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Trade Shocks and Labor Adjustment: A Structural Empirical Approach

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The welfare effects of trade shocks turn on the nature and magnitude of the costs workers face in moving between sectors. Using an Euler-type equilibrium condition derived from a rational expectations model of dynamic labor adjustment, we estimate the mean and variance of workers' switching costs from the US CPS. We estimate high values of both parameters, implying slow adjustment of the economy and sharp movements in wages in response to trade shocks. However, import-competing workers can still benefit from tariff removal; liberalization lowers their wages in the short and long run but raises their option value. (*JEL* E24, F13, F16)

Perhaps the most urgent question facing trade economists is the effect of liberalization and other trade shocks on the welfare of workers. This question has generated a large body of research, but a feature shared by most of the extant trade literature on this is a reliance on static models, in which workers are assumed to be either instantly costlessly mobile, or perfectly immobile (we will discuss important exceptions below). This prevents the trade literature from even addressing, let alone answering, some central questions: What are the costs faced by workers who wish to move to a new industry in response to import competition? How long will the labor market take to adjust and find its new steady state? Will that steady state feature a lasting differential impact on workers in the import-afflicted sector, or will arbitrage equalize worker returns in the long run? What are the lifetime welfare effects on workers in different industries, taking into account moving costs and transitional dynamics?

This paper offers an approach to answering these questions. Within the context of a standard trade model, we specify a dynamic equilibrium model of costly labor adjustment, a model fully studied in Stephen Cameron, Chaudhuri and McLaren (2007). We then show how the structural moving-cost parameters of this model can be estimated, using Euler-equation-type techniques borrowed from macroeconomics. Estimating these parameters on data from the US Current Population Surveys (CPS), we then use these parameters to simulate stylized trade shocks and show their dynamic equilibrium impact.

A large number of studies in the trade economics field have attempted to measure the effects of trade shocks on wages. Some test labor-market predictions of the Heckscher-Ohlin model, as Robert Z. Lawrence and Matthew J. Slaughter (1993). Others regress changes in wages sector by sector

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on changes in import prices (as Ana L. Revenga 1992), trade policy (as Orazio Attanasio, Pinelopi Goldberg, and Nina Pavcnik 2004), or import penetration (as Lori G. Kletzer 2002). Slaughter (1998) provides an overview.

This literature has revealed much about the positive labor-market effects of trade, but for several reasons it is not well suited to address the normative questions that concern us (nor was it designed to). The first is that a given change in trade policy is likely to have very different effects depending on the dynamics of its implementation (for example, whether it is anticipated or not, delayed or immediate, gradual or sudden, announced as part of a change in policy or a one-time event). These distinctions are important in policy design, but the reduced-form studies do not shed any light on them; for this, a structural model is needed. Second, in a dynamic environment, wage changes at a given moment are insufficient for identifying the effect on a worker's lifetime utility, which is what really matters for welfare analysis. Third, perhaps most importantly, to move from calculation of *wage* effects to *welfare* effects, one needs to take account of the constant interindustry gross flows of workers observed in the data. These gross flows are large and have a large effect on welfare calculations. Indeed, we will see that due to these flow effects, welfare for workers in a given industry can go in the opposite direction from wages in that industry.

A small number of studies in the trade literature do study the empirics of dynamic labor market adjustment but focus on employer-side adjustment. Hâle Utar (2007) estimates a dynamic model of firm adjustment to trade shocks with heterogeneous firms. Raymond Robertson and Donald H. Dutkowsky (2002) use an Euler equation approach to estimate employers' labor adjustment costs in Mexico with a focus on international policy but employ a model that rules out gross flows in excess of net flows, thus ruling out an important feature of the data that is central to our approach.

On the other hand, a number of labor economists have developed highly sophisticated structural empirical models that allow them to estimate the impact of policy changes on labor adjustment in a manner similar in some respects to what we are doing here. Examples include Donghoon Lee (2005) and Michael P. Keane and Kenneth I. Wolpin (1997), who focus on occupational choices of workers rather than interindustry reallocation; John Kennan and James R. Walker (2003), who study movement of workers across US regions; and Lee and Wolpin (2006), who study mobility between the service sector and the goods sector. There are four key differences between those studies and our approach. First, with our emphasis on *intersectoral* reallocation (especially between import-competing and other sectors), we are tailoring our model to the analysis of trade policy, which cannot be addressed by those other studies. Second, with our Euler-equation approach, which appears not to have been used before in the analysis of workers' mobility choices, we do not need to calculate the workers' value function or make any strong assumptions about what workers know about the future (in particular, they do not need to know the future course of aggregate events with certainty, which is assumed in Keane and Wolpin 1997 and Lee 2005, for example). We assume that workers have rational expectations about the future, but we need make no assumption regarding *how much* information they have about the future. Third, our estimation method is simple and computationally cheap, allowing its application potentially to a very wide range of datasets. The most closely related paper to ours is Artuç (2009), which does estimate a general-equilibrium structural model of worker response to trade shocks but focuses on *intergenerational* distributional issues and does not use a Euler-equation approach.[1]

[1] Another related paper, Gueorgui Kambourov (2009), calibrates a model of labor reallocation, which is costly because of sector-specific human capital and firing costs, and applies it to trade reform. It turns out that firing costs have a large negative effect on the gains from trade reform. Unlike our paper, Kambourov's model does not provide workers with idiosyncratic shocks, so it cannot generate gross flows in excess of net flows. Given the importance of gross flows in the data, this is a significant feature of our approach.

In our approach, we present a dynamic rational-expectations model[2] in which each worker can choose to move from her current industry to another one in each period, but must pay a cost to do so. The cost has a common component, which does not vary across time or workers, and a time-varying idiosyncratic component, which can be negative, reflecting nonpecuniary motives that workers often have for changing jobs (such as tedium, a need to relocate for family reasons, and the like). We derive an equilibrium condition, which is a kind of Euler equation, estimate its parameters using the Current Population Survey (CPS), and simulate a trade liberalization to illustrate their implications. An important benefit of our theoretical approach is that it can be implanted quite easily in a conventional trade model and manipulated easily, facilitating its adoption as part of the trade economist's toolkit. For example, Chaudhuri and McLaren (2007) show that many analytical results can be obtained with this model regarding steady states, transition paths, welfare, and political economy in a Ricardo-Viner model with this labor adjustment model, and Artuç, Chaudhuri, and McLaren (2008) show how the model can be easily simulated numerically to address a number of trade policy questions.

Idiosyncratic shocks are broadly consistent with observed labor-market behavior, for two reasons. First, gross flows are an order of magnitude larger than net flows, implying large numbers of workers moving in opposite directions at the same time. Second, Audra J. Bowlus and George R. Newmann (2006) show that a significant fraction of workers who change jobs *voluntarily* move to jobs which pay less than the job the worker left behind. Approximately 40 percent of voluntary job changes have this feature, not very different from the 50 percent that would be expected if wage differences had *no* effect on mobility decisions. Both of these observations suggest a central role for idiosyncratic shocks in worker mobility.[3] We quantify this in our estimates and show that it is very important for evaluating the welfare effects of trade policy. In particular, the presence of these shocks implies that option value is an important element of each worker's utility calculation, which, although it can have a decisive effect on the welfare effects of trade reform, to our knowledge has never before been introduced into the literature on trade and labor.

The estimates we obtain show very high average moving costs, and a very high standard deviation of moving costs, both estimated to be several times average annual wages for moving from one broadly aggregated sector of the economy to another. These surprisingly high estimated costs are actually in line with related findings by other authors using different techniques; for example, Kennan and Walker's (2003) estimates of costs of moving between US regions, and Artuç's (2009) estimates of intersectoral moving costs.[4] In addition, as we will see, simulations based on these patterns produce realistic aggregate behavior. The message conveyed by these findings is that *US workers change industry a great deal, but those movements do not respond much to movements in intersectoral wage differentials*. Thus, nonpecuniary motives such as are captured by our idiosyncratic shocks must be driving a large portion of our workers' movements. This is important for the analysis of trade liberalization, as our simulations reveal. First, it suggests sluggish adjustment of the labor market to a trade shock, with the economy requiring several years to approach the new steady state. Second, as a corollary, it implies a large drop in wages in the import-competing sector that is hit by the liberalization; indeed, the wages in that sector never fully recover. Third, surprisingly, despite this wage drop, because of the high levels of mobility

[2] The model we use is presented in full in Cameron, Chaudhuri, and McLaren (2007). It is a full-employment model with moving costs for workers. An alternative approach would be to focus on search frictions, as in Arthur J. Hosios (1990); Carl Davidson, Lawrence Martin, and Steven J. Matusz (1999); and Davidson and Matusz (2006).

[3] Of course, some fraction of the voluntary moves could be to jobs that pay less initially but have steeper wage growth. Our point is that these two observations together make an approach based on idiosyncratic shocks a plausible starting point. We are grateful to a referee for clarifying our thinking on this.

[4] It should be noted that this is so even though Artuç (2009) uses a different dataset, namely the NLSY; this paper uses the CPS.

due to idiosyncratic shocks, *workers in the import-competing sector may benefit from the liberalization*. This is because the high volatility of their idiosyncratic shocks combined with rising real wages in other sectors implies that their option value is enhanced by the liberalization, and this effect can overwhelm the direct loss from the lower wages in their own sector.[5] This shows the utility of a dynamic structural approach; a reduced-form wage equation can document the drop in wages in the import-competing sector, but not the countervailing option-value effect.

In the following section we present the model with homogeneous workers, deriving its estimating equation and explaining the identification strategy intuitively; Section III then examines the data and its measurement issues; then in Section IV we present our estimates and interpret them. The next section deals with a number of measurement and specification issues, and Section VI studies simulations based on our estimated parameters. Finally, Section VII presents extensions of the model, estimation, and simulations to the case of heterogeneous workers, and shows that an import-competing worker's age, rather than human capital, is crucial for determining whether that worker will be harmed by liberalization in this model or not.

I. The Model

Essentially, the basic model is a Ricardo-Viner trade model with the addition of costly interindustry labor mobility.[6]

A. *Basic Setup*

Consider an n-good economy, in which all agents have preferences summarized by the indirect utility function $v(p,I) \equiv I/\phi(p)$, where p is an n-dimensional price vector, I denotes income, and ϕ is a linear-homogeneous consumer price index. Assume that in each industry i there are a large number of competitive employers, and that their aggregate output in any period t is given by $x_t^i = X^i(L_t^i, K^i, s_t)$, where L_t^i denotes the labor used in industry i in period t, K^i is a stock of sector-specific capital,[7] and s_t is a state variable that could capture the effects of policy (such as trade protection, which might raise the price of the output), technology shocks, and the like. Assume that X^i is strictly increasing, continuously differentiable, and concave in its first two arguments. Its first derivative with respect to labor is then a continuous, decreasing function of labor, holding K^i and s_t constant. Assume that s follows a stationary process on some state space S.[8]

The economy's workers form a continuum of measure $\overline{L}$. In the basic model, we will treat all workers as homogeneous; later we will explore variants that allow for heterogeneity. Each worker at any moment is located in one of the n industries. Denote the number of workers in industry i

[5] This is closely related to the empirical findings of Christopher S. P. Magee, Davidson, and Matusz (2005). They find, for low-turnover industries, that political action committees are much more likely to donate to pro-trade politicians if they represent an export sector than an import-competing sector; but for high-turnover sectors the difference between export and import-competing industries essentially disappears. They rationalize this using a search model of labor adjustment as in Arthur J. Hosios (1990) and Davidson, Martin, and Matusz (1999), but the underlying reason is similar: with a high degree of labor flows, workers do not identify closely with the industry in which they are currently located.

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

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

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

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

If worker l moves from industry i to industry j, she incurs a cost $C^{ij} \geq 0$, which is the same for all workers and all periods and is publicly known. In addition, if she is in industry i at the end of period t, she collects an idiosyncratic benefit $\varepsilon_{l,t}^i$ from being in that industry. These benefits are independently and identically distributed across individuals, industries, and dates, with density function $f: \Re \mapsto \Re^+, f(\varepsilon) > 0 \forall \varepsilon$, and cumulative distribution function $F: \Re \mapsto [0, 1]$. Without loss of generality, assume that $\int \varepsilon f(\varepsilon)\, d\varepsilon \equiv 0$. Thus, the full cost for worker l of moving from i to j can be thought of as $\varepsilon_{l,t}^i - \varepsilon_{l,t}^j + C^{ij}$. The worker knows the values of the $\varepsilon_{l,t}^i$ for all i before making the period-t moving decision.[9] We adopt the convention that $C^{ii} = 0$ for all i.

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

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

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

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

B. *The Key Equilibrium Condition*

Suppose that we have somehow computed the maximized value to each worker of being in industry i when the labor allocation is L and the state is s. Let $U^i(L, s, \varepsilon)$ denote this value, which, of course, depends on the worker's realized idiosyncratic shocks. Denote by $V^i(L, s)$ the average

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

of $U^i(L,s,\varepsilon)$ across all workers, or, in other words, the expectation of $U^i(L,s,\varepsilon)$ with respect to the vector ε. Thus, $V^i(L,s)$ can also be interpreted as the expected value of being in industry i, conditional on L and s, but before the worker learns her value of ε.

Assuming optimizing behavior, i.e., that a worker in industry i will choose to remain at or move to the industry j that offers her the greatest expected benefits, net of moving costs, we can write:[10]

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

$$= w_t^i + \beta E_t[V^i(L_{t+1},s_{t+1})] + \max_j\{\varepsilon_t^j + \overline{\varepsilon}_t^{ij}\}$$

where:

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

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

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

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

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

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

The average value to being in industry i can therefore be decomposed into three terms: (1) the wage, w_t^i, that an industry-i worker receives; (2) the base value of staying on in industry i, i.e., $\beta E_t[V^i(L_{t+1},s_{t+1})]$; and (3) the additional value, $\Omega(\overline{\varepsilon}_t^i)$, derived from having the option to move to another industry should prospects there look better (and which is simply equal to the expectation of $\max_j\{\varepsilon^j + \overline{\varepsilon}_t^{ij}\}$ with respect to the ε vector). We will call this the "option value" associated with being in that industry at that time. Note that, since $\overline{\varepsilon}_t^{ii} \equiv 0$, this is always positive.

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

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

$$= \beta E_t[w_{t+1}^j - w_{t+1}^i + \beta E_{t+1}[V^j(L_{t+2},s_{t+2}) - V^i(L_{t+2},s_{t+2})]$$

$$+ \Omega(\overline{\varepsilon}_{t+1}^j) - \Omega(\overline{\varepsilon}_{t+1}^i)], \text{ or}$$

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

Note that $\overline{\varepsilon}_t^{ij}$ is the value of $\varepsilon^i - \varepsilon^j$ at which a worker in industry i is indifferent between moving to industry j and staying in i. Condition (5) thus has the simple, common-sense interpretation

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

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

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

C. *The Estimating Equation*

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

$$f(\varepsilon) = \frac{e^{-\varepsilon/\nu-\gamma}}{\nu} \exp\{-e^{-\varepsilon/\nu-\gamma}\}$$
$$F(\varepsilon) = \exp\{-e^{-\varepsilon/\nu-\gamma}\},$$

implying:

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

(For further properties of the extreme-value distribution, see Jagdish Patel, C. H. Kapadia, and D. B. Owen 1976.)

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

By assuming that the ε^i_t are generated from an extreme-value distribution we are able to obtain a particularly simple expression for the conditional moment restriction, which we then plan to estimate using aggregate data. Specifically, it is shown in the Appendix[11] that, with this assumption:

$$(6) \qquad \bar{\varepsilon}^{ij}_t \equiv \beta E_t[V^j_{t+1} - V^i_{t+1}] - C^{ij} = \nu[\ln m^{ij}_t - \ln m^{ii}_t]$$

and:

$$(7) \qquad \Omega(\bar{\varepsilon}^i_t) = -\nu \ln m^{ii}_t.$$

[11] The Appendix is available online at the AER Web site.

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

The second expression says that the greater the probability of remaining in industry i, the lower the value of having the option to move from industry i.[12] Moreover, as the variance of the idiosyncratic component of moving costs increases, so too does the value of having the option to move. This also makes good sense.

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

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

This condition can be interpreted as a linear regression:

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

where μ_{t+1} is news revealed at time $t+1$, so that $E_t\mu_{t+1} \equiv 0$. In other words, the parameters of interest, C^{ij}, β, and ν, can then be estimated by regressing current flows (as measured by $(\ln m_t^{ij} - \ln m_t^{ii})$) on future flows (as measured by $(\ln m_{t+1}^{ij} - \ln m_{t+1}^{jj})$) and the future wage differential with an intercept. Of course, the disturbance term, μ_{t+1}, will in general be correlated with the regressors, requiring instrumental variables. The theory implies that past values of the flows and wages will be valid instruments, and the optimal weighting scheme can be derived as in the Generalized Method of Moment (GMM) (Lars Peter Hansen 1982). Note that while our choice of f obviously determined the form of the estimating equation, under the GMM estimation procedure, we do not need to make any additional assumptions about the process governing the state variables, s_t.[13]

Some strengths and weaknesses of this approach are now clear. The Euler equation approach saves us from having to evaluate the worker's value function along her whole lifetime, and thus from specifying a precise set of beliefs regarding future policy and future wages, as is required by the approaches of Keane and Wolpin (1997), Lee and Wolpin (2006), and related work. Further, the model can be extended to allow (to an extent) for observed worker heterogeneity, since if there are multiple observed worker types, (9) can be derived for each type, and the parameters can in principle be estimated for each type (an approach which we will explore shortly). In addition, as mentioned above, the approach fits nicely into a standard trade model. On the other hand, it does not provide much room for unobserved heterogeneity, and the elegance of (9) derives in part from the relatively unattractive i.i.d. assumption for the ε shocks. In a later section, we will explore in a limited way the addition of observed and unobserved worker heterogeneity into the model.

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

[13] In principle, the model can be estimated with any functional form for f, since, as shown in Cameron, Chaudhuri, and McLaren (2007), there is always an invertible mapping between the $\bar{\varepsilon}_t^{ij}$ and the m_t^{ij}, conditional on parameters, so that (5) can be written in terms of observables and parameters. However, there will generally not be a closed form.

D. *Identification*

It may be helpful to review how the model provides a strategy for identifying the parameters of interest to us. Roughly, the logic of the model tells us that the *level* of gross flows in the data helps us pin down the *ratio* of average moving costs to the variance of moving costs (that is, the ratios of the C^{ij}'s to ν), and the *responsiveness* of labor flows to anticipated wage differentials pins down the *level* of ν. Essentially, both the overall level of gross flows and their responsiveness to wages together pin down the values of the parameters. To see how, first note that worker flows are given by the following:

$$(10) \qquad m^{ij} = \frac{\exp(\bar{\varepsilon}^{ij}/\nu)}{\sum_{k=1}^{n} \exp(\bar{\varepsilon}^{ik}/\nu)}.$$

This is derived from the properties of the extreme-value distribution and is essentially the same as the outcome of the familiar extreme-value multinomial choice problem (a detailed deriviation is presented in the Appendix). Now consider a simplified version of the model in which labor demand in each industry is identical and nonstochastic, and $C^{ij} \equiv C \forall i \neq j$. In the steady state of such a model, $L^i = L^j$ and $V^i = V^j \forall i, j$. Therefore, $\bar{\varepsilon}^{ij} = -C \forall i \neq j$, and:

$$(11) \qquad m^{ij} = \frac{\exp(-C/\nu)}{1 + (n-1)\exp(-C/\nu)} = \frac{1}{\exp(C/\nu) + (n-1)}$$

$\forall i \neq j$.

Thus, the level of steady-state gross flows is a decreasing function of C/ν. This is easy to understand, as a rise in C raises costs of changing industries, discouraging mobility, and a rise in ν fattens the tails of the idiosyncratic shocks, increasing the probability that a given worker has an idiosyncratic moving cost below the threshold required to move. (Or, viewed differently, a rise in ν raises the importance of nonpecuniary factors in mobility decisions, making workers more likely to change industries for nonpecuniary reasons.)

Thus, in this simplified model, observing what fraction of workers change their industry per period allows us to pin down the ratio C/ν. Note that in our estimation equation (9) this ratio is proportional to the intercept, so that a general increase in gross flows in the data (for given β) will result in lower values for the C^{ij}/ν ratios. This can be illustrated with Figure 1. A high value of observed flows would imply a ray in C, ν space with a low slope, such as OA, while a lower value of gross flows would imply a point on a ray with a higher slope, such as OB. Now, what identifies the point upon that ray that the true parameter values must occupy?

Note from (9) that the coefficient multiplying the next-period wage differential is β/ν. A straightforward interpretation of this is that the coefficient β/ν measures the degree to which the future wage differential predicts the current rate of gross flow, $(\ln m_t^{ij} - \ln m_t^{ii})$. Thus, holding β constant, if future wage differentials are a good predictor for current labor flows, then we will obtain a low estimate for ν. This can be understood in two ways. First, realize that a high value of ν means that idiosyncratic and nonpecuniary factors are dominant in workers' mobility decisions, so that workers do not pay much attention to wages when making those decisions. Thus, a high value of ν implies that wages will be relatively irrelevant as a determinant of labor flows. A second interpretation is in terms of elasticities of labor supply: if we think of a labor supply model

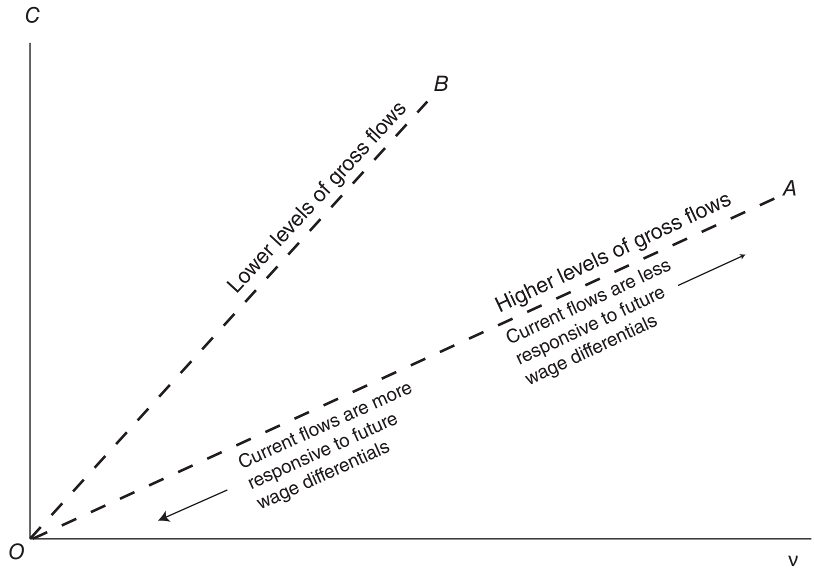

FIGURE 1. HOW THE MEAN AND VARIANCE OF MOVING COSTS ARE IDENTIFIED

in which workers have individual disutilities to work and will join the labor force only if the wage exceeds the disutility, then a high variance of that disutility in the population of potential workers implies a vertical labor-supply curve and a low elasticity of supply, so that the wage has a small effect on the amount of aggregate labor supplied. This is analogous to the effect observed in our model, but in a setting of dynamic, intersectoral labor supply: a high idiosyncratic variance implies a low elasticity of response to wages.

Thus, roughly, the overall level of gross flows pins down the C/ν *ratio*, and the level of responsiveness of labor flows to future wage differentials pins down the *level* of C and ν. For a given level of flows, if wages do not matter much for explaining variation in flows over time, a high value of both C and ν will be implied.

A note on measurement error may be appropriate here, as well. If systematic errors in coding of workers' industry are present so that spurious industry mobility occurs in the data, that will both put the parameters on a lower ray (by putting excess mobility into the data) and put them on a higher point along that ray (by making wages appear less relevant to mobility, since coding errors are likely uncorrelated with anticipated wages). Thus, coding errors can in principle result in over- or underestimates of C but will definitely provide an overestimate of ν and an underestimate of the ratio C/ν.

II. Data

Our estimation strategy hinges on observing aggregate gross flows across industries. Since there are no published data on gross flows, we construct gross flow measures from individual-level data. For this purpose, we use the US Census Bureau's March Current Population Surveys (CPS). Each year, the March CPS provides information on the individual's industry, occupation, and employment status at the time of the March interview, as well as the industry, occupation, and employment status in which the individual spent the most time during the previous calendar year (i.e., January to December). We use this information to construct rates of flow, m_{t-1}^{ij} for each date t. We also obtain industry wages w_t^i as the average wage reported in the CPS samples for industry

i at date t. These are deflated by the consumer price index (CPI), and normalized so that over the whole sample the average annualized wage is equal to unity. We restrict the sample to males aged 25 to 64 currently working full time who worked at least 26 weeks in the previous year and whose most recent weekly income was between \$50 and \$5,000.[14]

If we have n industries, then there are n^2 rates of gross flow to keep track of each period (or $n(n-1)$ if one excludes the fraction of workers in each industry who do not move). Thus, the number of directions for gross flows proliferates rapidly as the number of industries increases, leading in finite samples to zero observations and observations with very small numbers of individuals. As a result, we need to aggregate industries, and we aggregate to the following six: (i) Agriculture and Mining; (ii) Construction; (iii) Manufacturing; (iv) Transportation, Communication, and Utilities; (v) Trade; and (vi) All Other Services including government. As a result of this aggregation, the sample size for each regression is 720, since we have 26 years minus 2 to allow for lags, and 6 times 5 directions of flows.[15]

An additional issue with the CPS is imputed data. In the CPS interviews, if an answer to a particular question is not received or is inconsistent with other answers, a variety of complex procedures are followed to impute the missing or inconsistent information (see Current Population Survey 2002, chapter 9, for a lengthy summary). As Kambourov and Iourii Manovskii (2004) point out, the imputation procedures changed in 1976 and 1989, and at those dates, rates of gross flow across industries and occupations in the publicly released CPS data changed dramatically. In particular, apparent rates of gross flow dropped dramatically with the 1976 change in imputation procedures, and they increased dramatically with the 1989 change. Rates of gross flow are central to our estimation strategy, so we need to obtain the most reliable measures for such flows possible, and if imputation procedures introduce spurious flows we need to find a way to cleanse the data of these effects. From 1989 on, an indicator variable is recorded in the data to indicate if a portion of a given data record has been imputed. We follow Giuseppe Moscarini and Francis Vella (2003) and perform the following two steps to minimize the imputation problem: (i) we drop data prior to 1976 (for which Moscarini and Vella 2003 argue that the imputation procedures were very crude and introduced a great deal of spurious gross flows, and no indicator exists in the data to identify which records are affected by imputation); and (ii) we drop any individual subsequent to 1988 whose data are partially imputed. In principle, this could create a selection bias, but since the sample means for the individuals who have been dropped are very similar to those for the rest of the sample (except for gross flow rates, which are much higher for the dropped workers), it does not appear to be a problem in this case.

Descriptive statistics for the resulting data are shown in tables 1 and 2. Sample sizes added up across years range from 20,952 for Agriculture/Mining to 140,339 for Manufacturing and 173,012 for Service. Table 1 summarizes gross flows. Each cell of the table shows the average fraction of workers in the row sector who moved to the column sector in any given period; for example, on average, 0.56 percent of Construction workers in any year moved to Agriculture/Mining. The main diagonal shows the average fraction who did not change sector of employment (that is, m_t^{ii}), so one minus this value is a simple measure of the rate of gross flow. The value on

[14] Of course, this raises some sample selection issues, particularly regarding the exclusion of unemployed workers, but for now they seem to be unavoidable. We comment briefly on this in the Conclusion.

[15] There is, of course, an econometric issue with aggregation. If the "true" model has n sectors, with a cost of C to move between them, but we approximate it with a model with $n' < n$ sectors and estimate a cost of C' to move between them, of course there is no reason to assume that our estimator for C' will be a consistent estimator for C, nor is that what we want if we want to do policy simulations with the $n'-$ sector model. Of course, these aggregation issues exist for the entire literature; for example, Lee and Wolpin (2006) accomplish a great deal with a two-sector model. This issue could be studied by, for example, constructing a model economy, simulating its equilibrium, and then estimating and simulating an aggregated approximation to it, to see what the policy bias would be. This exercise would be a major undertaking, of course, far beyond the scope of this paper.

Table 1—Descriptive Statistics: Gross Flows, 1975–2000

	Agric/Min	Const	Manuf	Trans/Util	Trade	Service
Agric/Min	0.9292	0.0126	0.0142	0.0075	0.0160	0.0206
	(0.0146)	(0.0040)	(0.0046)	(0.0032)	(0.0063)	(0.0057)
Const	0.0056	0.9432	0.0139	0.0063	0.0119	0.0191
	(0.0028)	(0.0108)	(0.0029)	(0.0023)	(0.0027)	(0.0040)
Manuf	0.0020	0.0041	0.9708	0.0031	0.0080	0.0120
	(0.0008)	(0.0008)	(0.0035)	(0.0010)	(0.0012)	(0.0021)
Trans/Util	0.0025	0.0044	0.0068	0.9643	0.0081	0.0138
	(0.0011)	(0.0018)	(0.0016)	(0.0050)	(0.0023)	(0.0033)
Trade	0.0030	0.0061	0.0135	0.0055	0.9469	0.0250
	(0.0011)	(0.0015)	(0.0033)	(0.0017)	(0.0073)	(0.0036)
Service	0.0018	0.0043	0.0079	0.0037	0.0103	0.9720
	(0.0008)	(0.0011)	(0.0013)	(0.0008)	(0.0014)	(0.0033)

Notes: Origin sector is listed by row, destination sector by column. Each cell of table contains mean flow rate followed by standard deviation in parentheses.

Table 2—Descriptive Statistics: Wages, 1975–2000

	Mean[a]	Standard deviation[a]	Mean[b]	Standard deviation[b]	Sample size
Agric/Min	34,739	24,978	0.8374	0.6021	20,952
Const	38,432	21,623	0.9265	0.5213	44,943
Manuf	42,655	21,706	1.0283	0.5233	140,339
Trans/Util	43,608	20,552	1.0512	0.4954	55,699
Trade	37,024	23,288	0.8925	0.5614	83,833
Service	43,617	26,810	1.0514	0.6463	173,012

Notes:
[a] In year 2000 dollars
[b] Normalized

the diagonal varies from 0.9292 for Agriculture/Mining to 0.9720 for Services, implying a rate of gross flow that varies across sectors from 2.8 percent to 7.1 percent. It is important to note that gross flows are an order of magnitude larger than net flows throughout the data. This is shown in Figure 2, which plots gross flows and net flows for each year, and which demonstrates that the former are consistently about ten times the latter.[16]

Table 2 shows descriptive statistics for wages. Normalized wages (that is, normalized to have a unit mean) averaged across time range from 0.8374 for Agriculture/Mining to 1.0514 for Services.

III. Results

Before showing estimations, we should point out that we do not attempt to estimate β. This model is not designed to estimate rates of time preference, and although it could be done in principle, in practice it turns out that that one parameter is very poorly identified.[17] Since it is

[16] For this figure, gross flows in a given year are the number of workers who changed sector in that year, divided by the total number of workers. Net flows are the absolute value of workers entering sector i from other sectors minus workers leaving i for other sectors, added up for $i = 1, \ldots, 6$, divided by two to eliminate double counting, and again divided by the total number of workers in that year.

[17] This is easy to understand in light of our simulations in Sections VI and VII. It turns out that estimating and simulating the model with different values of β produces nearly identical time paths for key observable variables, so

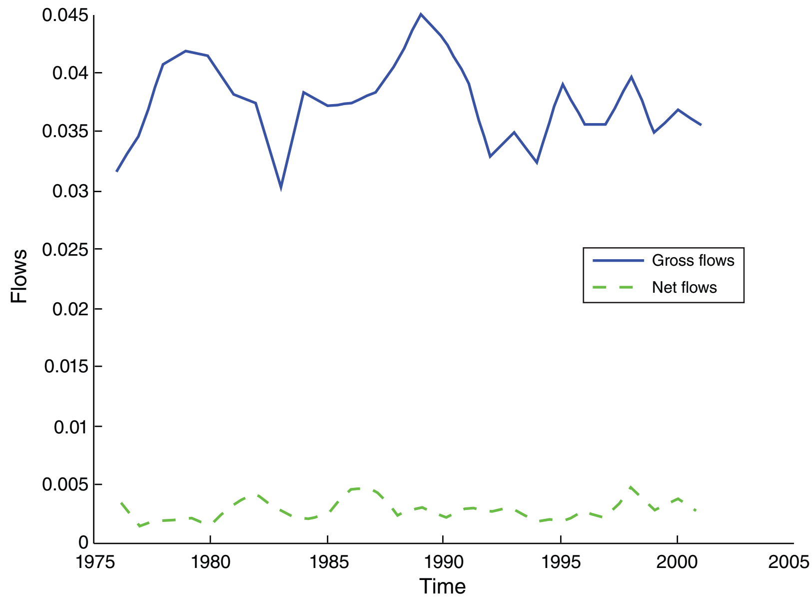

Figure 2. Gross Flows and Net Flows

not a parameter of interest for us, and since it is the one parameter for which we have strong information a priori (namely that it should lie between 0 and 1, and be closer to 1 than to 0), we simply impose a value of β in all that follows. To check for sensitivity to the choice of β, we report estimations with both $\beta = 0.9$ and $\beta = 0.97$.[18]

Table 3 shows the results from the basic regression. For the simplest implementation of the model, we impose $C_{ij} \equiv C \forall i \neq j$, so that the mean moving cost for any transition from one industry to any other is the same. We will explore specifications that allow the C^{ij}'s to vary shortly. Throughout the table, the data are from 1976 to 2001, and the t-statistics are reported in parentheses.

Throughout the table, the first two columns report results for $\beta = 0.97$, and the last two report results for $\beta = 0.9$. Panel I shows the results for the full sample with no instruments, which (recalling (8)) amounts to regressing $(\ln m_t^{ij} - \ln m_t^{ii}) - \beta(\ln m_{t+1}^{ij} - \ln m_{t+1}^{jj})$ on a constant and the future wage differential $w_{t+1}^j - w_{t+1}^i$ by OLS, with β set equal to 0.97 or 0.9. Of course, this is likely to be biased, as the residual contains the shock revealed at time $t+1$, which is likely to be correlated with date-$t+1$ wages. For this reason, henceforth we use as instrumental variables the values of endogenous variables date $t-1$, which must be uncorrelated with any new information revealed at time $t+1$.[19] The estimates using the instrumental variables are reported in panel II. Henceforth, unless otherwise stated, all estimates use this instrumental-variables approach.

it is not surprising that it is hard to identify econometrically. However, the different choices for β do matter greatly for welfare analysis.

[18] The choices of $\beta = 0.9$ and $\beta = 0.97$ roughly bracket the range commonly used in calibration work in macroeconomics; for example, Hugo A. Hopenhayn and Juan Pablo Nicolini (1997) use an annual discount factor of 0.95, and Lars Ljungqvist and Thomas J. Sargent (2004) use a quarterly rate of 0.97 to 0.99, implying annual rates from 0.89 to 0.96. We are grateful to an anonymous referee for clarifying our thinking on this.

[19] We use GMM with the White heteroskedasticity-consistent variance estimator as a weighting matrix, as laid out in William H. Greene (2000, pp.483–5). The instruments are a constant, $(w_{t-1}^j - w_{t-1}^i)$, and $(\ln m_{t-1}^{ij} - \ln m_{t-1}^{jj})$.

TABLE 3—REGRESSION RESULTS FOR THE BASIC MODEL

$\beta = 0.97$		$\beta = 0.9$	
Panel I. Full sample: OLS			
ν	C	ν	C
4.466	22.065	2.085	10.261
(1.829**)	(1.780**)	(3.731***)	(3.684***)
Panel II. Full sample with instruments			
ν	C	ν	C
2.897	13.210	1.600	7.699
(2.667***)	(2.558***)	(4.606***)	(4.561***)
Panel III. Time averaging			
ν	C	ν	C
3.338	8.477	1.424	4.320
(7.932***)	(6.035***)	(10.401***)	(10.117***)
Panel IV. Annualized flows			
ν	C	ν	C
1.884	6.565	1.217	4.703
(3.846***)	(3.381***)	(5.700***)	(5.626***)
Panel V. Correction for composition effects (linear, basic)			
ν	C	ν	C
2.750	9.586	2.266	8.756
(1.974**)	(1.914**)	(2.259**)	(2.257**)
Panel VI. Correction for composition effects (linear, extra interactions)			
ν	C	ν	C
2.539	8.848	2.051	7.924
(2.143**)	(2.065**)	(2.491***)	(2.488***)
Panel VII. Correction for composition effects (log-linear, basic)			
ν	C	ν	C
2.978	10.378	2.177	8.413
(2.394***)	(2.288**)	(3.121***)	(3.116***)
Panel VIII. Correction for composition effects (log-linear, extra interactions)			
ν	C	ν	C
2.795	9.743	2.051	7.924
(2.489***)	(2.369***)	(3.225***)	(3.219***)

Note: T-statistics are in parentheses.

One-tailed significance:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

For the basic specification, estimation with and without instrumental variables produces extremely high estimates of both C and ν, with both parameters highly significant. The high-β instrumental-variables estimate of C in panel II amounts to approximately 13 times average annual wage earnings (given our normalization of average wages to unity). The value of ν of 2.897 implies a variance of the idiosyncratic shock equal to 13.8, or a standard deviation of 3.7; of course, the standard deviation of the idiosyncratic moving cost is twice that (since it is the difference between two idiosyncratic shocks). In other words, the mean moving cost between two industries is 13 times the average wage, but its standard deviation is about seven times the average wage. The low-β values are lower, about eight and four times annual wages respectively, but still very high. We will argue in the following section that these estimates are likely to be biased upward, and we will present lower estimates following corrections for the bias, but these strikingly high figures do convey an important message that is robust to all corrections: *Labor* *movements in response to a differential in wages are very sluggish. The labor market acts as if it is very costly to change sectors, but at the same time a significant number of workers do so anyway, not in response to differences in wages, but because of unobserved and possibly nonpecuniary factors that are at least as important as wages in workers' decisions.* Later, in the simulations, we will see that the aggregate labor market behavior implied by our estimates is quite realistic and fits well with some reduced-form regression results in the literature.

IV. Possible Sources of Bias

There are several notable reasons the very high estimates we have obtained for C and ν may be the result of bias. Sampling error in industry wages, and possible misinterpretation of mobility rates in the CPS data due to timing issues may both be a problem. Wage differences across sectors may reflect different compositions of workers, which we have ignored, instead of moving costs. There is also the possibility that constraining all C^{ij} values to the same is a misspecification that generates its own bias. We discuss these in turn.

A. *Sampling Error in Wages*

We measure the industry wages w_t^i as the average wage in the industry in the CPS sample. If the sampling error is significant, the industry wage will be measured with noise, resulting in a classical errors-in-variables bias. Given the estimating equation (9), this will lower the estimated value β/ν, thus raising the estimated value of ν and thus C. We investigate this possibility in two ways.

First, we redo the estimation using time-averaged values of the variables. To the extent that the high estimates are driven by serially uncorrelated noise in the measured variables, this should reduce their level. We break the sample into consecutive, nonoverlapping five-year segments. For each industry i, we average w_t^i over each segment, and for each i and j we average m_t^{ij} over the segment. The results are reported in panel III of Table 3.

Note that although the estimated moving costs are much smaller now, nonetheless C is estimated at eight and a half times (four times) average wages and the standard deviation of moving costs equal to eight times (twice) annual wages in the high-β (low-β) case. This specification is not useful for policy analysis, since the implied five-year period for each worker reallocation is unrealistically long, but it does make the point that only a portion of the explanation for the high moving costs could plausibly be due to sampling error in wages.

Second, we redo the regression using wage data from the Bureau of Labor Statistics' Current Employment Surveys (CES) in place of the wage data we have constructed from the CPS. Since the CES is a broad employer-based survey with a large sample size, it is likely to have less of a problem with sampling error in the wages. The industry classifications for the two datasets are not exactly the same, but the nearest match produces quite similar wage series,[20] and very similar regression results.[21]

We thus conclude that the high estimates of C and ν are *not* likely to be artifacts of sampling error in wages.

[20] The correlation between the two wage series is 63 percent for Agriculture/Mining; 91 percent for Construction; 44 percent for Manufacturing; 56 percent for Transportation/Utilities; 61 percent for Trade; and 55 percent for Government and other services.

[21] For example, for the OLS regression in Table 3, the point estimate and t-statistic for ν are 4.466 (1.829) for the CPS wage data and 4.237 (2.031) for the CES data respectively. The estimates for C are 22.065 (1.780) for the CPS wage data and 20.921 (2.021) for the CES data respectively.

B. *Timing and the Misinterpretation of Flow Rates*

Kambourov and Manovskii (2004) point out a difficulty in interpreting flow rates that come out of the March CPS retrospective questions. Respondents are asked their industry and occupation in their longest-held job of the previous year. If the duration of jobs is distributed randomly, and respondents remember correctly, on average they will be reporting their employment status as of the middle of the previous year, and thus mobility at a nine-month window (June to March) rather than a 12-month window. However, if a respondent has had more than one job during that year and recalls the details of the later job more clearly, the later one might incorrectly be reported as the longest job. In this case, the respondent might be reporting details of his or her employment in October, for example, implying that what is being measured is mobility at a six-month window.

Therefore, although it appears superficially to be annual, the mobility measured by the March CPS is something less than annual. Kambourov and Manovskii (2004) point out that, consistent with this, occupational gross flow rates as measured by the March CPS tend to be smaller than those measured from other sources.

We can attempt to correct for this in the following way. Suppose that the gross flow rate we observe is the flow rate over some interval that is K months long and denote the matrix of gross flow rates thus observed by $\tilde{m}$. We first convert this into a matrix of monthly gross flows, $\hat{m}$, by solving the equation $\hat{m}^K = \tilde{m}$, where $\hat{m}^K$ denotes the matrix $\hat{m}$ multiplied by itself K times.[22] Without loss of clarity, we can denote this matrix as $\tilde{m}^{1/K} = \hat{m}$. Suppose that within a year, the monthly flow rate matrix $\hat{m}$ is constant. Then the year-by-year matrix of flow rates will be given by $m^{ANN} \equiv \hat{m}^{12} = \tilde{m}^{12/K}$, or the $\hat{m}$ matrix multiplied by itself 12 times. We have data on gross flow rates from the National Longitudinal Survey of Youth (NLSY), which we can denote $m_t^{ij,NLSY}$ and which do not suffer from the timing problems just described for the March CPS. We choose K to minimize the following loss function:[23]

$$\sum_{i,j,t} ((\tilde{m}_t^{12/K})^{ij} - m_t^{ij,NLSY})^2 \tag{12}$$

for the portion of our sample restricted to younger workers. This results in a value of $K = 5$, implying that the March CPS measures mobility at a five-month horizon. We then replace our measured gross flows $\tilde{m}$ with the annualized gross flows $m^{ANN} = \tilde{m}^{12/K}$ throughout and perform the estimation again.

As expected, the annualized rates show higher gross flows overall. Table 4 provides a comparison of the original rates of gross flow (meaning $1 - \tilde{m}^{ii}$ for $i = 1, \dots 6$) with the annualized rates of gross flow (meaning $1 - (m^{ANN})^{ii}$ for $i = 1, \dots 6$).

The regression results are as shown in Panel IV of Table 3. Comparing them with the results in panel II shows that, as expected, the values for C and ν are lower for each version of the regression. For both cases, the drop in the estimates of C and ν is substantial; for example, the results from the high-β case imply a mean moving cost of about six and a half times average annual wages (compared with 13 in panel II) and a standard deviation of moving costs of five times annual wages (compared with seven times for panel II).

Overall, we find strong indications that the timing problem due to the nature of CPS questions does bias our estimates for C and ν upward substantially, but correcting for this still

[22] For example, in the two-industry case, if $K = 2$, the fraction of workers in industry 1 at the beginning of the two-month interval who are in industry 2 at the end of the two-month interval is equal to $\hat{m}^{12}\hat{m}^{22} + \hat{m}^{11}\hat{m}^{12}$, which is the product of the first row and the second column of the $\hat{m}$ matrix.

[23] To clarify, $(\tilde{m}_t^{12/K})^{ij}$ is the ij element of the matrix $m_t^{ANN} = \tilde{m}_t^{12/K}$.

Table 4—Rates of Gross Flow, Original and Annualized

	Raw data	Annualized data
Agric/Min	0.071	0.161
Const	0.057	0.130
Manuf	0.029	0.068
Trans/Util	0.036	0.083
Trade	0.053	0.122
Service	0.028	0.065

leaves large values for moving costs, with C never falling below four times average annual wages. Since this annualization correction appears to be important, we will henceforth treat this as our benchmark regression.

C. *Sectoral Composition Effects*

We have to this point been maintaining the fiction that all workers are homogeneous. It is conceivable that this is part of the explanation for the high estimated moving costs, because it may be that in truth the intersectoral wage differentials reflect differences in the composition of workers across industries, rather than differences in earning opportunities for any one worker. In Section VII we will explore estimation of the model with worker heterogeneity more seriously, but we can run an easy test to see if this is where the high moving costs are coming from. We can remove labor composition effects from the wage data by performing a cross-section wage regression for each year of the data with industry fixed effects much as in Alan B. Krueger and Lawrence H. Summers (1988), and then using the industry fixed effects in estimation of (9) in place of the actual wages.

The first way we have executed this is as follows. For each year, using the individual-level CPS data, we perform a cross-sectional regression of the wage for each worker l on six sector dummies; a dummy for some college, a dummy for college graduate (so that "no college" is the omitted category); $(A_l - 25)$, where A_l is the worker's age; $(A_l - 25)^2$; and the two educational dummies interacted with $(A_l - 25)$ and $(A_l - 25)^2$. We then take the estimated industry fixed effects for each year and replace the wages in (9) with them (once again using the annualized flows). The result is in Table 3, panel V, marked as the "basic" correction for composition effects. Clearly, removing composition effects in this way does not eliminate the high estimated moving costs but actually *increases* them compared to the benchmark regression of panel IV.

We have tried a few variants of this idea to see if removing composition effects in a slightly different way would change the result. First, we added some additional terms to the wage regression, in the form of interactions between the industry dummies and the educational dummies, in effect allowing the intersectoral wage differential to vary by educational status, and then evaluated the intersectoral wage differentials in each year for a worker of economywide average education. The result of this is reported in panel VI of Table 3, marked as "extra interactions." Next, we did the wage regression in logs. In that case, the exponential of the estimated industry effects minus 1 is the *proportional* industry differential; we convert this into the differential required to estimate (9) by evaluating the age and education variables at their economywide median values. Panel VII of Table 3 reports the result of this procedure using the same regressors as in the "basic" regression, and panel VIII reports the result using the "extra interactions." There is no meaningful effect on the result. (The wage regressions are available on request.)

These results are difficult to interpret or use, because they have not been derived from a model with heterogeneous workers. We will explore how to do that in Section VII. What is

Table 5—Sector-Specific Entry Costs

	$\beta = 0.97$		$\beta = 0.9$	
	Estimate	t-statistic	Estimate	t-statistic
ν	1.512***	(3.476)	1.070***	(4.667)
C^1 (Agric/Min)	4.124	(1.281)	4.342***	(3.390)
C^2 (Const)	4.899**	(1.766)	4.096***	(3.814)
C^3 (Manuf)	4.994***	(2.426)	3.967***	(4.954)
C^4 (Trans/Comm/Util)	8.311***	(3.469)	5.313***	(5.229)
C^5 (Trade)	3.703*	(1.353)	3.30***	(3.394)
C^6 (Other Services)	5.589***	(2.762)	3.779***	(5.277)

Notes: Full sample, with instruments. Gross flows are annualized as in panel IV of Table 3.

One-tail significance:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

clear, however, is that our high estimated values of moving costs do not spring from sectoral composition effects.

D. *Misspecification of Moving Costs*

A last possible source of bias comes from the fact that we have imposed uniform moving costs for all sectors, so that $C^{ij} = C \forall i, j$. Degrees-of-freedom concerns prevent us from estimating the full set of C^{ij} parameters without restriction, but we have also estimated the model with a slightly richer specification allowing for sector-specific "entry costs." In this approach, $C^{ij} = c^j$ for $i = 1, \ldots, 6$. Table 5 shows the results of this regression with annualized data. Results are reported for both values of β and are virtually identical for the two cases.

Compared with the benchmark regression (IV) from Table 3, we find that most sectors exhibit lower entry costs (mostly between four and five, compared to 6.6 for panel IV of Table 3), but sector 4, Transport, Communications, and Utility exhibits substantially higher entry costs—more than eight times average annual wages. This reflects the fact that sector 4's wages are relatively high, but few workers wind up in this sector. For example, from Table 2, note that wages for both Services and sector 4 are about five percent above the whole-sample average, but sector 4 has fewer than a third as many workers. Alternatively, note from a comparison of the fourth and sixth columns of Table 1 that the rate of flow from each other sector into sector 4 is in each case around one third the rate of flow into sector 6, despite that fact that on average the wages in these two sectors are about identical. This indicates some implicit obstacle (or disutility) to entering sector 4 compared to other sectors, thus implying a high value of C^4.

We can conclude that a portion of the reason for the high values estimated for C in the earlier regressions is the need to account for the unusually low flows into Transport, Communications, and Utilities. However, even when this effect is separated out, most of the other sectoral moving costs are still high—at least four times average annual wages.

V. Simulation: A Sudden Trade Liberalization

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

$$y_t^i \;=\; \psi^i(\alpha^i(L_t^i)^{\rho^i} + (1 - \alpha^i)(K^i)^{\rho^i})^{1/\rho^i}, \tag{13}$$

where y_t^i is the output for sector i in period t, K^i is sector i's capital stock, and $\alpha^i > 0$, $\rho^i < 1$, and $\psi^i > 0$ are parameters. Given the number of free parameters and our treatment of capital as fixed,[24] we can without loss of generality set $K^i = 1 \forall i$. This implies that the wages are given by:

$$w_t^i \;=\; p_t^i \alpha^i \psi^i (L_t^i)^{\rho^i - 1}\big(\alpha^i (L_t^2)^{\rho^i} + (1 - \alpha^i)\big)^{(1-\rho^i)/\rho^i}, \tag{14}$$

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

For simulations, we need to choose values of production-function parameters to provide a plausible illustrative numerical example, broadly consistent with quantitative features of the data. To do this, we set the values α^i, ρ^i, and ψ^i to minimize a loss function given our assumptions on prices (see below). Specifically, for any set of parameter values, we can compute the predicted wage for each sector and that sector's predicted share of GDP using (14) and (13) together with empirical employment levels for each sector and our assumptions about prices as described below. The loss function is then the sum across sectors and across years of the square of each sector's predicted wage minus mean wage in the data, plus the square of labor's predicted share of revenue minus the actual share, plus the square of the sector's predicted minus its actual share of GDP. (The sector GDP and labor's share of revenue figures are from the Bureau of Economic Analysis (BEA), but the remaining figures are from our sample.) In addition, we assume that all workers have identical Cobb-Douglas preferences, using consumption shares from the Bureau of Labor Statistics (BLS) consumer price index calculations for the consumption weights. The parameter values that result from this procedure are summarized in Table 6.

The moving-cost parameters used are found in our preferred specification, the annualized-flow-rate approach of panel IV of Table 3.

Then, to provide a simple trade shock, we assume the following:

(*i*) Units are chosen so that the domestic price of each good at date $t = -1$ is unity. (Given our available free parameters, this is without loss of generality.)

(*ii*) There are no tariffs on any sector aside from manufacturing, at any date.

(*iii*) The world price of manufacturing output is 0.7 at each date. The world price of all other tradable goods is equal to unity at each date.

(*iv*) There is initially a specific tariff on manufactures at the level 0.3 per unit, so that the domestic price of manufactures is equal to unity.

[24] We assume that capital is fixed in order to focus on the workers' problem and to keep the model manageable. Of course, capital should also be expected to adjust to trade liberalization, and that should also be expected to affect wages. We have experimented with simple simulations with perfect capital mobility, obtaining similar welfare results but sharper movements in wages. We defer a full treatment of this issue to future work.

TABLE 6—PARAMETERS FOR SIMULATION

	α^i	ρ^i	ψ^i	Consumer share	Domestic price	World price
Agric/Min	0.691	0.6828	0.6733	0.07	1	1
Const	0.6544	0.4924	0.7653	0.3	1	1*
Manuf	0.3224	0.3553	1.6965	0.3	1	0.7
Trans/Util	0.5721	0.5664	1.0393	0.08	1	1*
Trade	0.5714	0.445	0.9125	0	1	1*
Service	0.3418	0.5576	2.2135	0.25	1	1

Note: * Under the second simulation specification, the sectors marked with an asterisk are non-traded, so they have no world price.

(v) Initially, this tariff is expected to be permanent, and the economy is in the steady state with that expectation.

(vi) At date $t = -1$, however, after that period's moving decisions have been made, the government announces that the tariff will be removed beginning period $t = 0$ (so that the domestic price of manufactures will fall from unity to 0.7 at that date), and that this liberalization will be permanent.

Thus, we simulate a sudden liberalization of the manufacturing sector. We compute the perfect-foresight path of adjustment following the liberalization announcement, until the economy has effectively reached the new steady state. This requires that each worker, taking the time path of wages in all sectors as given, optimally decides at each date whether or not to switch sectors, taking into account that worker's own idiosyncratic shocks. This induces a time path for the allocation of workers, and therefore the time path of wages, since the wage in each sector at each date is determined by market clearing from (14) given the number of workers currently in the sector. Of course, the time path of wages so generated must be the same as the time path each worker expects. It is shown in Cameron, Chaudhuri, and McLaren (2007) that the equilibrium exists and is unique.[25] The computation method is described at length in Artuç, Chaudhuri, and McLaren (2008).

We present two versions of the simulation. In the first, all goods are assumed to be traded, so all output prices are exogenous. In the second, some sectors are non-traded, and so their prices are determined as part of the equilibrium.

A. *Specification I: All Output is Tradable*

The simulation output is plotted in figures 3 and following. In each figure, the two plots in the left-hand column show results from the simulation with all sectors traded, and plots in the right-hand side show results with non-traded sectors. In each column, the upper plot shows results with $\beta = 0.97$, and the lower plot shows results with $\beta = 0.9$. The results from the simulation with all goods tradable can be seen in Figure 3, which plots the fraction of the labor force in each of the six sectors at each date, and Figure 4, which plots the time path of wages. Figure 5 shows the payoff V_t^i to being a worker in sector i at time t.

[25] Strictly speaking, the proof there applies to the case with all goods traded, but it can be extended mechanically to the case with non-traded goods under free trade.

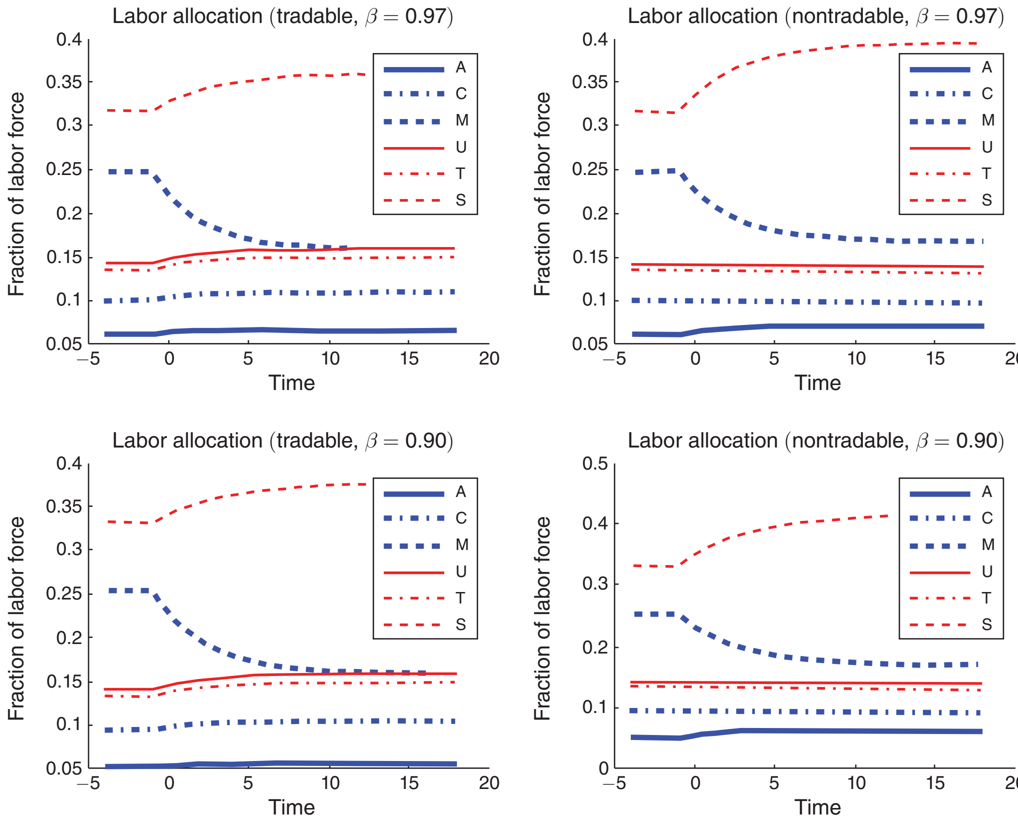

FIGURE 3. LABOR ALLOCATION—BASIC SIMULATIONS

Before looking at the specific results, note that neither in the pre-liberalization steady state nor in the free-trade steady state are wages equalized across sectors. This is a basic feature of this model, as discussed at length in Cameron, Chaudhuri, and McLaren (2007) and Chaudhuri and McLaren (2007). The reason is that with the idiosyncratic shocks influencing workers' location decisions, the long-run intersectoral elasticity of labor supply is finite. Consider a two-sector model with symmetric moving costs ($C^{12} = C^{21}$). If the steady-state wages for the two sectors were equal, then the fraction of workers in sector 1 who would wish to switch to sector 2 each period would be equal to the fraction of sector 2 workers who wish to switch to sector 1 ($m^{12} = m^{21}$). As a result, the steady-state number of workers in each sector would have to be equal. In general, the only way to get equal wages in the steady state is to have equal numbers of workers in each sector in the steady state. Further, the sector that loses its protection always loses in long-run real wage relative to the other sectors; that is the only way the sector can have a net loss of workers in the steady state (Chaudhuri and McLaren 2007, Proposition 5). This point will help in following the logic of the simulations.

Consider first the simulation with all sectors traded and $\beta = 0.97$. It is clear from Figure 3 that the employment share of manufacturing drops sharply as a result of the liberalization, from an old steady-state value of 25 percent to a new steady-state value of 16 percent, with corresponding modest gains to all other sectors. This transition is substantially complete within eight years. The loss of manufacturing's share is of course not surprising given that manufacturing has lost its protection. It is also clear from Figure 4 that real wages in manufacturing fall as a result of the

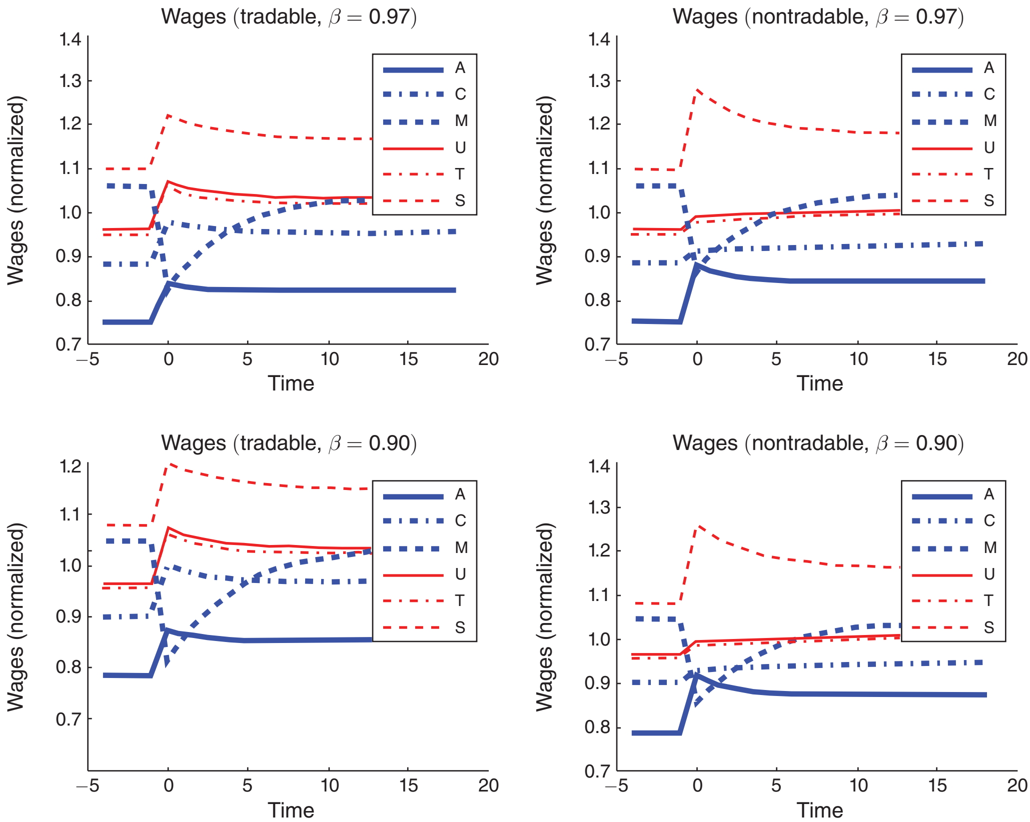

Figure 4. Wages—Basic Simulations

liberalization, from an old steady-state value of 1.06 to a new steady-state value of 1.03, and with corresponding modest gains to all other sectors due to the drop in consumer prices.

Figure 4 shows, in addition, that each sector sees a nonmonotonic path for real wages. The real wage in manufacturing overshoots its long-run value, with an initial drop of 22 percent and a new steady state just 2.45 percent below the original steady state. This overshooting occurs because after the sudden shock of the drop in domestic manufacturing prices, workers begin to move out of the sector, moving up and to the left along the sector's demand-for-labor curve and gradually bringing wages up.[26] Similar overshooting occurs in each of the other sectors, in the opposite direction, for parallel reasons.

Note that at each date following the liberalization announcement, the real wage in manufacturing is below what it was in the old steady state. It would be tempting to conclude that for this reason manufacturing workers must be worse off because of the liberalization. However, that is not true. As can be seen in Figure 5, which plots $V^i(L_t, s_t)$ from equation (3), *all* workers see a rise in their expected discounted lifetime utilities at the time of

[26] In principle, it is possible that this process could continue so that real wages in the liberalizing sector could rise past their original value and wind up higher in the new steady state than in the old, but that does not happen in this case. See Artuç, Chaudhuri, and McLaren (2008) for examples.

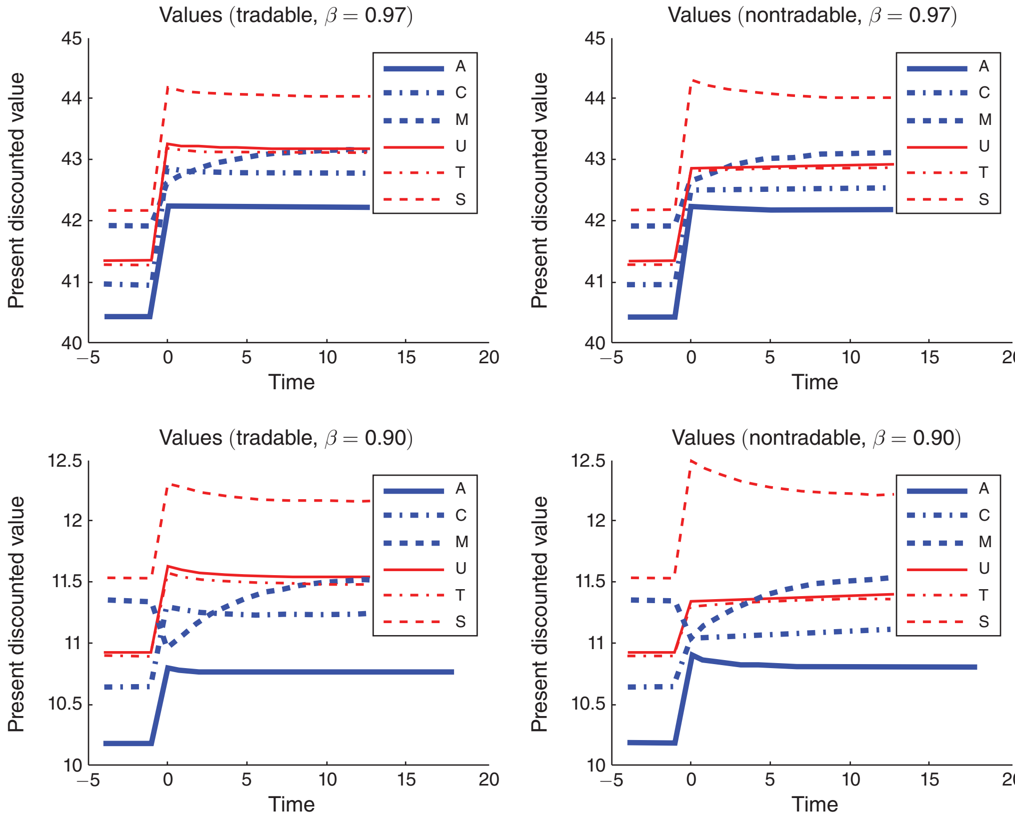

Figure 5. Values—Basic Simulations

the announcement, *including* manufacturing workers.[27] The reason is the presence of gross flows. Each manufacturing worker understands that, because of the liberalization, manufacturing wages are permanently lower but real wages in all other sectors are permanently higher. Further, there is in each period a positive probability that the manufacturing worker will choose to move to one of those other sectors and enjoy those higher wages. Taking into account these probabilities, the manufacturing worker considers himself/herself lucky to be hit with the liberalization.

Put differently, the liberalization lowers the wages in the manufacturing sector but *raises the option value* to workers in the sector by more than enough to compensate. Thus, in this case, despite the estimation of extremely high moving costs, the model predicts that even workers in import-competing sectors will welcome liberalization. This underlines the crucial importance of gross flows in welfare analysis.[28]

Finally, we can compute trade flows from the simulation. At each date with free trade, GDP can be computed from the labor allocation and production functions; from the utility function,

[27] The rise in lifetime utility is between 4.5 percent and 5 percent in nonmanufacturing sectors and 1.7 percent in manufacturing.

[28] We also have simulated exactly the same policy experiment with the estimates from the sector-specific "entry-cost" specification of Table 5. The results are qualitatively and quantitatively very similar, with rather higher wages overall for Transportation, Communications, and Utilities.

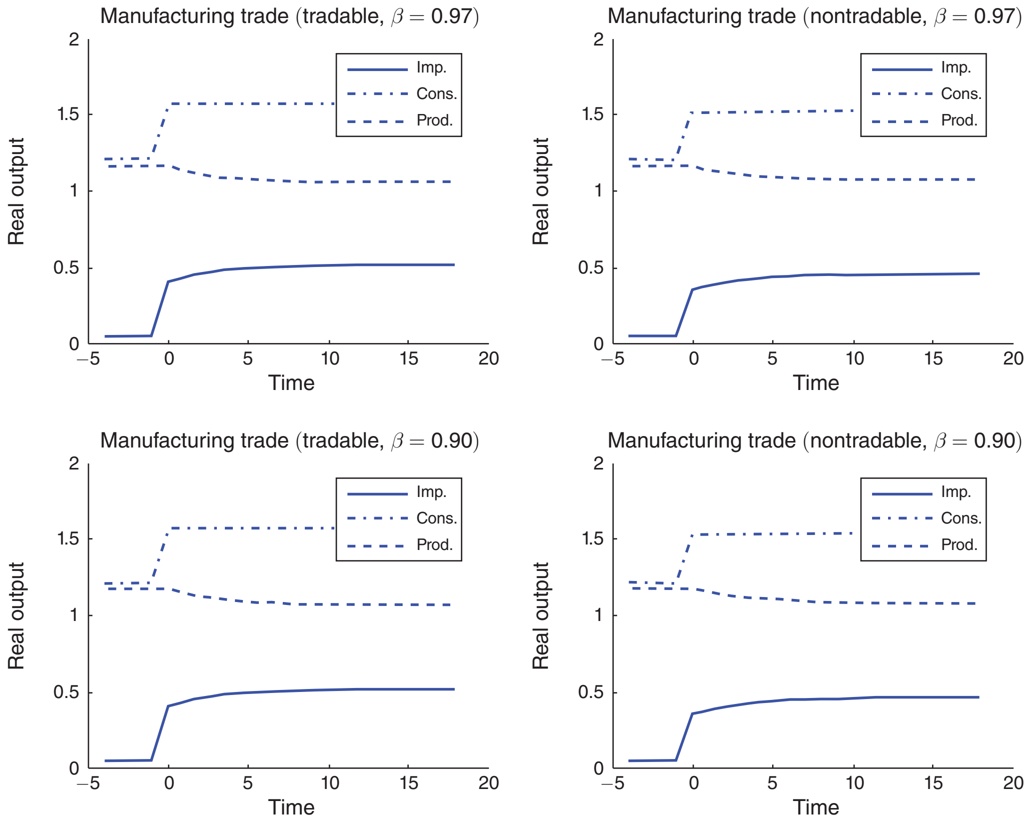

Figure 6. Trade—Basic Simulations

we can compute consumption of each sector's output and subtract the quantity produced to derive net imports. In the initial steady state with the tariff, calculation is slightly more complicated, as we need to add tariff revenue to income and compute consumption with domestic prices instead of world prices. Figure 6 shows the result for manufacturing output. At the date of liberalization, manufacturing consumption jumps up because of the abrupt drop in the domestic price of manufactures. Thereafter, it trends upward slightly because of increases in GDP as the economy reallocates its labor. Throughout, domestic production of manufactures falls, as workers leave the sector. Note that this implies that following the liberalization, manufactures imports continue to rise for several years, even as manufacturing wages rise. Thus, if one regressed manufacturing wages on import penetration and the date $t = -1$ was not part of the data, one would find a positive coefficient, while including the date $t = -1$ would change the sign to negative. This suggests that regressions that relate current manufacturing wages to current import penetration measures, such as are explored in Richard B. Freeman and Lawrence F. Katz (1991) and Kletzer (2002), need to be interpreted with great care.

Turning to the case with $\beta = 0.9$, we can see that the time path of labor allocations, real wages, and trade are virtually identical to the case with $\beta = 0.97$, but there is an important difference in welfare effects: With the lower discount factor, the option value effect no longer outweighs the direct effect of the lower manufacturing wage, and manufacturing workers are hurt by the liberalization (see the downward turn in the manufacturing workers' value function as plotted in the lower left-hand plot of Figure 5).[29] We can conclude that the discount rate does not matter much for the positive predictions of the model (perhaps why it is difficult to estimate), but it does matter for the normative analysis of policy.

Another point can be seen regarding the interpretation of reduced-form regressions. Revenga (1992), in her simplest specification, regresses changes in log industry wages and employment for the years 1981–1985 on changes in log industry import prices for the same period and finds an elasticity of 1.74 for employment and 0.40 for wages. An analogous wage "elasticity" can be computed from our simulation, as

$$\left(\frac{w_3^{manuf} - w_{-1}^{manuf}}{w_{-1}^{manuf}}\right)\left(\frac{p_{-1}^{manuf}}{p_3^{manuf} - p_{-1}^{manuf}}\right) = -\frac{1}{0.3}\left(\frac{w_3^{manuf} - w_{-1}^{manuf}}{w_{-1}^{manuf}}\right), \tag{15}$$

where w_t^{manuf} and p_t^{manuf} denote the period-t manufacturing wage and domestic output price, respectively. The employment "elasticity" is analogous. The employment "elasticity" from our simulation is 0.88, and the wage "elasticity" is 0.38. Thus, the orders of magnitude are similar to the Revenga elasticities and the signs match up—despite the tremendous differences in method. However, as pointed out above, our estimates are derived from a general equilibrium model that allows welfare analysis, and the welfare findings—that manufacturing workers benefit—cannot be inferred from the change in wage alone. The equilibrium analysis, together with option value, is needed for that.

It may be possible, however, to use reduced-form wage predictions to *approximate* the full lifetime welfare effects without computing the value functions. To see how, recall the worker's Bellman equation (3) and consider what happens if we implement a small change in policy that changes real wages in each sector at each date. For concreteness, suppose that the change is a change in the price of sector k output, due to a change in tariff, which occurs unnannounced in period 0 and is expected to be permanent. Employing the Envelope Theorem repeatedly, the effect on the welfare of a worker in sector i can be written as:

$$\frac{\partial V^i}{\partial p^k} = \sum_{t=0}^{\infty}\sum_{j=1}^{n} \beta^t \pi_t^{ij} \frac{\partial w_t^j}{\partial p^k}, \tag{16}$$

where p^k is the price of sector-k output and π_t^{ij} is the probability that a worker who is in sector i at date 0 will be in sector j at date t and can be computed from the gross flows $m_{t'}^{ij}$ for $t' = 0, \ldots, t$. This is the derivative of:

$$\sum_{t=0}^{\infty}\sum_{j=1}^{n} \beta^t \pi_t^{ij} w_t^j, \tag{17}$$

which is the expected discounted wage for a worker in sector i as of period 0, taking gross flows into account, and which might be called the "actuarial wage." Table 7 shows how well the actuarial wage predicts welfare changes in our model for the two values of the discount factor we are using. For each panel of the table, the first row shows the percentage change in lifetime welfare for a worker in the sector indicated upon announcement of the trade liberalization, as simulated in our model without any approximations. Row II shows the corresponding change in the actuarial wage computed with the wages and gross flows simulated by the model both pre- and postliberalization (so that both the w_t^j's and the π_t^j's are taken from the preliberalization

[29] Recalling (3), neither the wage nor the option value term in the value function is multiplied by the discount factor, but recalling (2), the discount factor does affect the $\bar{\varepsilon}^{ij}$'s and therefore does affect the calculation of option value indirectly.

TABLE 7—WELFARE PREDICTIONS WITH ACTUARIAL WAGES

	Agric/Min	Const	Manuf	Trans/Util	Trade	Service
Panel A. $\beta = 0.90$						
I	0.56	0.60	−0.35	0.63	0.62	0.69
II	0.54	0.59	−0.34	0.63	0.61	0.71
III	0.52	0.56	−0.43	0.60	0.59	0.67
IV	0.71	0.77	−0.31	0.82	0.81	0.92
Panel B. $\beta = 0.97$						
I	1.77	1.82	0.70	1.86	1.85	1.95
II	1.73	1.79	0.69	1.84	1.83	1.99
III	1.62	1.68	0.50	1.73	1.71	1.83
IV	2.48	2.56	1.26	2.62	2.61	2.79

Notes: Percentage increase in lifetime utility of worker in each industry at date of liberalization announcement. First row is computed value from simulation, and three following rows are approximations using the actuarial wage, as described in text.

steady state for the preliberalization value of the actuarial wage, and from the postliberalization transition path for the postliberalization actuarial wage). Row III uses the simulated wages but uses only the preliberalization gross flows to compute the π_t^j's. Row IV is as in row III but allows only manufacturing wages to change (apart from the change in consumer prices), to allow for the fact that reduced-form wage equations typically do not allow for a change in one sector's tariff to affect other sectors' wages.

Thus, row I is the correct evaluation of the welfare effect, and the other rows are approximations based on different amounts of imperfect information one might glean from a reduced-form estimation. Row II presumes that we have information on how wages and gross flows will change; row III presumes that we have information on how wages alone will change; and row IV presumes that we have information on how only the wages in the directly affected sector will change.

Clearly, from the table, the approximation works quite well in this case, getting the right sign in each case and getting the magnitude quite close except in row IV, where the approximation is poor. We conclude that *if* one is able to predict wage changes well from a reduced-form regression, and *if* one has information on gross flows before the liberalization, one can predict the welfare effects quite accurately (of course, we make no guarantees that this will work with other datasets). However, these requirements are not trivial. It is important to predict the wage effects for all sectors, not just the sector whose tariff is being changed. Further, the whole time path of wage changes is required, while the reduced-form approach typically yields a prediction on simply the immediate impact effect. Finally, as mentioned in the introduction, the reduced-form approach cannot help much in predicting the effect of *anticipated* liberalizations on wages. Subject to these qualifications, this approximation may be useful in some settings.

B. *Specification II: Non-Traded Sectors*

In our second simulation specification, Construction, Transportation/Utilities, and Trade are taken to be non-traded.[30] Thus, their prices are endogenous and adjust so that the quantity

[30] This division is, of course, to some degree arbitrary. It is difficult to argue that Services should be classified as non-traded, since services trade has occupied much attention and created much controversy at the WTO. On the other hand, the "Trade" sector is, of course, mainly domestic wholesale and retail trade and thus not *internationally* traded, which is the meaning of "non-traded" here.

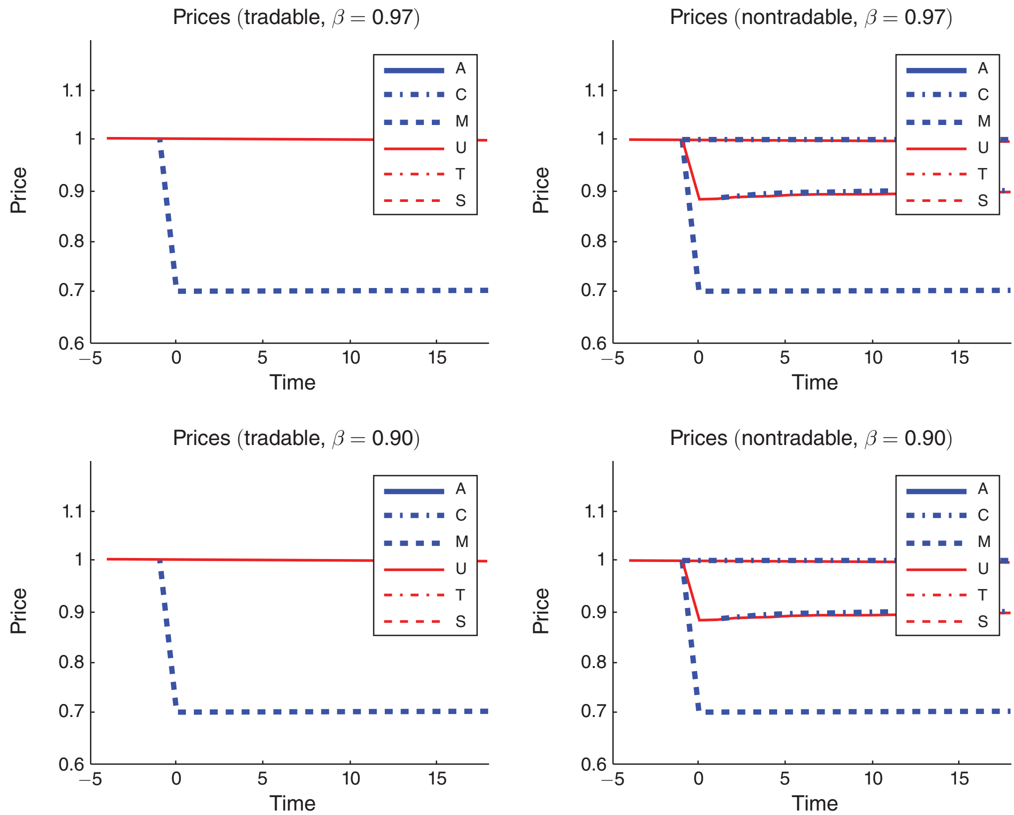

FIGURE 7. PRICES—BASIC SIMULATIONS

produced in each of those sectors at each date (as determined from the production function and the number of workers in the sector at that date) is equal to the quantity demanded, given GDP and tradable-goods prices. The endogenous domestic prices are shown in the right-hand column of Figure 7, which can be contrasted with the exogenous prices of the plots in the left-hand column. The right-hand column of Figure 3 shows the reallocation of labor. Compared with the left-hand column, the pattern is similar, but the non-traded sectors expand less while the traded sectors expand more. This is because the suddenly less expensive manufactured goods cause consumer expenditure to switch toward manufacturing and away from non-traded goods, effectively shifting the demand curve for non-traded goods sharply downward at the date of the liberalization. This is reflected in the sudden drop in non-traded prices exhibited in the time plot of domestic prices shown in Figure 7. As a result, the movement in wages in non-traded sectors is much less sharp in the right-hand column of Figure 4 than in the left-hand column. Figure 6 shows that, once again, liberalization increases the imports of manufactures, with an initial jump and gradual adjustment over the following several years.

The main point is unchanged. Real wages in manufacturing fall sharply and never recover, as shown in Figure 4, but if $\beta = 0.97$ workers in manufacturing benefit from the liberalization along with workers in all of the other sectors, as shown in Figure 5. Once again, the explanation is enhanced option value for workers in the liberalized sector. If $\beta = 0.9$, however, the option value effect is diminished, and manufacturing workers are hurt.

VI. Worker Heterogeneity

Until this point we have maintained the fiction that workers are homogeneous. Of course, much of the potential distributional effect of trade liberalization is driven precisely by different capabilities for adjustment on the part of different kinds of worker. A full examination of heterogeneity is beyond our scope (indeed, beyond the scope of any single paper), but we offer here two exploratory exercises showing how the model can be adapted to take worker heterogeneity into account. We draw here on the methods for modeling aging and unobserved heterogeneity in Artuç (2009), which in all other respects uses a very different estimation strategy.

A. *Observed Worker Heterogeneity*

In principle, the estimating equation (9) can, with very little modification, be conditioned on any observable information and estimated for any subclass of worker. If one had enough data, one could compute gross flow rates and wages for 49-year-old workers with college degrees, for 50-year-old workers with college degrees, and 49-year-old high-school graduates, and so on, deriving a Euler equation for each group and estimating different moving cost parameters for each group. Unfortunately, our data do not allow us to estimate separate parameters for any very fine partition of the data, but we are able to explore a very simple life-cycle model, which illustrates how worker heterogeneity affects the distributional effects of trade, and which can suggest the possibilities for further exploration with richer datasets. What we will show here is a model with four classes of workers, distinguished by whether they are young or old and less educated or more educated.

Assume that everything about a worker's education of relevance to labor-market outcomes can be summarized by whether or not that worker has a college degree. Assume that a worker enters the labor market either with or without a college education, and that that educational status will not change over the worker's lifespan. Assume as well that everything about a worker's age can be summarized by whether workers are "young" or "old." New workers entering the labor market are young and, each period, may become old with probability λ^Y. An old worker each period may drop out of the market with probability λ^O, with the retiring old workers replaced each period by an equal number of new young ones.

Other than the existence of four types of labor and the age transitions each worker goes through, the model is exactly the same as the main model. All workers face the same idiosyncratic shock distribution but may face different values of the common cost $C^{E,A,ij}$, where E is the educational state, taking values N for no college degree and C for a worker with a college degree, and A is the age, taking values Y for a young worker and O for an old worker. Of course, we need to keep track of different wages $w_t^{E,A,i}$ and gross flows $m_t^{E,A,ij}$ for the four worker types. It is shown in Appendix 2 that the following variant of the Euler equation (9) holds for young workers:

$$
\begin{aligned}
(18)\qquad & E^t\left[\frac{\beta}{\nu}[((1-\lambda^Y)w_{t+1}^{E,Y,j}+\lambda^Y w_{t+1}^{E,O,j})-((1-\lambda^Y)w_{t+1}^{E,Y,i}+\lambda^Y w_{t+1}^{E,O,i})\right] \\
& +\beta[(1-\lambda^Y)\ln m_{t+1}^{E,Y,ij}+\lambda^Y\ln m_{t+1}^{E,O,ij}-((1-\lambda^Y)\ln m_{t+1}^{E,Y,jj}+\lambda^Y\ln m_{t+1}^{E,O,jj})] \\
& +\frac{(\beta(1-\lambda^Y)-1)C^{E,Y,ij}+\beta\lambda^Y C^{E,O,ij}}{\nu} \\
& -(\ln m_t^{E,Y,ij}-\ln m_t^{E,Y,ii})] = 0.
\end{aligned}
$$

Table 8—Estimates from the Life-Cycle Model

	$\beta = 0.97$	$\beta = 0.9$
ν	1.606	1.429
	(3.148***)	(3.365***)
$C^{N,Y}$ (young, no college degree)	3.666	4.553
	(2.277**)	(3.222***)
$C^{C,Y}$ (young, college degree)	7.054	6.294
	(2.103**)	(3.006***)
$C^{N,O}$ (old, no college degree)	5.054	5.552
	(2.346***)	(3.102***)
$C^{C,O}$ (old, college degree)	9.817	8.566
	(2.397***)	(3.028***)

Notes: Full sample, with instruments. Gross flows are annualized as in panel IV of Table 3.

One-tail significance:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

In the case of an old worker this version holds:

$$E_t\bigg[\frac{\beta}{\nu}(1 - \lambda^O)[(w_{t+1}^{E,O,j}) - (w_{t+1}^{E,O,i})] + \beta(1 - \lambda^O)[(\ln m_{t+1}^{E,O,ij} - \ln m_{t+1}^{E,O,jj})] + \frac{(\beta(1 - \lambda^O) - 1)\,C^{E,O,ij}}{\nu} - (\ln m_t^{E,O,ij} - \ln m_t^{E,O,ii})\bigg] = 0. \tag{19}$$

The main difference between these is that a young worker knows that there is some probability that next period she will be old next year, so her Euler equation has both $C^{E,Y,ij}$ and $C^{E,O,ij}$ in it. We can estimate as before using GMM (modifying the approach slightly to take into account that now we have a system of equations) and simulate as before.

Note that theory gives no presumption as to what the relative values of $C^{E,A,ij}$ for the four different types should be. In particular, human capital is often sector specific (as for doctors, engineers, or economics professors) but also can be fairly footloose (accountants and IT professionals can be hired by a wide variety of employer). It is unclear *a priori* whether to expect higher or lower moving costs for the college educated. Our estimated parameters are shown in Table 8.

The estimates are similar in magnitude to our benchmark specification but vary greatly across the four groups. In particular, older workers face strictly higher moving costs than younger workers (as found in Artuç 2009); and college-educated workers have substantially higher moving costs than non-college-educated workers. The higher estimated costs for the college educated are not hard to understand; in the data, those workers have similar rates of gross flow compared with the non–college educated but tend to have much higher wage differentials across sectors.[31]

[31] The probability that a younger worker changes industry in any given year across all of the data (that is, the average of $1 - m_t^{E,Y,ii}$) is 0.1291 for a worker with no college degree, compared with 0.1270 for a young worker with a college degree. The figures for older workers are 0.0646 and 0.0788 respectively. Thus, college-educated workers move 1.6 percent less when they are young and 22 percent more when they are old, compared with other workers. The average absolute value of intersectoral wage differentials $|w_t^{E,Y,j} - w_t^{E,Y,i}|$ is 0.0957 for young workers without college and 0.1168 for young college graduates, compared with 0.1158 and 0.1762 for non–college graduates. Therefore, college-educated workers face wage differentials across sectors that are on average 22 percent higher when they are young and 52 percent higher when they are old, compared with non–college educated.

TABLE 9—WALD TESTS FOR DIFFERENCES IN MOVING COSTS ACROSS TYPES

Null hypothesis	$\beta = 0.97$	$\beta = 0.9$
$C^{N,Y} = C^{C,Y}$	1.437	2.624
$C^{N,O} = C^{C,O}$	2.103	3.443*
$C^{N,Y} = C^{N,O}$	3.676*	3.556*
$C^{C,Y} = C^{C,O}$	1.824	3.152*

Notes: Wald tests, based on estimation in Table 8.

One-tail significance:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

However, only for the case of $\beta = 0.9$ and only for older workers is the difference between the college graduate and non–college graduate moving cost statistically significant, as is shown in Table 9. That table shows Wald statistics for tests of hypotheses that the moving-cost parameters for the various groups are equal. The second column of the second row shows the rejection of the hypothesis that the older college graduates and non–college graduates have the same moving costs. On the other hand, the third row shows that we reject equality of young and old moving costs for blue-collar workers.

To simulate a trade liberalization, we first need to augment each sector's production function to include the four types of labor. Details are in the Appendix, but the main points are as follows. We assume a CES aggregator for young and old labor, and for each sector a CES aggregator for college graduates and capital, and write a CES production function with noncollege labor and the college/capital aggregate as arguments. We then construct an illustrative numerical example by choosing parameters to match some moments in the data. New entrants are divided between college graduates and noncollege in the same proportions as they are observed in the data, 29 percent to 71 percent. They choose their sector in the same way as incumbent workers choose whether or not to move, except with no common moving cost (so that, in effect, for the first year of a worker's career, $C^{E,Y} = 0$). As before, we run four simulations: all sectors traded, with $\beta = 0.97$ and then $\beta = 0.9$; and only manufacturing, services, and agriculture traded, with the two values of β. Once again, the liberalization takes the form of elimination of a tariff on manufactures.

Consider first the case with all goods traded and $\beta = 0.97$. This simulation is plotted in Figure 8 to 11. Each figure has four panels, and in each panel, the outcomes for one of the four types of labor are plotted. Figure 8 shows the allocation of labor, Figure 9 the time path of real wages, Figure 10 the value function for each type of worker, and Figure 11 the time path for domestic prices and manufacturing trade. Before looking at the simulation results, we might wish to pause to consider what to expect. Note that historically in the data, manufacturing has been the largest sector of employment for blue-collar workers, with services second, while the service sector has been the largest for white-collar workers, with manufacturing second. This is because the service sector is much more skill intensive. Indeed, historically manufacturing has employed approximately four non–college educated workers to each college graduate, (similar to trade, transport/utilities, agriculture, and construction, at 4:1, 5:1, 5:1, and 8:1 respectively). By contrast, the service has historically employed one non–college educated worker for each college graduate, making it by far the most skill-intensive sector in the economy. With a trade economist's habit of thinking of specific-factors models as a good short-run model and Heckscher-Ohlin as a good long-run model, a sensible guess could be that real manufacturing wages would fall in the short run while other real wages rise, but in the long run all college-educated real wages rise, and all non-college-educated real wages fall—the story of the Stolper Samuelson theorem.

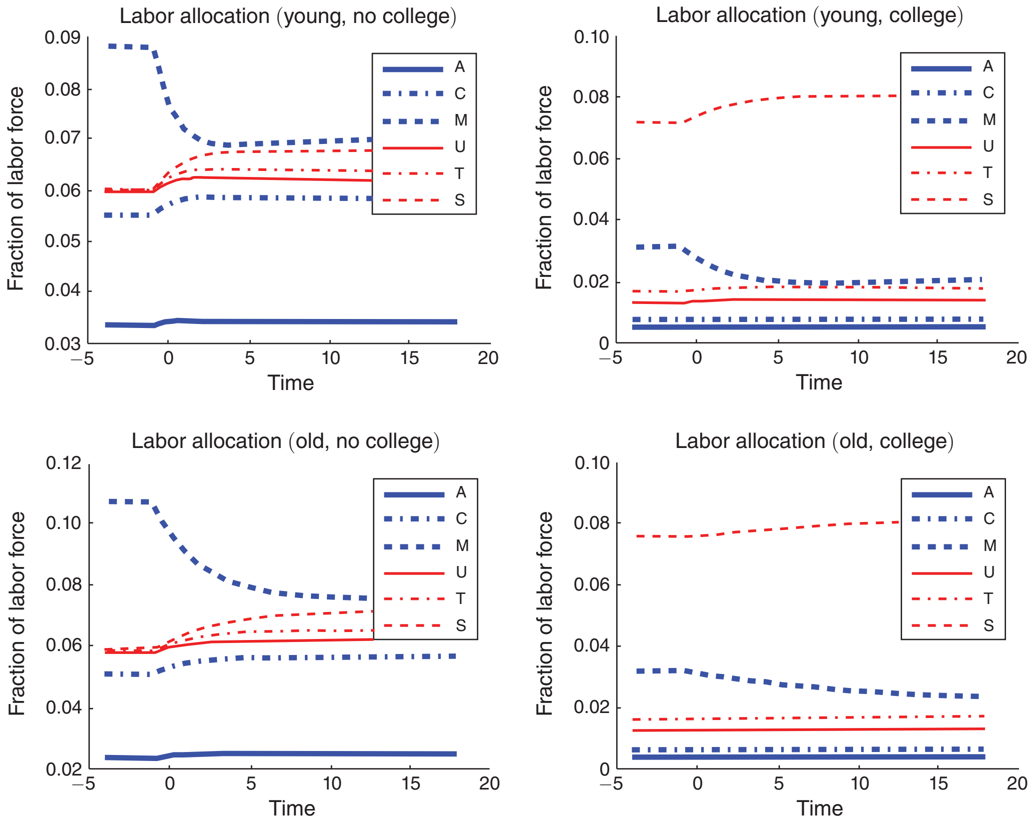

Figure 8. Labor Allocation—Simulation (*heterogenous agents*)

In fact, for each type of labor the story is similar to what we saw in the simulation with a single type of worker: Manufacturing real wages fall in the short run, and, although they recuperate to a degree, they never regain their initial value; all other wages rise in the short run, and although they deteriorate somewhat over time, they never fall as far as their initial value. Once again, we do not observe equalization of wages for any labor type in the short run *or* in the long run. Because of the idiosyncratic shocks, the long-run intersectoral elasticity of labor supply is positive and finite. There is therefore no reason for the movement of wages to follow a Stolper-Samuelson pattern in the long run, and with these parameters they follow a sectoral pattern, falling in the sector that has lost its protection and rising in the others, for all types of labor.

The welfare results shown in Figure 10 also are different from what Stolper-Samuelson would predict. As a result of the liberalization, the welfare of every type of worker in every sector rises, with one exception: older workers in manufacturing. Clearly, although real manufacturing wages fall at every date following the liberalization compared to the status quo ante, young manufacturing workers see enough prospect of eventually leaving the sector that they are pleased with the liberalization. Put differently, the rise in their option value is large enough to compensate them for the loss of their current wages. However, older workers have no such hope, both because of their higher moving costs (see Table 8) and because of their shorter expected remaining working life. *Contra* Stolper-Samuelson thinking, in this policy experiment, *age* (together with sector of employment), and not educational class, is the key criterion determining whether or not a worker benefits from trade. This is consistent with some available survey data showing that

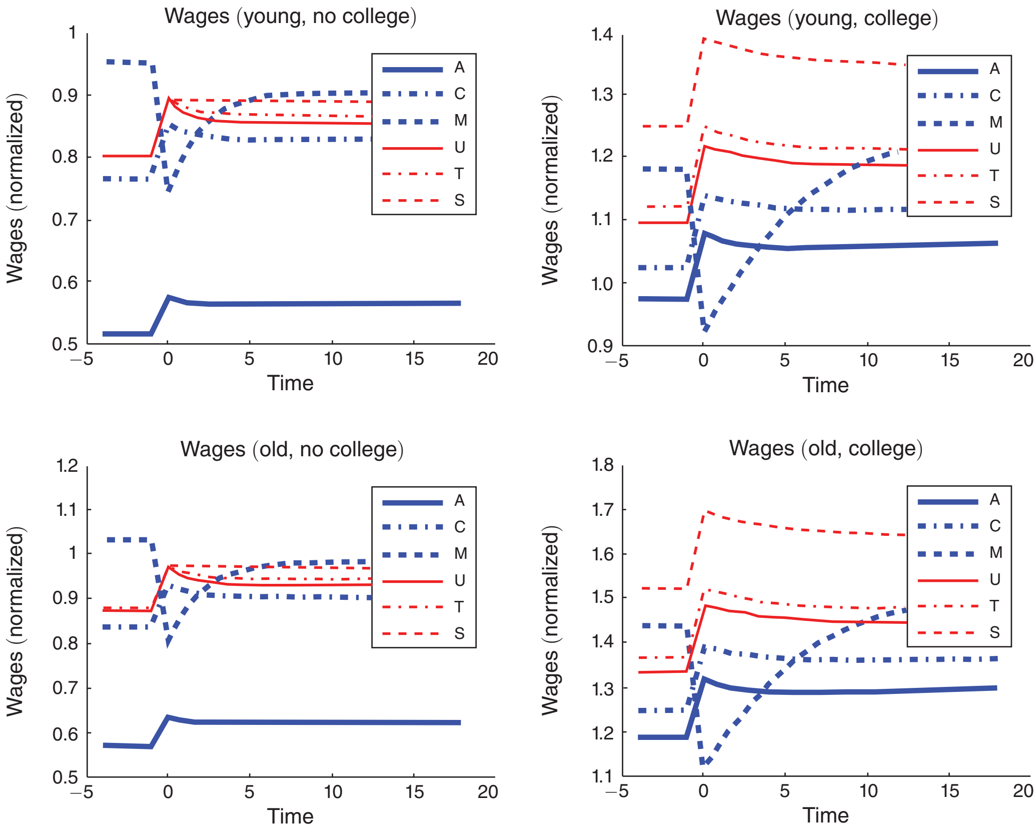

FIGURE 9. WAGES—SIMULATION (*heterogenous agents*)

young workers in many countries have more favorable attitudes toward trade liberalization than older workers; see Artuç (2009) for a detailed discussion.

The results for the remaining simulations are not shown but are available on request. In the case with $\beta = 0.9$, the movement of labor allocations and wages is very similar to the $\beta = 0.97$ case, but the welfare analysis is simpler: each worker's welfare moves at the date of liberalization in the same direction as the short-run movement in that worker's real wage. Thus, all workers, of all four types, who work in manufacturing see a fall in welfare, while all other workers see a rise.

For the case of non-traded sectors, once again the output price falls in each non-traded sector in response to consumer substitution away from non-traded goods and toward the now cheaper manufactures, but real wages in the non-traded sectors rise because the drop in manufactures prices more than compensates. The pattern of welfare changes for both values of β is exactly as it was in the tradables case.

We do not intend to push these precise results as a guide to policy analysis, because more work is needed to establish confidence in the magnitude of the parameters, but they do show how the effects of policy are affected by the parameters and thus tell us much about what we need to know. To summarize these simulations:

(*i*) All workers in nonliberalizing traded-goods sectors and non-traded sectors experience a rise in real wage in the short and long runs and benefit from the liberalization.

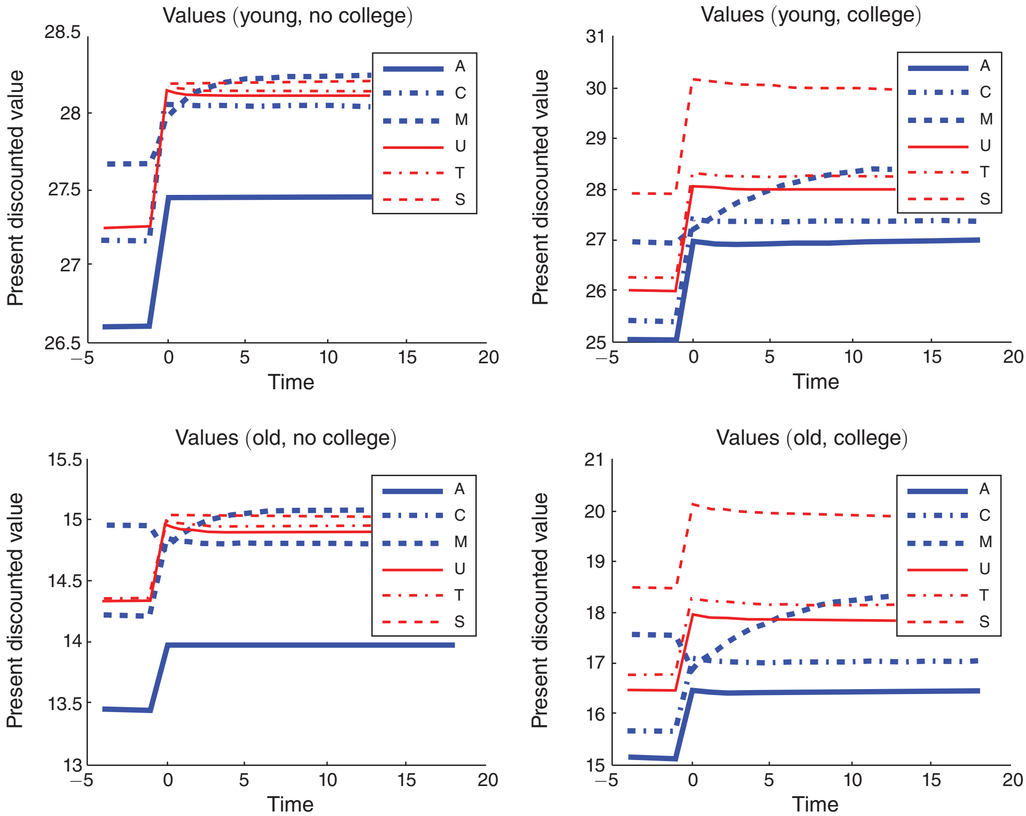

FIGURE 10. VALUES—SIMULATION (*heterogenous agents*)

(*ii*) Workers in the liberalizing sector suffer a loss of real wages in the short and long runs but an increase in option value due to the rise in real wages in the rest of the economy.

(*iii*) A worker in the liberalizing sector benefits from the liberalization if the option value effect is large enough to outweigh the direct effect of the lower wage. This is more likely if β is high or if the worker has a low C and a long enough expected career time remaining—both more likely if the worker is young.

B. *Unobserved Worker Heterogeneity*

Perhaps the biggest weakness in the Euler-equation approach we have pursued here is that it assumes away workers with unobserved permanent or persistent differences in moving costs. A full exploration of such effects probably requires a structural micro approach. However, we can add a small amount of persistent unobserved heterogeneity without abandoning the Euler-equation approach. Suppose that a fraction of the work force in each sector cannot change sectors at all, while the remainder can change exactly as specified in the main model. In that case, Euler equation (9) applies only to the fraction of workers who are able to move if they choose, and so the gross flows m_t^{ij} need to be recalculated as the fraction of the movable workers in i who move to j (so the denominator is reduced, but the numerator is unchanged).

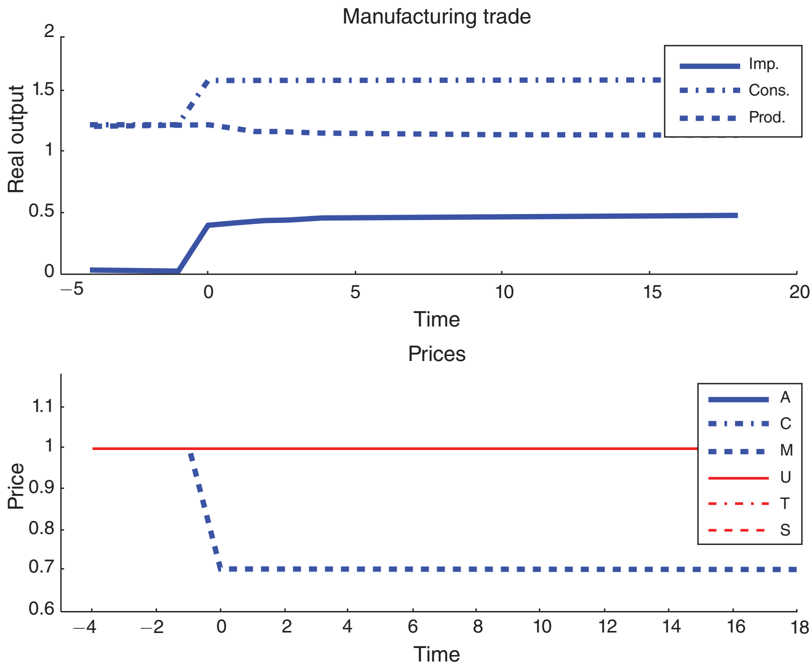

FIGURE 11. TRADE AND PRICES—SIMULATION (*heterogenous agents*)

As a simple illustrative way of exploring this idea, suppose that initially a fraction a of workers in each sector are unable to move. Each period, a worker who can move may become unable to move with probability λ^1, and each worker who is unable to move may become able to move with probability λ^2. Suppose that we impose the constraint that α is the steady state fraction of unmovables in the labor force implied by the transition probabilities λ^1 and λ^2. Assume for the moment that λ^1 and λ^2 are known. For each sector, from the initial number of workers in the sector, we can then compute the number of initial immovables that implies for the sector and then update that number of immovables for every subsequent period using λ^1, λ^2, and the gross flows.

In this modified model, (9) no longer applies even for the movable workers, because each currently movable worker understands that there is a positive probability that she will not be able to move next period. As a result, with positive probability, the Euler equation will not be satisfied next period, and the recursive algebra used to derive (9) no longer applies. However, Appendix 3 shows how a related estimating equation can be derived from the Euler equation. In principle, this can be used to estimate the parameters ν, C, β, α, λ^1, and λ^2, but for this illustrative example, we will choose values for the other parameters and show how they affect estimated values for ν and C. Here, we set $\alpha = 0.751$, $\lambda^1 = 0.441$, and $\lambda^2 = 0.146$, along with our earlier choices of β, to provide an example with substantial numbers of unmovable workers and substantial persistence in immobility. (Appendix 3 explains how these numbers were selected.) The resulting parameters are presented in Table 10.

It should not be surprising that the estimated moving costs are dramatically smaller than in our main model, if one thinks of the values of C in the main model as an average of the C for movable workers and the C for unmovable workers—the latter being infinite.

The model can then be simulated as the main model was, mutatis mutandis. The result is a more rapid move toward the new steady state after a liberalization, but the qualitative features of the simulation are the same as in the previous simulations. (Detailed simulation results are available

Table 10—Unobserved Heterogeneity

	$\beta = 0.97$	$\beta = 0.9$
ν (for movable workers)	0.926***	0.661***
	(4.037)	(5.684)
C^1 (for movable workers)	2.076**	1.526***
	(1.721)	(4.431)

Notes: Full sample, annualized data, with instruments.

One-tail significance:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

on request.) Perhaps strikingly, the welfare conclusions are entirely unchanged by the addition of the unobserved worker heterogeneity. With $\beta = 0.97$, all workers benefit from the liberalization, but with $\beta = 0.9$, all manufacturing workers are hurt. The fact that with the lower discount rate *even immobile manufacturing workers* would benefit from liberalization is surprising, especially since we have made the immobile state very persistent by setting $\lambda^2 = 0.146$. However, every immobile worker knows that at some point over the next few years she may become mobile (the probability of become mobile at some point within five years equals 71 percent), and since the cost of moving for a mobile worker is so low, she expects to be able to take advantage of the higher wage opportunities in the other sectors soon.

Obviously, this is merely a suggestive exercise, and a full inquiry into unobserved heterogeneity could be quite fruitful. The point is that the framework can be extended in this sort of direction fairly easily.

VII. Conclusion

We have presented a dynamic, rational expectations model of labor adjustment to trade shocks, which is, through Euler-equation techniques, easy to estimate econometrically, yielding structural parameters. It is then easy to simulate to study policy. Among our findings are the following.

(*i*) Since gross flows of workers across industries are substantial but do not respond much to intersectoral wage differences, both the mean and the standard deviation of workers' moving costs implied by the model are large—several times an average workers' annual earnings, in fact.

(*ii*) Because of this, the model predicts somewhat sluggish reallocation of workers following a trade liberalization. In our simulation of the elimination of a 30 percent tariff on manufacturing, 95 percent of the reallocation is completed in eight years.

(*iii*) This implies sharp movement of wages in response to the liberalization, with the short-run response overshooting the long-run response by a wide margin.

(*iv*) Option value, not previously part of the discussion in analysis of trade policy, matters a great deal in evaluating the welfare effects of trade liberalization. In simulations, wages in sectors hit by trade shocks fall both in the short run and in the long run, but quite often workers in those sectors are better off than before the liberalization because of their enhanced option value. This echoes some findings by Magee, Davidson, and Matusz (2005) on patterns in political contributions.

(*v*) Our model generates aggregate behavior broadly similar to what is found in some reduced-form regression results but provides a microfounded welfare analysis.

(*vi*) When observed heterogeneity among workers is added to the model, we find that a worker in a vulnerable sector is more likely to be hurt by trade, ceteris paribus, if the worker is older or if the discount rate is high. With our low-end choice of annual discount factor, $\beta = 0.9$, all workers in a liberalizing import-competing sector are hurt by trade in all simulations, regardless of age or education.

(*vii*) A very robust finding is that both the mean and standard deviation of moving costs are high, amounting to several times average income. This implies that, although workers change sectors quite often, wages are not equalized across sectors either in the short run or in the long run, and the effects of trade liberalization on wages and on workers' welfare in the short run and in the long run in no way resemble Stolper-Samuelson effects. Indeed, whether a worker benefits from liberalization or not depends much more closely on what sector the worker is in initially than on the worker's educational class.

We regard this as a first exploration and hope that this work will help to put these questions onto the research agenda. We have shown, for example, that discount rates matter for the direction, as well as the magnitude, of welfare effects of trade, but we have not been able to estimate them. If subsequent work is able to shed light on this, it would be quite valuable. Many other possible avenues for fruitful research suggest themselves, for example:

(*i*) Pinning down relative cost parameters for finer classes of workers, including a more realistic treatment of age, would be facilitated by using the rich labor-force surveys available in various countries. It would also be of interest to divide workers by their level of job tenure, allowing for workers with more sector-specific human capital to have higher wages and an endogenously lower propensity to switch sectors. This requires larger sample sizes than the CPS in order to compute the gross flow matrices without a large number of empty cells, but a number of countries, particularly in Europe, have labor force surveys with large sample sizes, or even administrative datasets based on tax records, that could accommodate this. In principle, with enough cross-sectoral detail, the model could be estimated on a short time series, allowing estimation with young datasets from some middle-income developing countries.

(*ii*) Drawing on the now-extensive literature on heterogeneous firms, gross flows could be modeled as generated by firm entry and exit due to different productivity across firms (as in Andrew B. Bernard, Stephen J. Redding, and Peter K. Schott 2007, for example) or due to productivity shocks that hit individual firms over time (as in Utar 2007, for example). In this way, one could estimate a model that incorporates a serious treatment of labor-demand-side adjustment with the labor-supply-side adjustment that has been our focus. One possibility is that a worker displaced by contraction or exit of her firm of employment may face different moving costs compared to a worker who is currently employed, and this could be estimated.

(*iii*) It would make sense, more generally, to include a role for unemployment within the model, both because the rise of unemployed workers from the contracting sector could be an important consequence of the liberalization experiment, and because the moving costs for workers already displaced for other reasons, such as firm-specific events, could be quite different from moving costs for other workers.

(*iv*) Our treatment of unobserved heterogeneity is rudimentary, with unobserved costs left as a black box. A fuller treatment of unobserved heterogeneity would allow, for example, for the possibility that different workers who are identical to the econometrician have different productivities as well as, possibly, different moving costs. If workers differ systematically across sectors in unobservables, the computation of intersectoral wage differentials is more complicated than we have allowed for here. All of these effects would allow for a much richer account of moving costs than is provided in this paper, with more nuanced welfare effects.

If subsequent work obliterates the specific results of this paper but provides us with a firmer understanding of labor adjustment costs and thus a better guide to the incidence of trade policy, then we will have achieved a key goal.

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