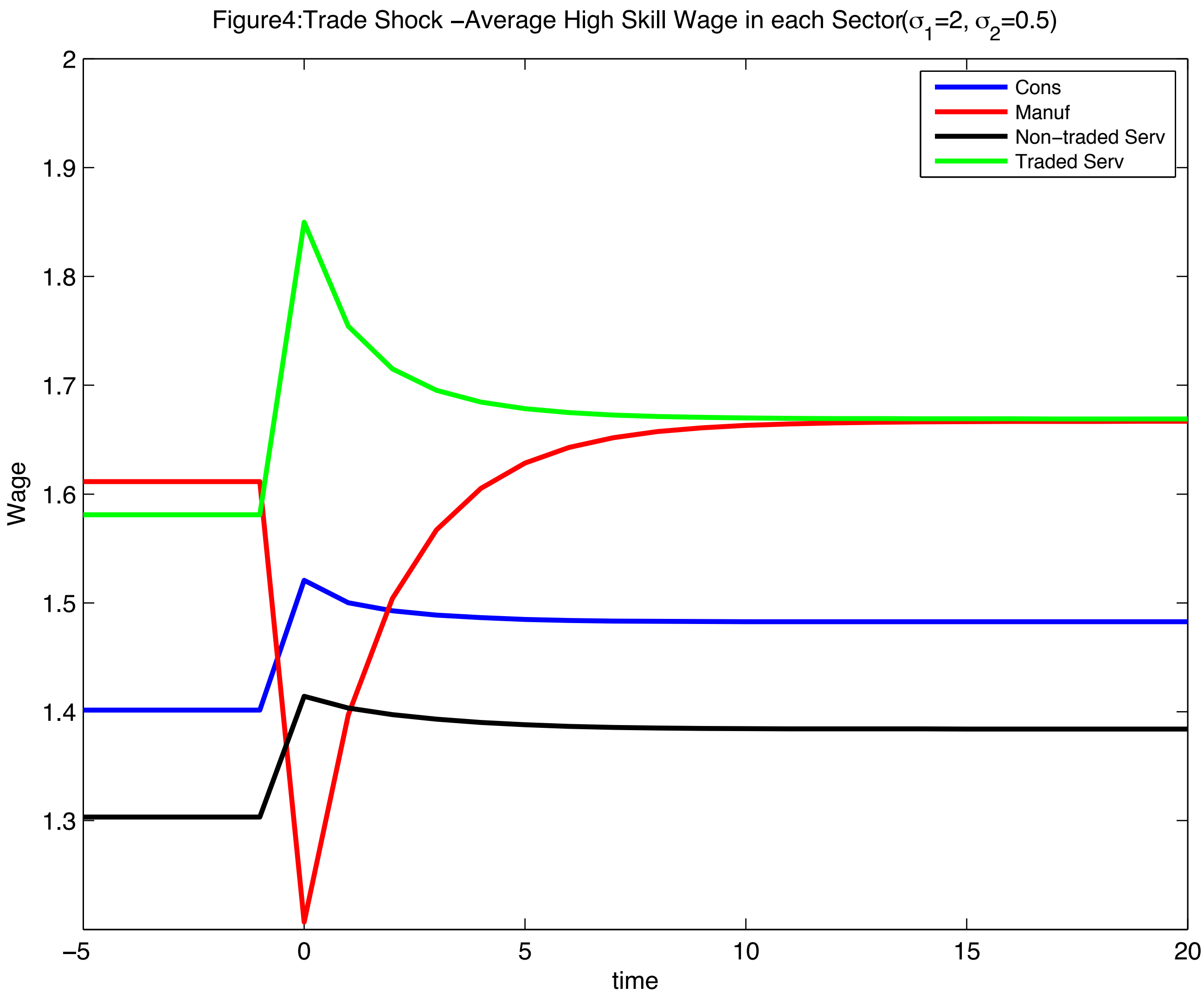


Figure4:Trade Shock –Average High Skill Wage in each Sector(σ_1=2, σ_2=0.5)
Cons
Manuf
Non–traded Serv
Traded Serv
Wage
time
2
1.9
1.8
1.7
1.6
1.5
1.4
1.3
–5
0
5
10
15
20

Figure5:Trade Shock –Detailed Low Skill Labor Allocation, Manuf(σ_1=2, σ_2=0.5)

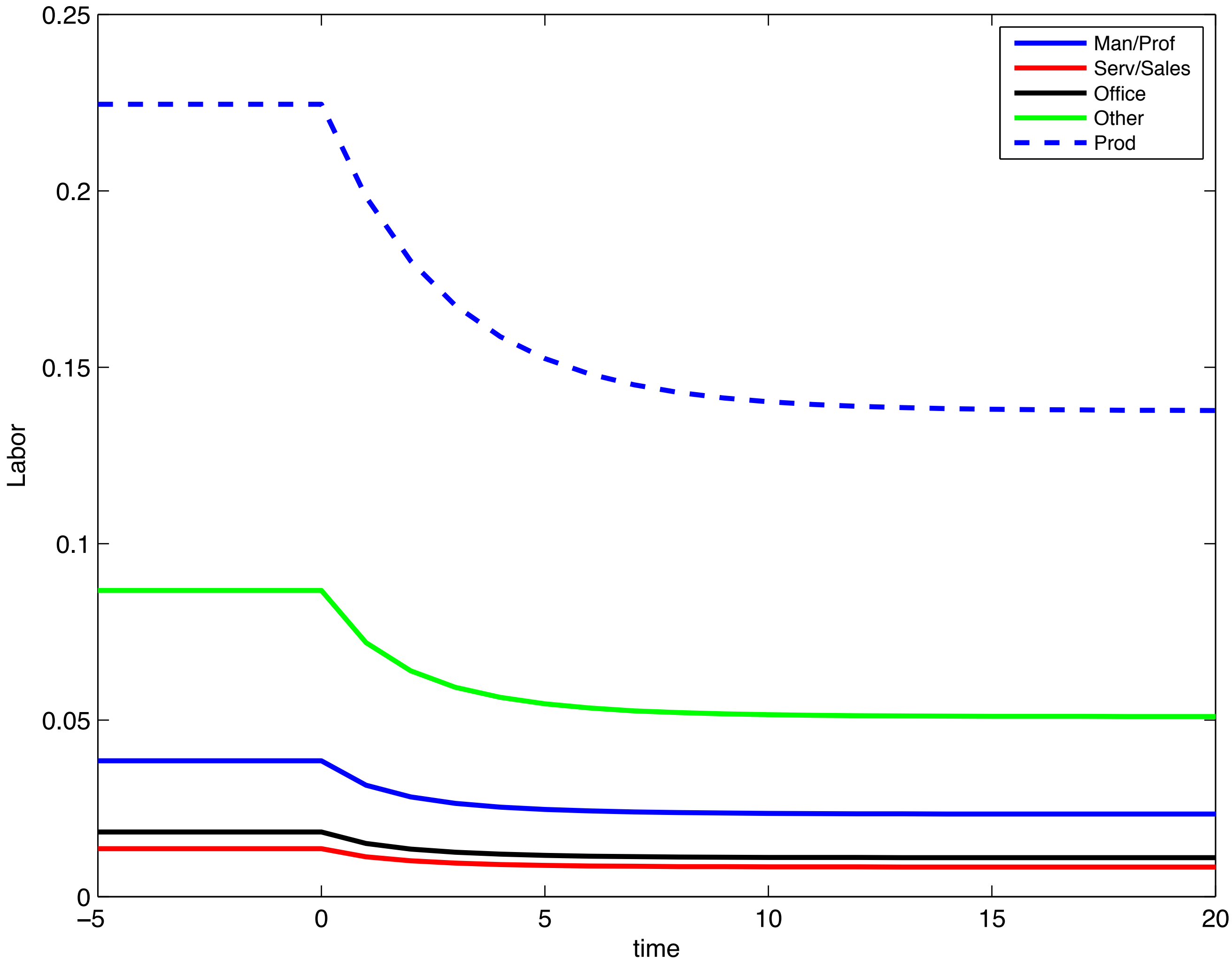
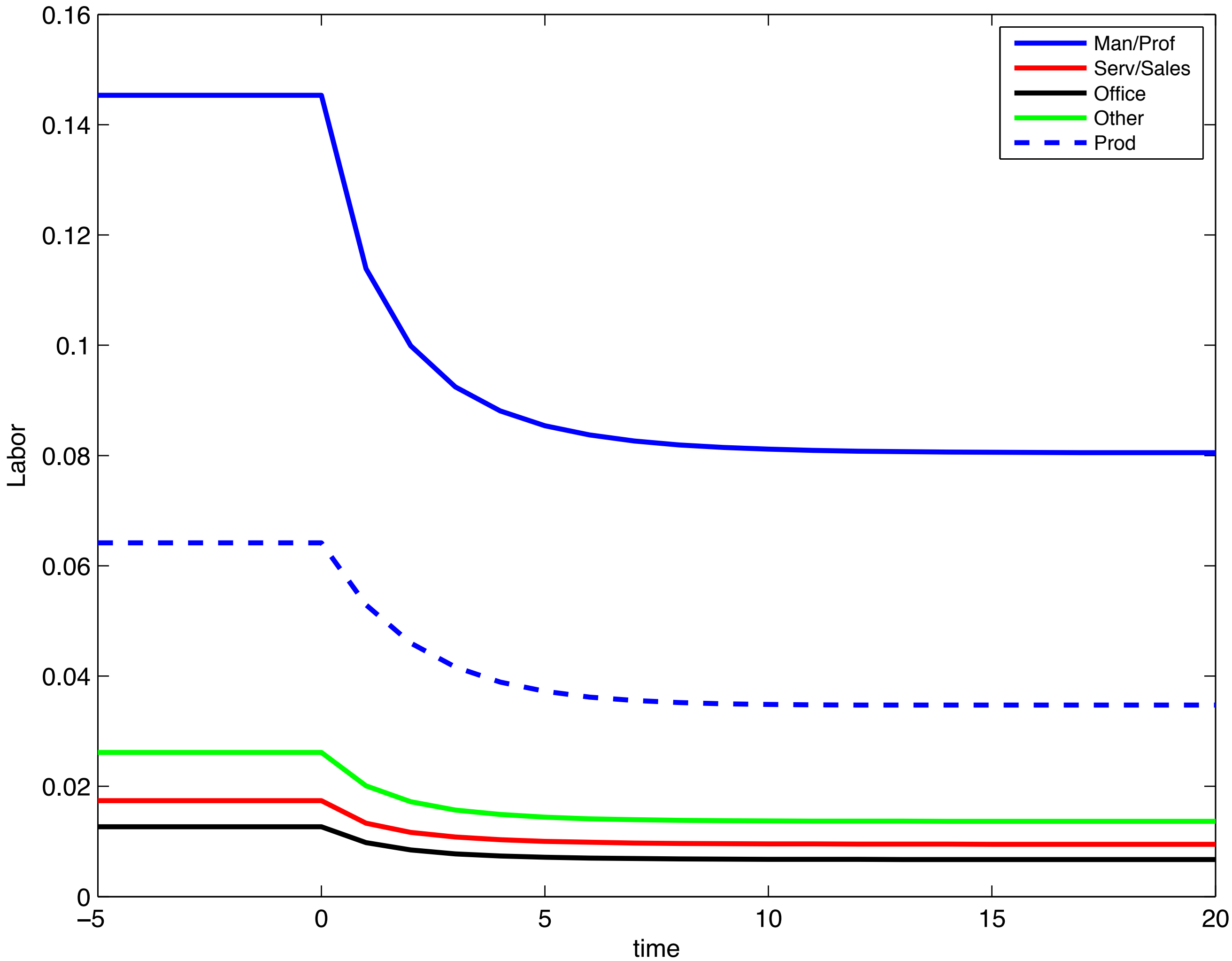


Figure6:Trade Shock –Detailed High Skill Labor Allocation, Manuf(σ_1=2, σ_2=0.5)



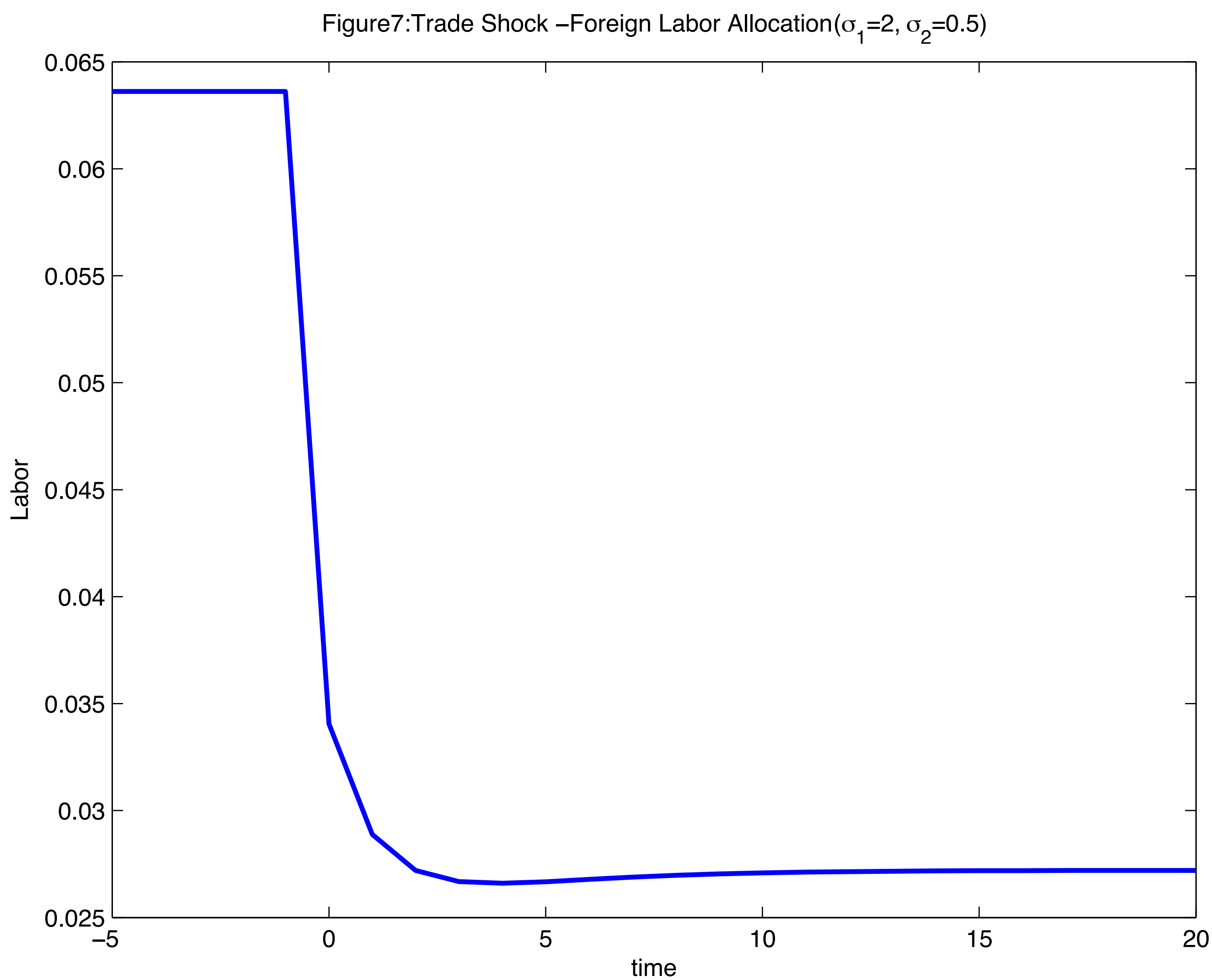
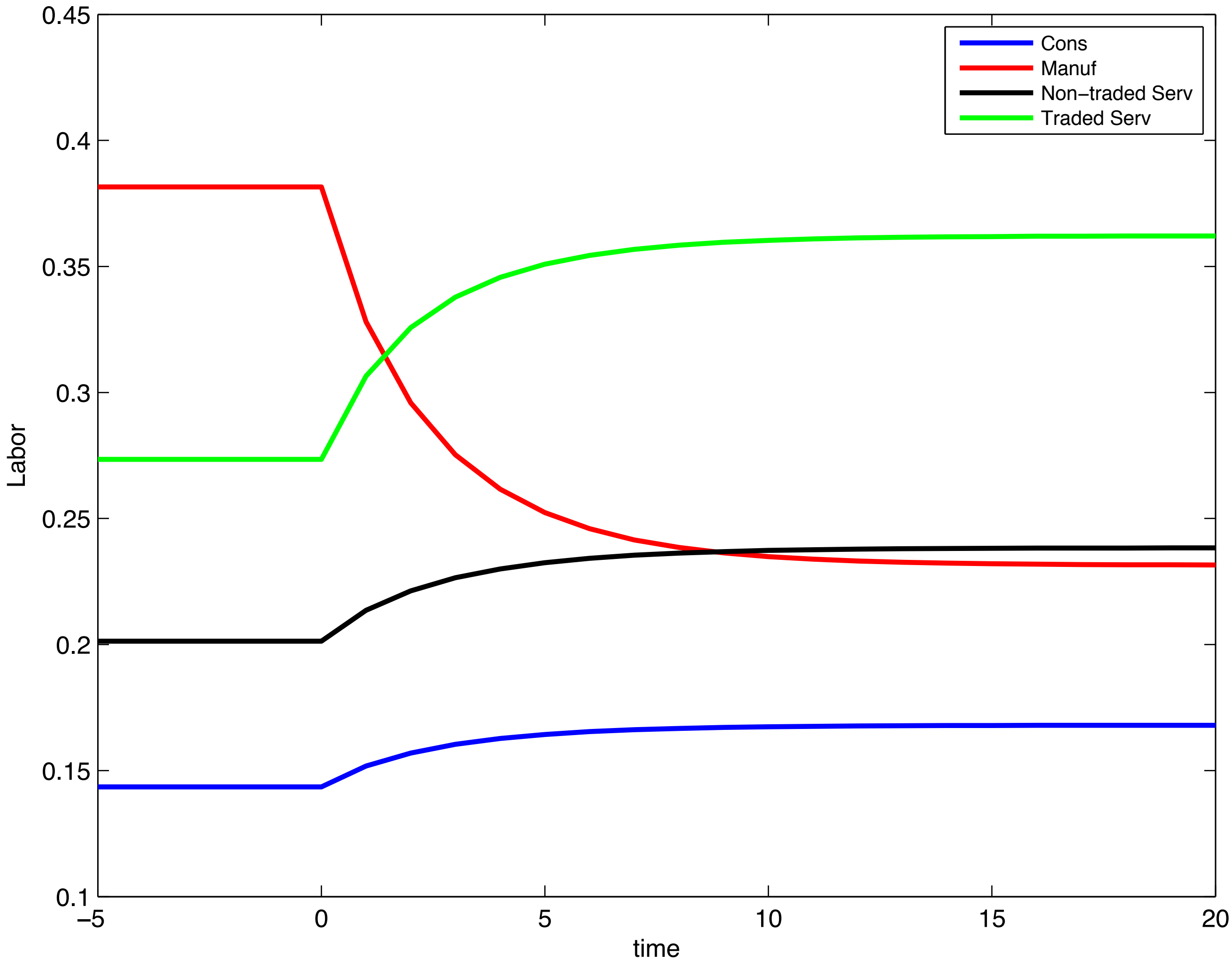


Figure7:Trade Shock −Foreign Labor Allocation(σ_1=2, σ_2=0.5)
0.065
0.06
0.055
0.05
0.045
0.04
0.035
0.03
0.025
Labor
−5
0
5
10
15
20
time

Figure8:Trade Shock –Total Low Skill Labor in each Sector(σ_1=2, σ_2=0.5)



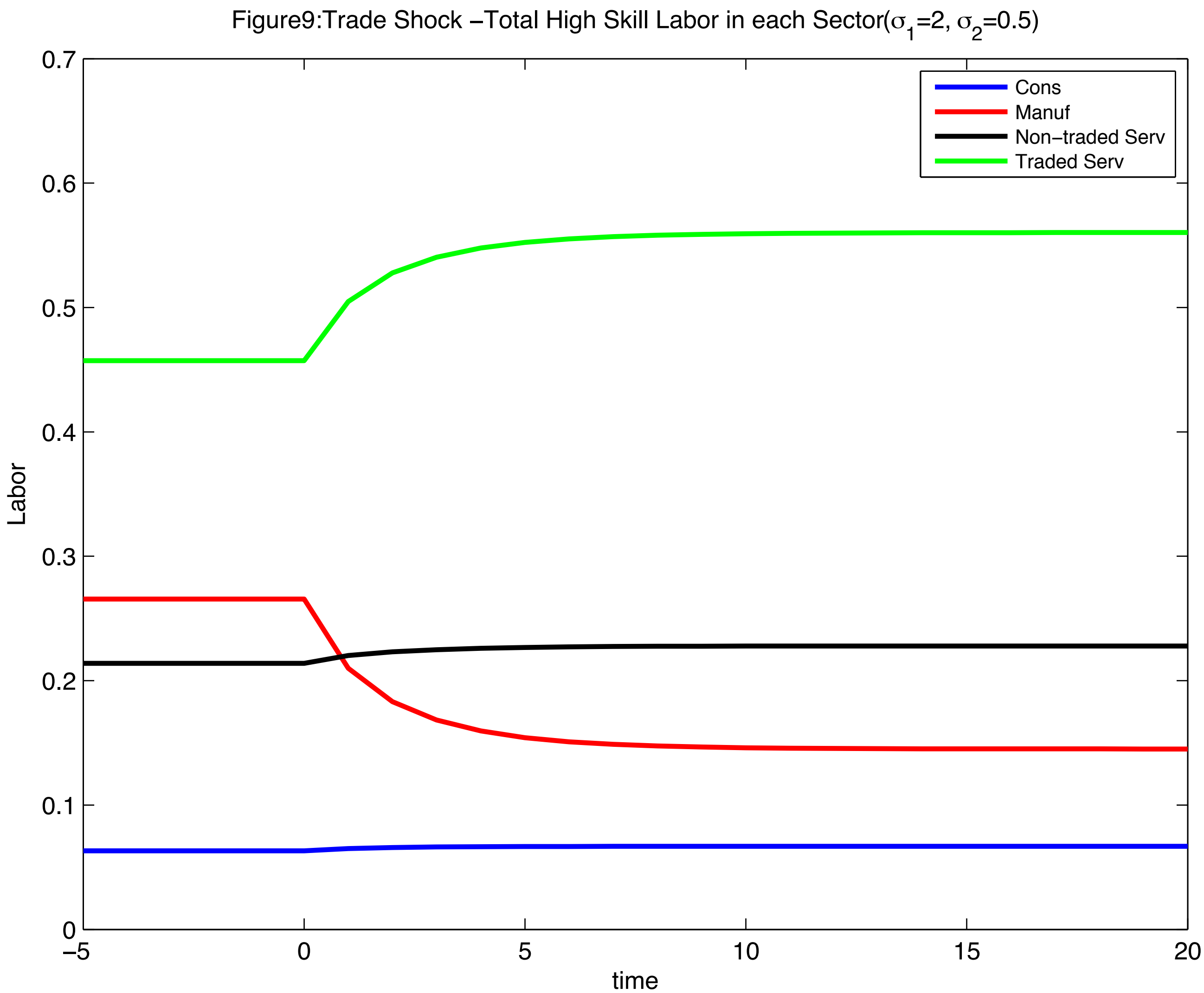


Figure9:Trade Shock −Total High Skill Labor in each Sector(σ1=2, σ2=0.5)
Cons
Manuf
Non−traded Serv
Traded Serv
Labor
time
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
−5
0
5
10
15
20

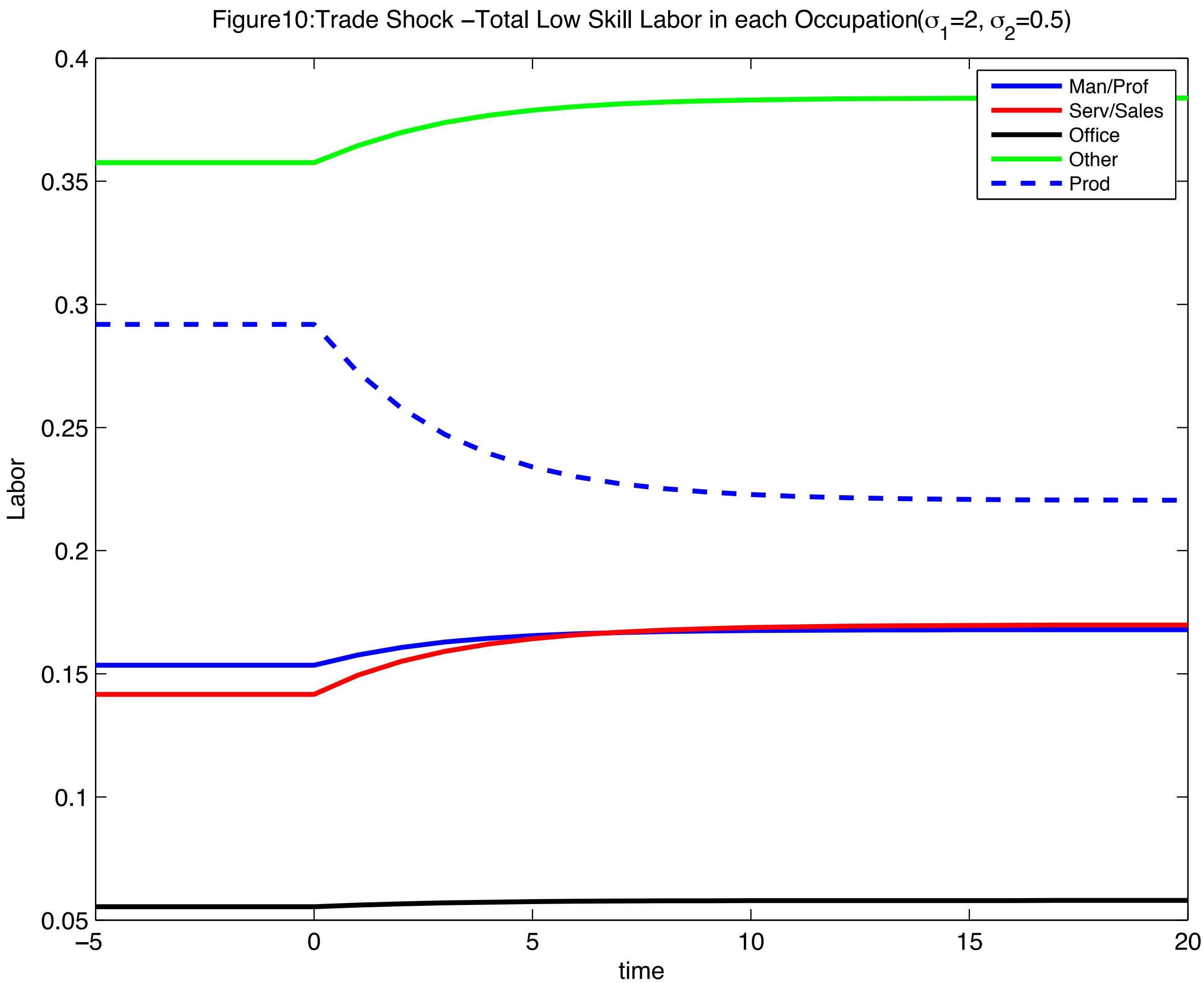


Figure10:Trade Shock –Total Low Skill Labor in each Occupation(σ_1=2, σ_2=0.5)
Labor
time
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
–5
0
5
10
15
20
Man/Prof
Serv/Sales
Office
Other
Prod

Figure11:Trade Shock −Total High Skill Labor Allocation in each Occupation(σ_1=2, σ_2=0.5)

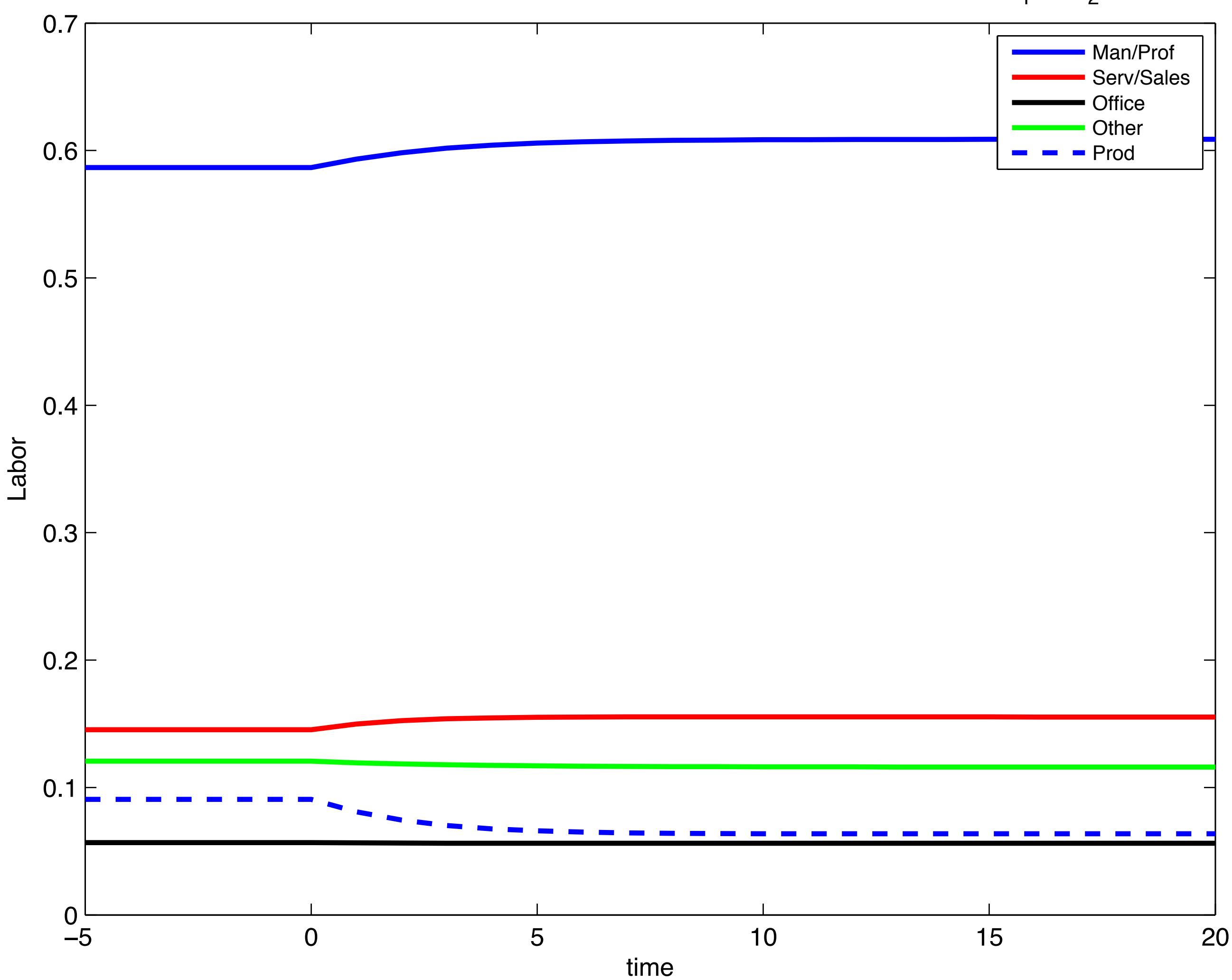


Figure12:Offshoring Shock –Average Low Skill Wages in each Occupation(σ_1=2, σ_2=0.5)

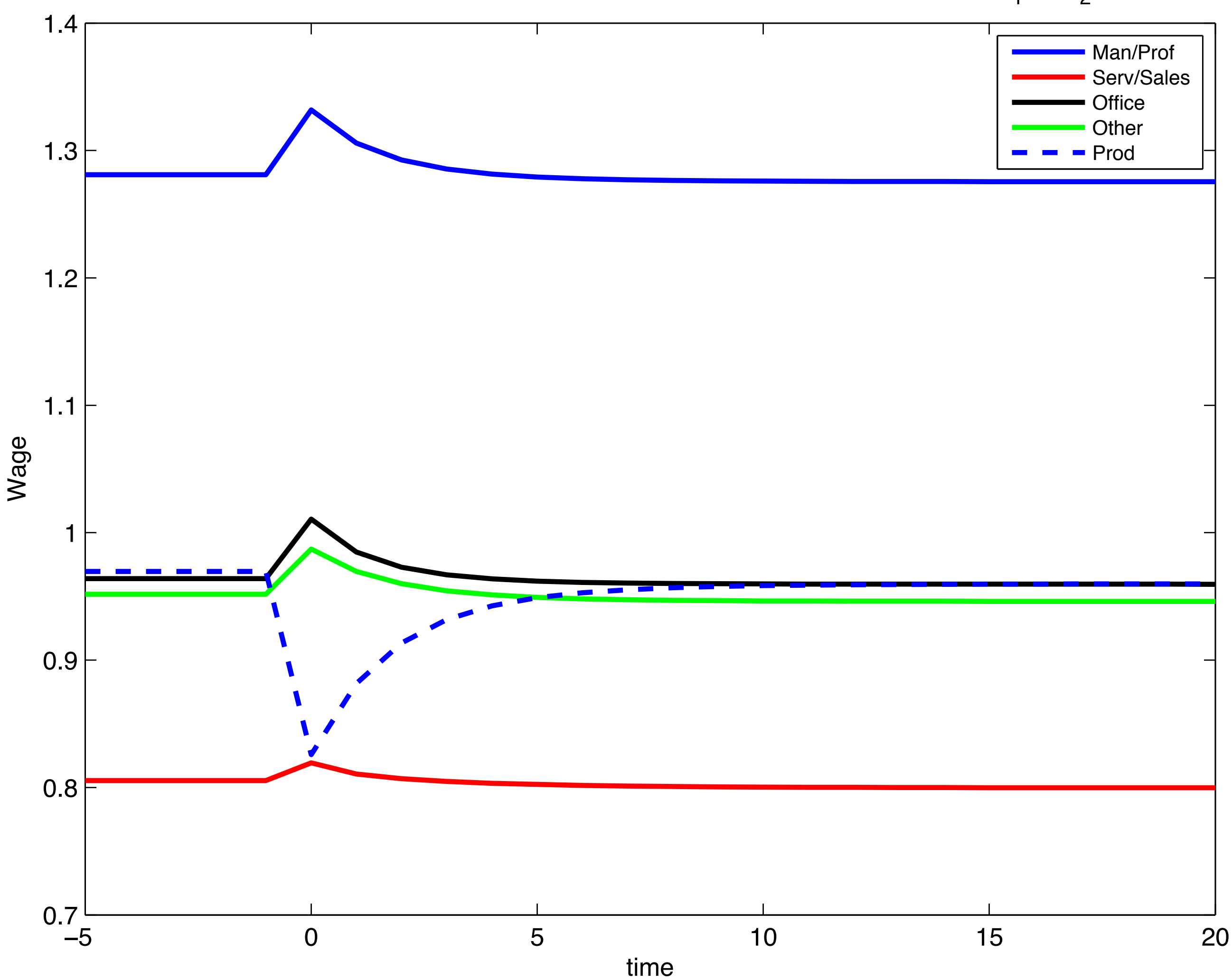


Figure13:Offshoring Shock –Average High Skill Wages in each Occupation(σ_1=2, σ_2=0.5)

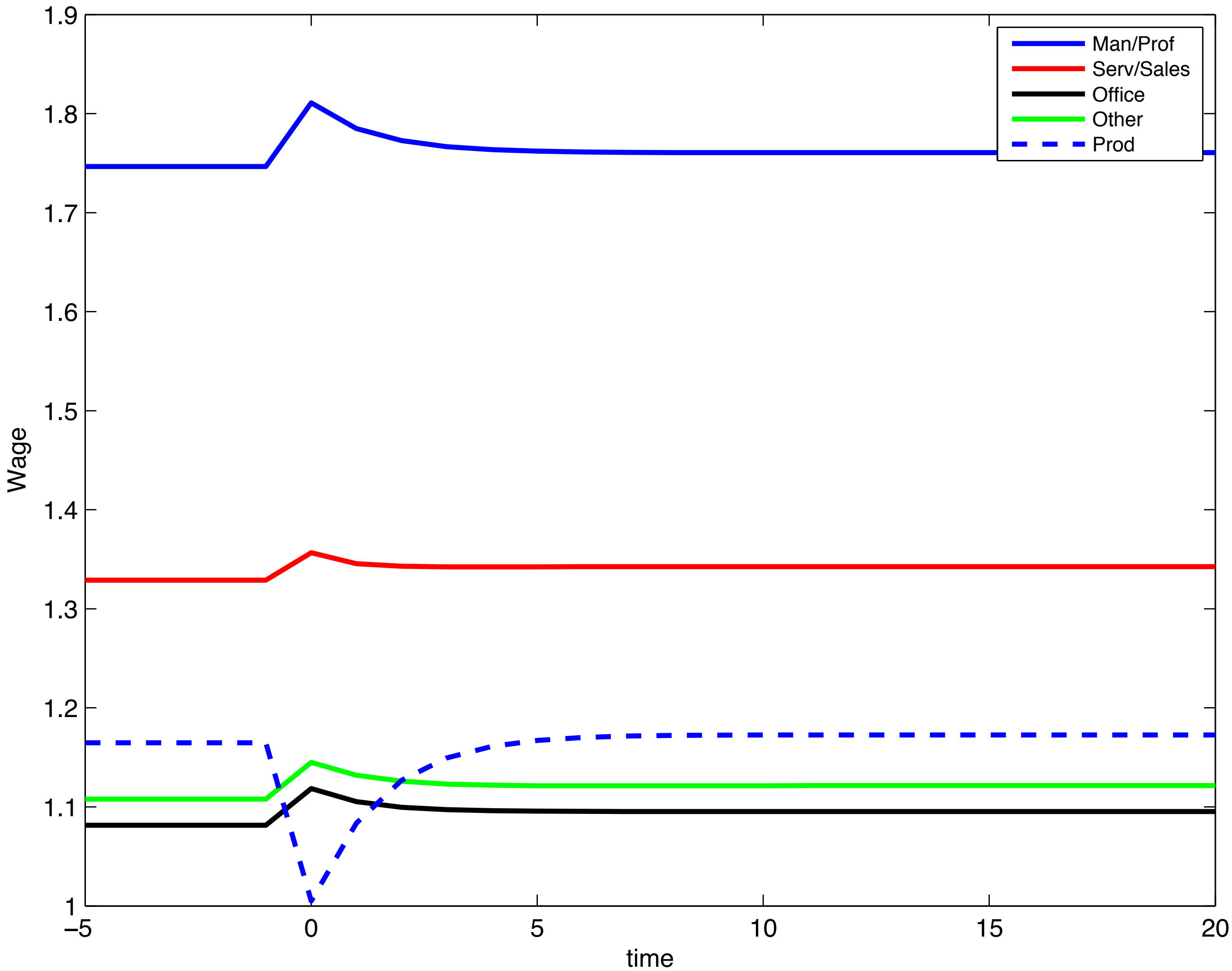


Figure14:Offshoring Shock −Average Low Skill Wages in each Sector(σ_1=2, σ_2=0.5)

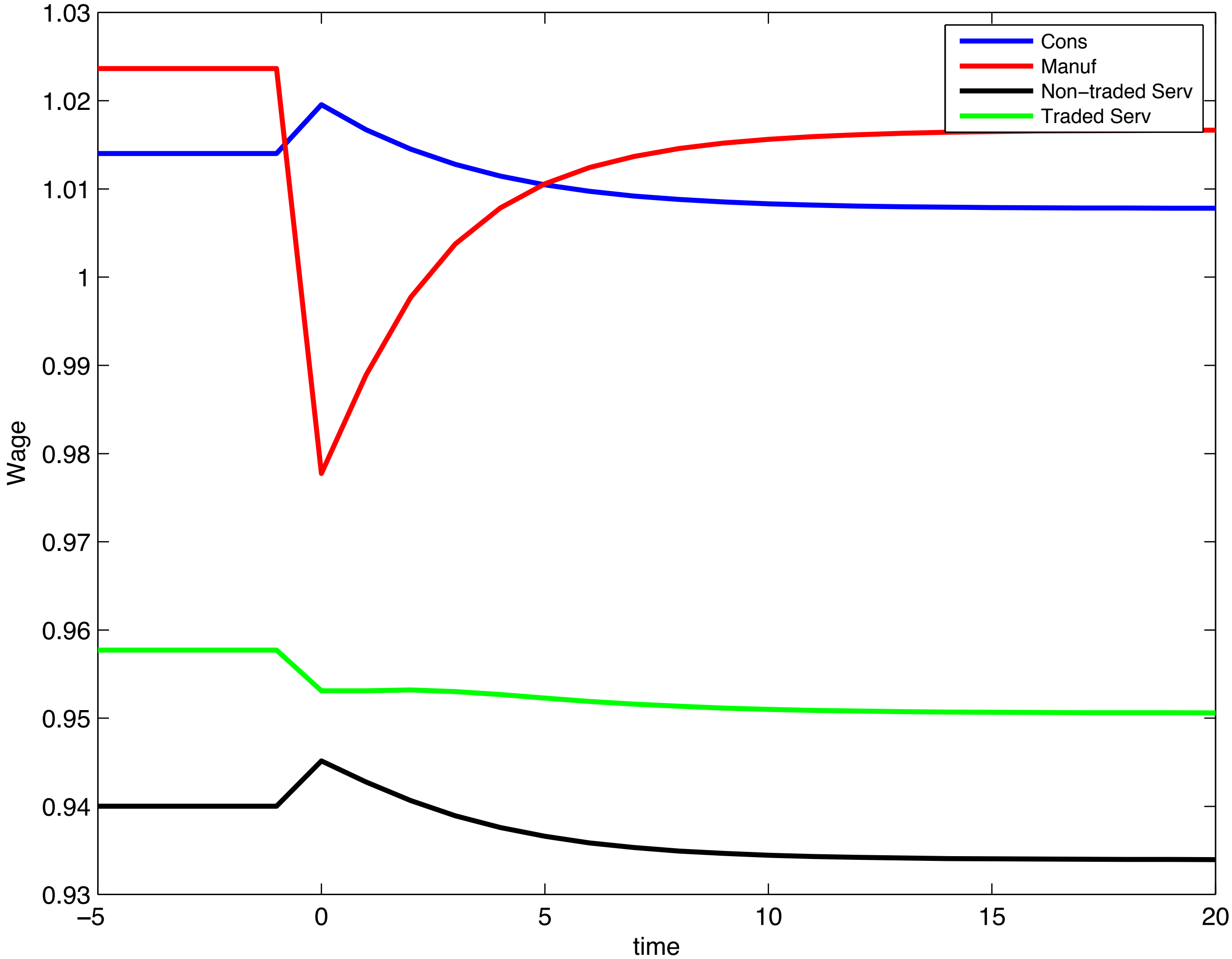


Figure15:Offshoring Shock –Average High Skill Wage in each Sector(σ_1=2, σ_2=0.5)

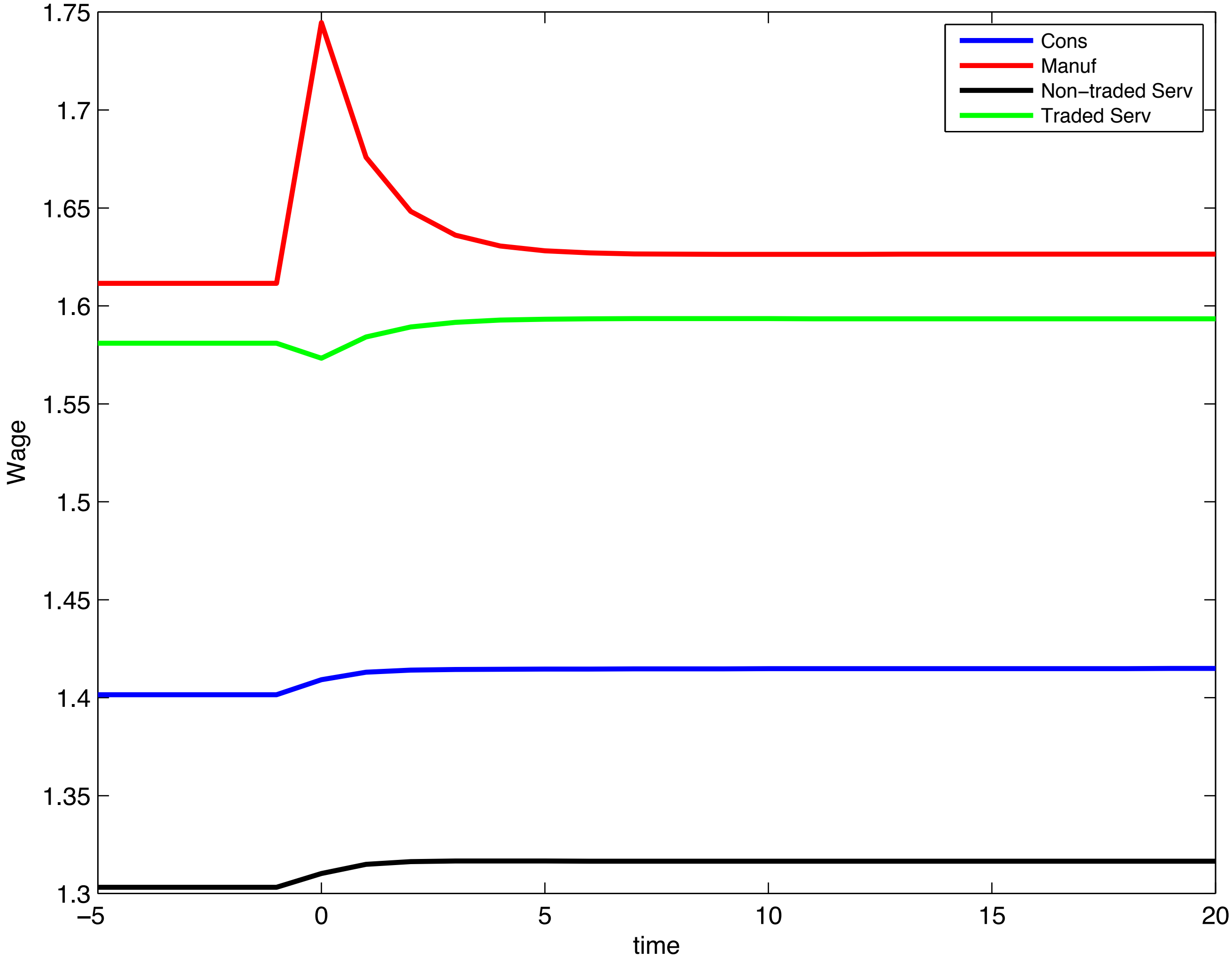


Figure16:Offshoring Shock –Detailed Low Skill Labor Allocation, Manuf (σ_1=2, σ_2=0.5)

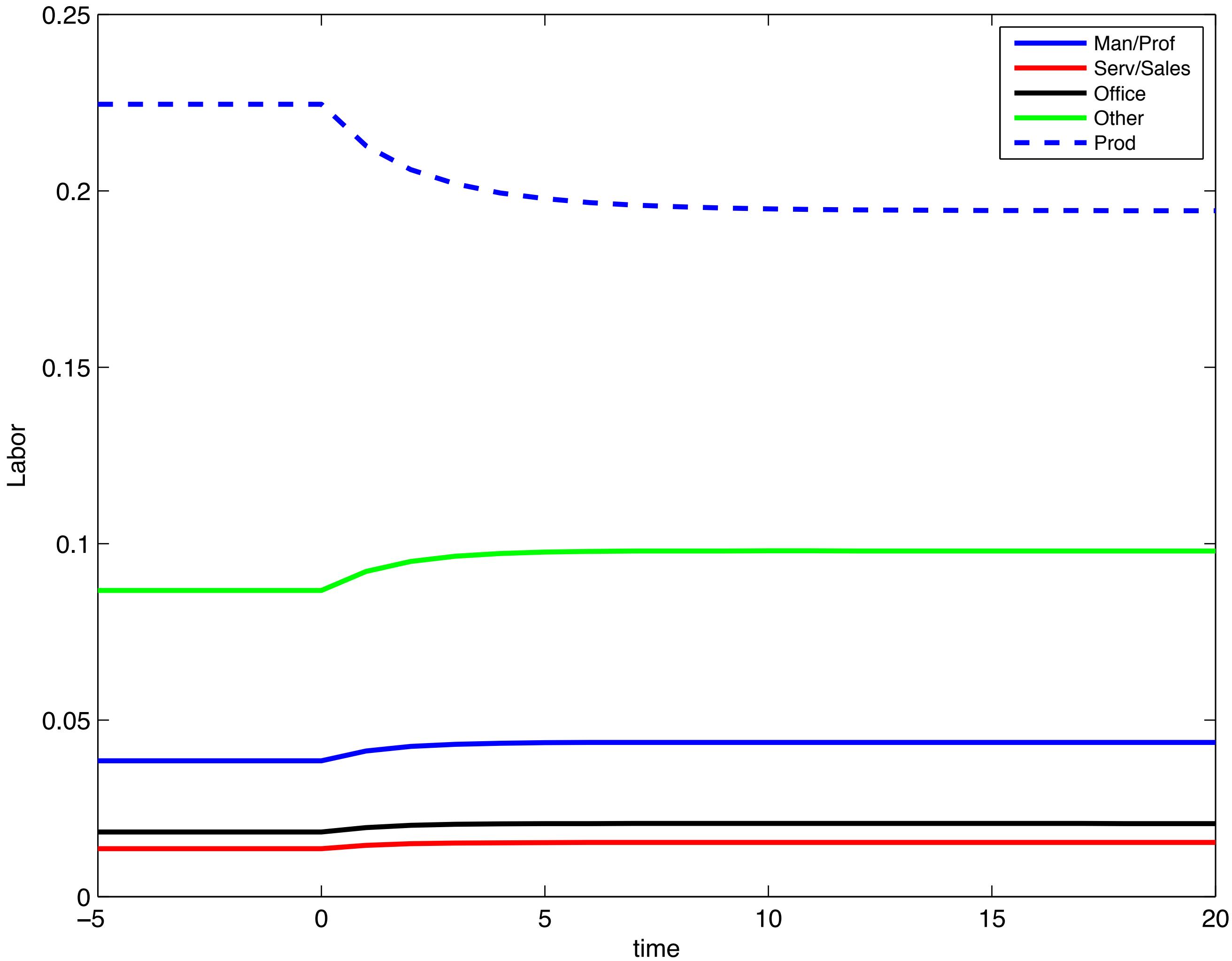
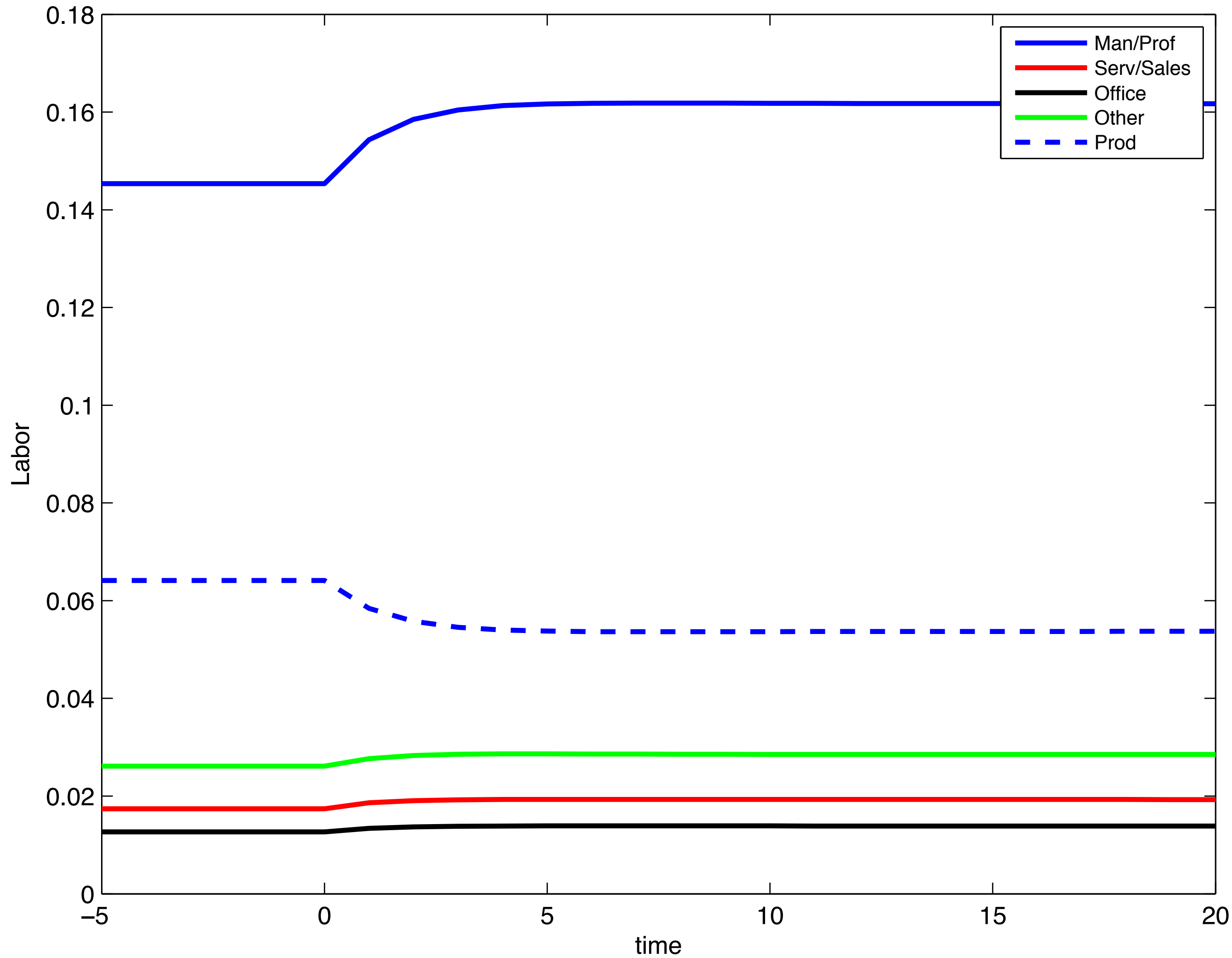


Figure17:Offshoring Shock –Detailed High Skill Labor Allocation, Manuf (σ_1=2, σ_2=0.5)



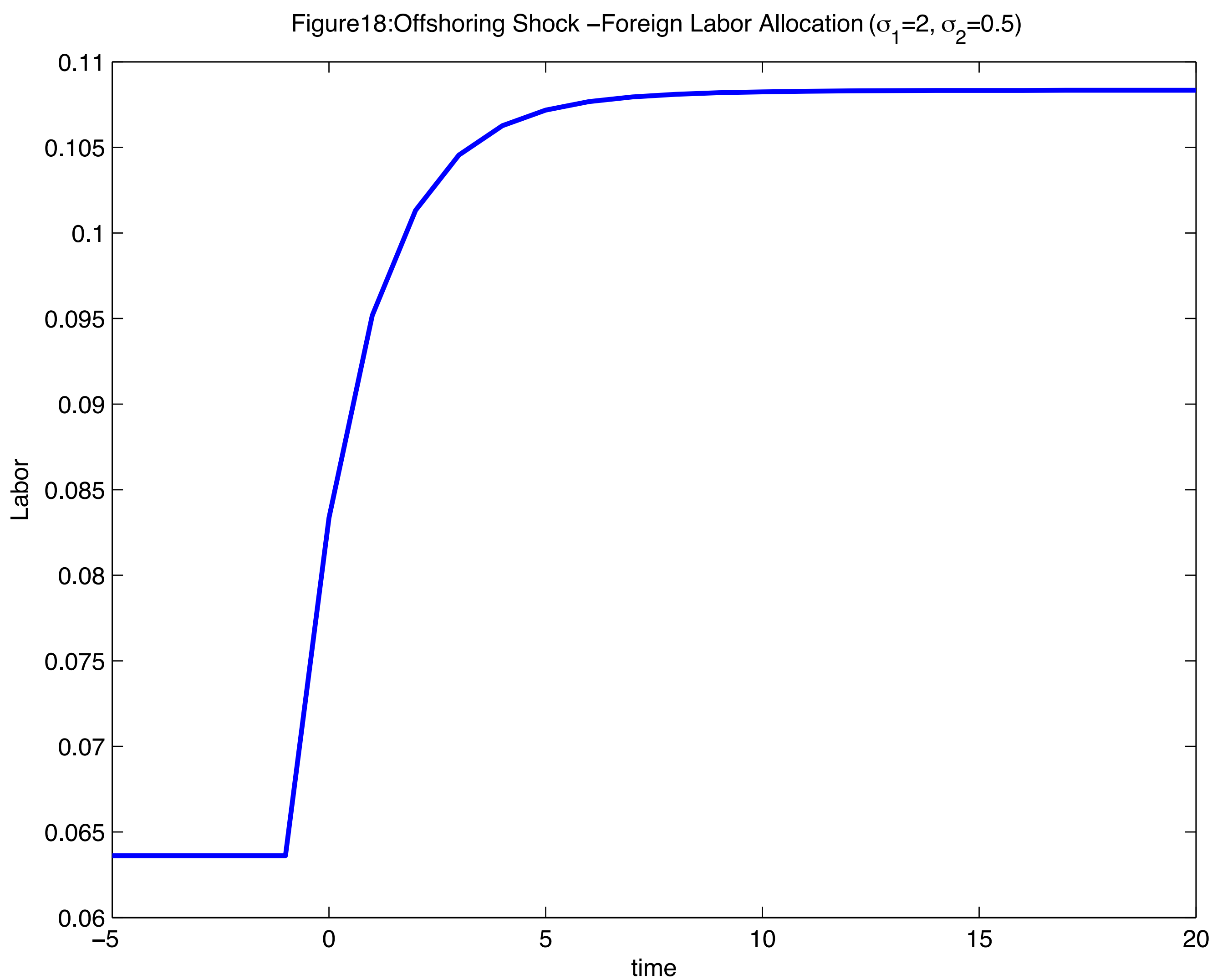


Figure18:Offshoring Shock −Foreign Labor Allocation (σ_1=2, σ_2=0.5)
Labor
time
0.11
0.105
0.1
0.095
0.09
0.085
0.08
0.075
0.07
0.065
0.06
−5
0
5
10
15
20

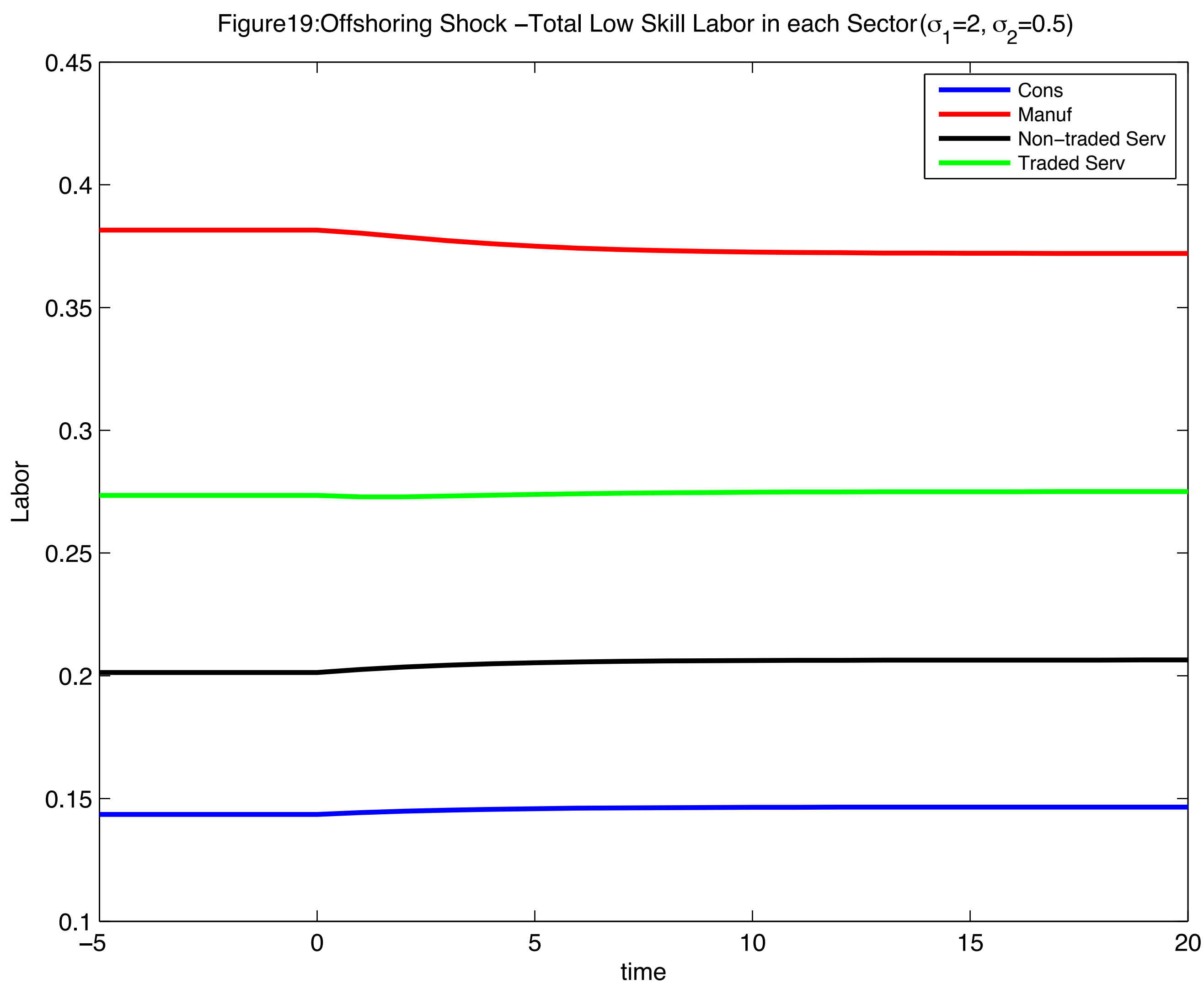
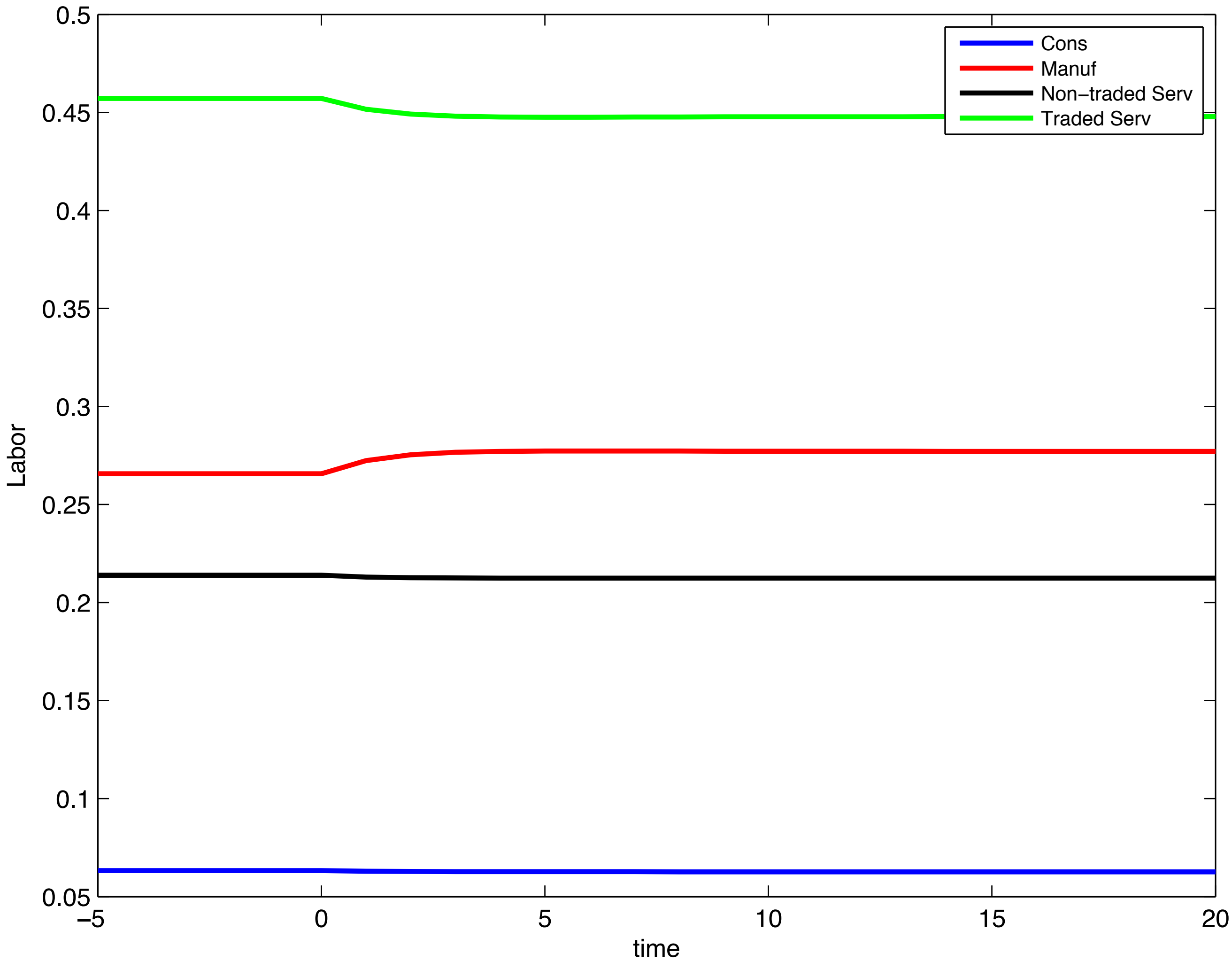


Figure19:Offshoring Shock −Total Low Skill Labor in each Sector(σ_1=2, σ_2=0.5)
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
Labor
−5
0
5
10
15
20
time
Cons
Manuf
Non−traded Serv
Traded Serv

Figure20:Offshoring Shock –Total High Skill Labor in each Sector(σ_1=2, σ_2=0.5)



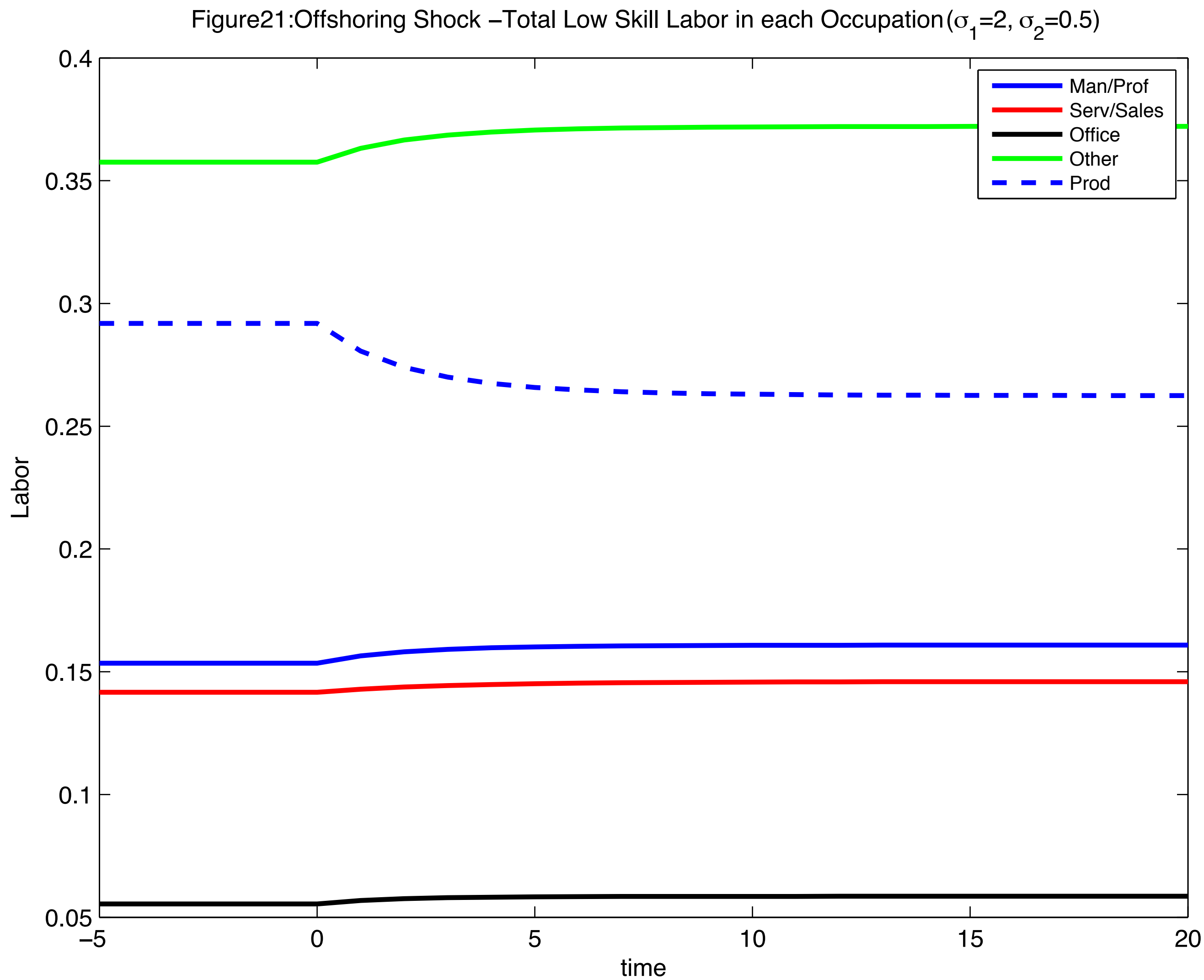


Figure21:Offshoring Shock –Total Low Skill Labor in each Occupation(σ_1=2, σ_2=0.5)
Man/Prof
Serv/Sales
Office
Other
Prod
Labor
time
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
–5
0
5
10
15
20

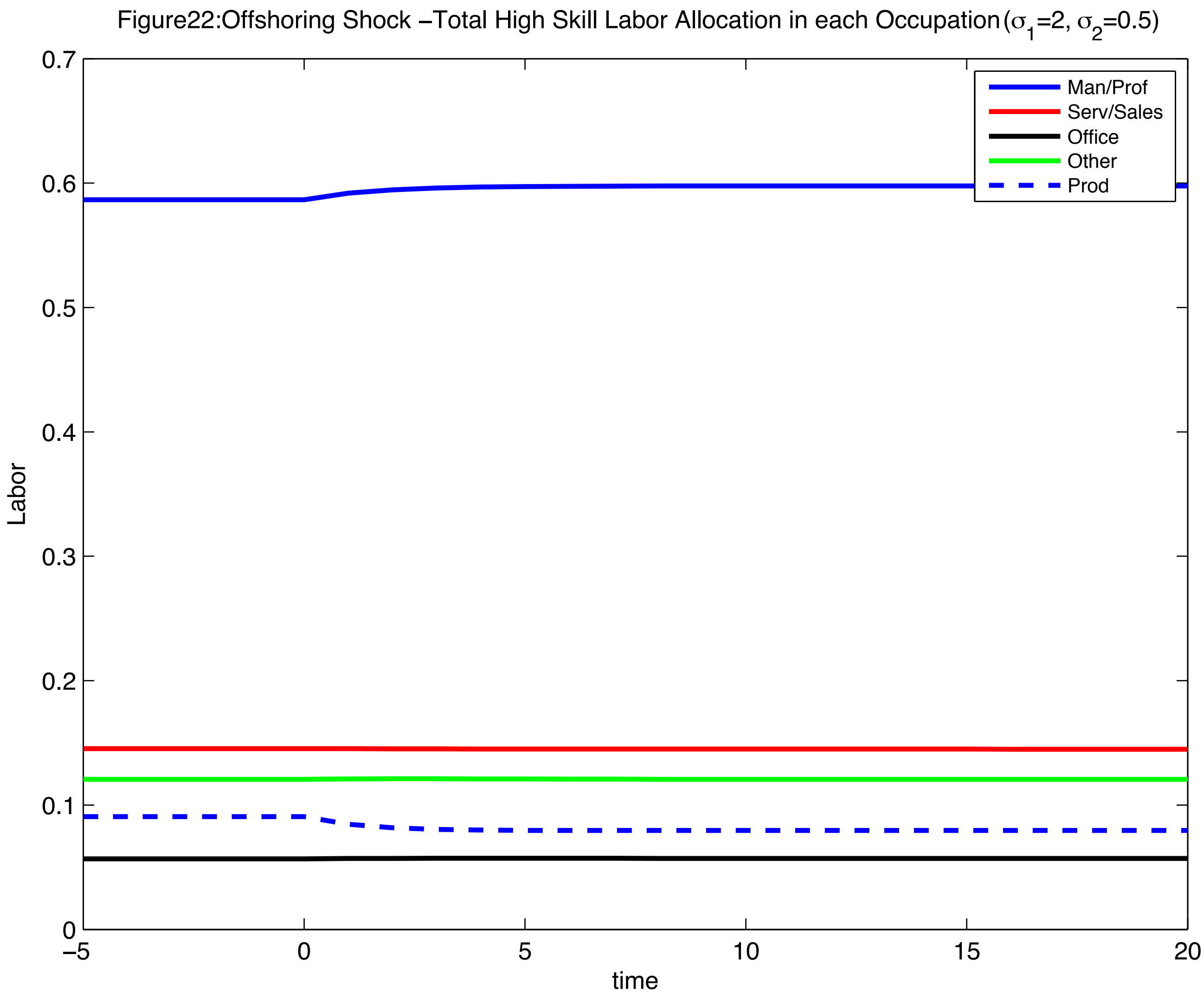


Figure22:Offshoring Shock –Total High Skill Labor Allocation in each Occupation (σ_1=2, σ_2=0.5)
Man/Prof
Serv/Sales
Office
Other
Prod
Labor
time
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
–5
0
5
10
15
20