Trade Liberalization and Labor Market Dynamics

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Abstract

I study trade-induced transitional dynamics by estimating a structural dynamic equilibrium model of the Brazilian labor market. The model features a multi-sector economy with overlapping generations, heterogeneous workers, endogenous accumulation of sector-specific experience and costly switching of sectors. The model's estimates yield median costs of mobility ranging from 1.4 to 2.7 times annual average wages, but a high dispersion across the population. In addition, sector-specific experience is imperfectly transferable across sectors, leading to additional barriers to mobility. Using the estimated model for counter-factual trade liberalization experiments, the main findings are: (1) there is a large labor market response following trade liberalization but the transition may take several years; (2) potential aggregate welfare gains are significantly mitigated due to the delayed adjustment; (3) trade-induced welfare effects depend on initial sector of employment and on worker demographics. The experiments also highlight the sensitivity of the transitional dynamics with respect to assumptions regarding the mobility of capital.

Keywords: Trade Liberalization, Labor Market Dynamics, Distributional Effects of Trade Policy, Adjustment Costs, Worker Heterogeneity

1 Introduction

One of the least controversial lessons of neoclassical economics is that free trade increases aggregate welfare by efficiently allocating resources within countries. However, free trade also generates distributional conflicts: there will be winners and losers.

The arguments supporting aggregate welfare gains from trade are typically based on long-run theories where only an initial state (typically autarky) and a final state (free or less-distorted trade) are considered, with no predictions of what happens in between. Perfect factor mobility is usually assumed and less than full employment or unemployment are seldom modeled.[1] On the other hand, theories that emphasize distributional conflicts following trade liberalization rely on extreme assumptions regarding

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[1] Notable exceptions are Mussa (1978), Neary (1978), Davidson, Martin and Matusz (1999), Helpman and Itskhoki (2009) and Helpman, Itskhoki and Redding (2010).

factor mobility in order to identify winners and losers. For example, in the long-run Hecksher-Ohlin model, with perfectly mobile factors, the winners and losers are characterized by what factors they own (e.g., skilled versus unskilled labor or labor versus capital). In the short-run Ricardo-Viner model, with immobile factors, winners and losers are characterized by their industry affiliation (e.g, import-competing versus export-oriented industries).

At the same time, free trade is far from being widely practiced, especially in developing countries. Even countries that implemented important trade reforms in the 1980s and 1990s, such as Brazil, Colombia and India, still apply high import tariffs in many industries (see Kee, Nicita and Olarreaga (2006)). The existence of distributional conflicts is indeed an important consideration limiting the adoption of free trade (Rodrik (1995) and Limão and Panagariya (2007)). Nevertheless, a considerable source of concern for policy makers is that we still lack a good understanding of how the economy will behave in the short-to medium-run in the aftermath of trade liberalization. This is important in order to determine how fast the gains from trade can be realized, and to better characterize who the winners and losers from trade liberalization actually are.

Perhaps surprisingly, economists are still not in a comfortable position to answer relevant policy questions such as: How long should we expect the labor market transition to last? To what extent will the potential gains from trade be mitigated due to the slow adjustment of the economy to the new free trade equilibrium? What are the characteristics of the workers who will lose the most from trade liberalization? What labor market policies are most promising for reducing adjustment costs, speeding up adjustment and compensating the losers?

This paper provides a better understanding of these issues by estimating a structural dynamic equilibrium model of the labor market within a small open economy with a non-tradeable sector and a non-employment option. The labor demand side is given by perfectly competitive sector-representative firms with Cobb-Douglas production functions and three factors of production - human capital from unskilled workers, human capital from skilled workers and physical capital. The labor supply side features overlapping generations, forward looking heterogeneous workers who have comparative advantage across sectors, endogenous accumulation of sector-specific experience, self-selection into sectors based on observable and unobservable components of wages and costly switching of sectors. Wages are determined as the equilibrium prices that equate aggregate supply to aggregate demand of human capital.

The model includes two important margins through which the labor market can adjust in response to trade reform. It features overlapping generations where older, possibly less-mobile workers retire, and younger, possibly more-mobile workers choose where to work for the first time. This implies an important role for younger generations: that of speeding up reallocation after trade reform. The model also includes a labor supply decision, so that workers can decide to temporarily drop out of the formal labor market when they are hit with bad shocks.

I employ Indirect Inference and a large panel of workers constructed from matched employer-employee data from Brazil in order to estimate the model. These data are particularly well suited to the analysis carried out in this paper due to the large sample size, the ability to follow workers over time and across industries and the ability to construct sector-specific experience for all workers.

The model's estimates imply that workers' median costs of switching range from 1.4 to 2.7 times individual annual average wages, but these vary tremendously across individuals with different observable characteristics (gender, education, age). This produces a very dispersed distribution of mobility costs within the population. Female and less educated workers, for example, face substantially higher costs of switching sectors (as a fraction of individual wages).[2] In line with previous research (Neal (1995)), I find that sector-specific experience is imperfectly transferable across sectors, leading to additional barriers to mobility.

The estimated model is subsequently used as a laboratory for counter-factual experiments. In all the experiments, the price of the import-competing sector (High-Tech Manufacturing) faces a once-and-for-all decline in order to simulate a trade liberalization episode. I focus on this particular shock since tariffs in the High-Tech Manufacturing sector remain high (both in relative and absolute terms) despite the Brazilian trade liberalization episode of 1988-1994 (see Kume, Piani and Souza (2000)).

My findings indicate that: (1) The duration and magnitude of the transition are very sensitive to assumptions regarding the mobility of physical capital. (2) There is a large labor market response following trade liberalization but the transition may take several years. If capital is perfectly mobile or immobile, 95% of the reallocation of workers is completed only after 5 years. Under the assumption of imperfect capital mobility, and depending on its degree of mobility, this duration can be an order of magnitude longer. (3) Workers employed in High-Tech Manufacturing prior to the shock face substantial losses in welfare, especially those with higher educational attainment. (4) Adjustment costs - defined as the fraction of the potential gains from trade that are lost due to the slow and costly adjustment - may be as large as 16% to 42% depending on the degree of mobility of capital. (5) A moving subsidy that covers switching costs performs better than a retraining program in compensating the losers, although at the expense of higher welfare adjustment costs. (6) These last two labor market policies also have distinct implications for redistribution within the target population. Finally, (7) Costs of mobility appear to be more important than sector-specific experience in explaining the slow adjustment of the labor market.

On the methodological side, this paper is most related to Lee (2005) who studies the general equilibrium effects of a college subsidy and to Lee and Wolpin (2006) who investigate possible explanations for the growth of the service sector in the United States.

In terms of focus, this paper contributes to a rapidly growing empirical and quantitative literature studying the impact of foreign competition on the labor market. Recent papers in this literature include Autor, Dorn and Hanson (2011), Hakobyan and McLaren (2011) and Kovak (2011) who study the impact of foreign competition on local labor markets; Menezes-Filho and Muendler (2011) who study resource reallocation across firms and sectors following large-scale trade reform; and Kambourov (2009), Coşar (2011), Coşar, Guner and Tybout (2011) and Ritter (2011) who study trade-induced labor adjustment using calibrated models of frictional labor markets and trade. Within this literature, my paper is most closely related to a recent but already influential and highly cited paper by Artuç, Chaudhuri and McLaren (2010) - henceforth ACM. In this paper, they study trade-induced inter-

[2] As I discuss later, even though the costs of switching as a fraction of average conditional wages are largely insensitive to age, when expressed as a fraction of expected present values it increases steeply with age, implying that it is much more difficult for older workers to arbitrage wage differentials.

sectoral labor adjustment within a structural dynamic model of the labor market with competitive product and factor markets. Workers face mobility costs in order to switch sectors and are homogeneous, apart from *iid* idiosyncratic preference shocks for sectors, which allows them to obtain a closed form structural equation that relates gross flows across sectors to inter-sectoral wage differentials. This equation can then be estimated using standard *GMM* methods to recover structural parameters.

My paper estimates a model similar in spirit to that paper, but incorporates several important features which were shown to be crucial in explaining the inter-sectoral wage structure. Indeed, obtaining the best possible measures for individual counter-factual wages across sectors is key for the identification and estimation of mobility costs, which drive the dynamic response of the labor market to trade reform and its distributional consequences. In order to obtain counter-factual wages, I allow workers to have comparative advantage across sectors along several dimensions of observable heterogeneity (gender, education and age). Furthermore, workers endogenously accumulate sector-specific experience, which has differential returns across sectors. This re-enforces comparative advantage across sectors and may lead to an important additional barrier to mobility. Finally, my model also accounts for self-selection into sectors based on unobserved wage components, allows for non-pecuniary preferences for sectors and introduces a non-employment choice. Heckman and Sedlacek (1985 and 1990) show that all these ingredients are crucial in explaining the inter-sectoral wage structure, and as a result, for obtaining the best possible measures for individual counter-factual wages across sectors. In addition, the introduction of a rich set of worker heterogeneity allows for the study of how trade-induced sectoral price changes interact with workers' demographic characteristics such as age and education.[3]

Modeling the features just outlined is potentially important on a priori grounds. Indeed, doing so generates results that are quantitatively quite different. For example, the baseline specification in ACM yields average costs of mobility in the order of 6 times annual average wages using data from the United States. Artuç and McLaren (2010) also apply that methodology to Turkish data and obtain costs of mobility ranging from 9.5 to 23 times annual average wages. In Dix-Carneiro (2010), I apply that same specification to the Brazilian data used in my current paper and find average costs of mobility in the order of 50 times annual average wages. In contrast, when I use the methodology outlined in this paper, I find that the median of inter-sectoral mobility costs for Brazil are much lower and range from 1.4 to 2.7 times individual annual average wages, depending on what sector a worker is considering to switch into. As will be explained in greater detail later, the main reason why their methodology leads to extremely high costs of mobility is due to the fact that observed average sector-specific wages are used as measures of counter-factual wages across sectors.[4] In addition to our very different estimated costs of mobility, our estimated models also differ considerably in terms of their welfare implications, on who are the winners and losers from trade reform and on the properties of the trade-induced transitional labor market dynamics.[5]

[3]In recent work, Artuç (2009) extends ACM in order to analyze how trade reform differentially impacts older and younger workers. In his model workers self-select into sectors based on unobservable shocks in wages. However, these selection effects are not taken into account in the derivation of a key equation of the paper, on which his empirical strategy and results are based.

[4]It is widely understood in the labor economics literature that observed sector-specific average wages reflect selection on observable and unobservable worker characteristics and hence cannot be used as counter-factual wage measures.

[5]Beyond their baseline specification, ACM also introduce some heterogeneity to costs of mobility, and consider

The paper is organized as follows. In Section 2, I outline the model. Section 3 describes the data used in the estimation. Section 4 provides a detailed presentation of the estimation procedure. In Section 5, I present and discuss the estimation results. Section 6 presents the description and analysis of the counter-factual experiments. Finally, Section 7 presents a conclusion.

2 Empirical Framework

The framework in this paper is an equilibrium dynamic version of the Roy Model (Roy (1951), Heckman and Sedlacek (1985), Heckman and Honoré (1990)). This type of model has been estimated by Lee (2005) in order to study the equilibrium effects of a college subsidy and by Lee and Wolpin (2006) in order to study the growth of the service sector in the United States.

The economy is divided into four productive sectors and a non-productive Residual Sector, indexed as follows: (0) Residual Sector; (1) Agriculture and Mining (Primary); (2) Low-Tech Manufacturing; (3) High-Tech Manufacturing; and (4) Non-Tradeables.

For the time being, let us think of the Residual Sector as home production or an "out of the labor force" decision. In fact, home production is only one component of the Residual Sector, but I postpone a detailed definition of the Residual Sector to the next section, when I present and discuss the data.

The production side of the model has sector-representative firms. Factors of production are human capital from unskilled workers (of lower educational achievement), human capital from skilled workers (of higher educational achievement) and physical capital. Firms' decisions yield the demand for each type of human capital in each sector.

The human capital supply side has forward-looking heterogeneous workers supplying human capital to the sector-representative firms. Workers have comparative advantage: the amount of human capital they can supply differ across sectors. However, a worker can supply human capital to one sector at the most. Sector-specific human capital has a deterministic component that depends on observed individual characteristics such as education, age and sector-specific experience, but also depends on unobserved components that include a time invariant sector-specific match and sector-specific and time varying idiosyncratic shocks. At each period, workers draw new idiosyncratic shocks for the amount of human capital they can supply to each sector. Workers also repeatedly draw idiosyncratic sector-specific preference shocks before deciding to work in the sector that maximizes the expected present value of utility. If the worker decides to work in a different sector than that of the last period, a switching cost must be incurred. Finally, new generations come to the labor market and older generations retire each year. The decisions of individual workers aggregate to the supply of human capital for each sector. Human capital prices are determined in equilibrium - they equate aggregate demand to aggregate supply of each type of human capital in each sector.

"Young/College", "Young/No College", "Old/College" and "Old/No College" categories. They still obtain very high costs of mobility - there are still no controls for sector-specific experience and no correction for selection on unobservables.

2.1 Production

Production is undertaken by sector level representative firms with Cobb-Douglas production functions. **Value added**[6] in sector s is given by:

$$Y_t^s = p_t^s A_t^s \left(H_t^{0,s}\right)^{\alpha_t^{0,s}} \left(H_t^{1,s}\right)^{\alpha_t^{1,s}} \left(K_t^s\right)^{1-\alpha_t^{0,s}-\alpha_t^{1,s}} \tag{1}$$

Where p_t^s is the price of output of sector s at time t; A_t^s is the productivity of sector s at time t; $H_t^{0,s}$ is the aggregate human capital employed in sector s at time t coming from unskilled workers; $H_t^{1,s}$ is the aggregate human capital employed in sector s at time t coming from skilled workers; and K_t^s is the aggregate physical capital employed in sector s at time t.

Firms act competitively, and hence demand for the two types of human capital and physical capital are given by:

$$\begin{aligned} r_t^{0,s} &= \alpha_t^{0,s} \frac{Y_t^s}{H_{st}^0} \\ r_t^{1,s} &= \alpha_t^{1,s} \frac{Y_t^s}{H_{st}^1} \\ r_t^{K,s} &= \left(1 - \alpha_t^{0,s} - \alpha_t^{1,s}\right) \frac{Y_t^s}{K_t^s} \end{aligned} \tag{2}$$

Where $r_t^{0,s}$ is the price of one unit of human capital in sector s at time t coming from unskilled workers; $r_t^{1,s}$ is the price of one unit of human capital in sector s at time t coming from skilled workers; and $r_t^{K,s}$ is the rental price of one unit of physical capital in sector s. This rental price can differ across sectors, depending on what assumptions are made regarding the mobility of physical capital.

In (1), unskilled and skilled human capital are complementary in order to allow trade liberalization to affect the skill premium, i.e., the ratio $\frac{r_t^{1,s}}{r_t^{0,s}}$. Whether a worker is skilled or unskilled only depends on her educational attainment and is assumed to be exogenous.

2.2 Workers

An individual worker decides in what sector to work at each point in time in order to maximize the expected present value of her utility. Wages that are received must be totally consumed in that same year. There is no saving nor borrowing. If the worker chooses the Residual Sector, she receives no wages and hence cannot consume any produced goods. For the time being, it can be thought of as the worker enjoying leisure and receiving utility w^0 from it. The only way of enjoying utility from leisure in the model is by choosing the Residual Sector. If the worker decides to work in a sector different from the one chosen in the previous period, she needs to incur a utility cost of mobility. Workers enter

[6] The emphasis on value added is based on available data from the Brazilian National Accounts.

the model at age 25 and retire at age 60.[7] [8] A worker's life cycle problem when she is of age a at time t is formally given by the following Bellman equations:

$$V_{at}\left(\Omega_{iat}\right) = \max_{s\in\{0,1,\dots,4\}} \left\{V_{at}^{s}\left(\Omega_{iat}\right)\right\} \tag{3}$$

$$V_{at}^{s}\left(\Omega_{iat}\right) = \begin{cases} w^{s}\left(\Omega_{iat}\right) + \tau^{s} + \eta_{it}^{s} - Cost^{(s_{i,t-1})s}\left(\Omega_{iat}\right) + \\ \rho E V_{a+1,t+1}\left(\Omega_{ia+1,t+1} | \Omega_{iat}, s_t = s\right) \text{ if } a < 60 \\ \\ w^{s}\left(\Omega_{iat}\right) + \tau^{s} + \eta_{it}^{s} - Cost^{(s_{i,t-1})s}\left(\Omega_{iat}\right) \text{ if } a = 60 \end{cases} \tag{4}$$
$$s = 0, 1, \dots, 4$$

Ω_{iat} is a collection of state variables for individual i with age a at time t, with all the information that worker needs in order to make her decision at time t. $w^{s}\left(\Omega_{iat}\right)$ is the real wage worker with state Ω_{iat} can get at sector s (if $s = 1, \dots, 4$) or the utility she can get at the Residual Sector (if $s = 0$); τ^{s} is a non-pecuniary preference parameter for sector s (common across individuals and time-invariant); η_{it}^{s} is a mean-zero idiosyncratic preference shock for sector s; $Cost^{(s_{i,t-1})s}\left(\Omega_{iat}\right)$ is the cost a worker with state Ω_{iat} faces in switching from sector $s_{i,t-1}$ (the sector chosen in period $t-1$) to sector s; ρ is the discount factor.

The collection of state variables Ω_{iat} is given by:

$$\Omega_{iat} = \begin{cases} \left\{Female_i, Educ_i, a, s_{i,t-9}, \dots, s_{i,t-1}, \mathbf{r}_{t}^{0}, \dots, \mathbf{r}_{t+60-a}^{0}, \boldsymbol{\theta}_i, \boldsymbol{\varepsilon}_{it}, \boldsymbol{\eta}_{it}\right\} \text{ if } skill(i) = 0 \\ \left\{Female_i, Educ_i, a, s_{i,t-9}, \dots, s_{i,t-1}, \mathbf{r}_{t}^{1}, \dots, \mathbf{r}_{t+60-a}^{1}, \boldsymbol{\theta}_i, \boldsymbol{\varepsilon}_{it}, \boldsymbol{\eta}_{it}\right\} \text{ if } skill(i) = 1 \end{cases} \tag{5}$$

Unskilled ($skill(i) = 0$) and Skilled ($skill(i) = 1$) workers face different state spaces because they face different human capital prices. The state space includes demographic information such as gender ($Female_i$), education level ($Educ_i$) and age (a); in what sector individual i worked up to a window of nine years ($s_{i,t-9}$, ..., $s_{i,t-1}$); current and future human capital prices until retirement ($\mathbf{r}_{t}^{0}, \dots, \mathbf{r}_{t+60-a}^{0}$ for unskilled workers and $\mathbf{r}_{t}^{1}, \dots, \mathbf{r}_{t+60-a}^{1}$ for skilled workers); the type of a worker ($\boldsymbol{\theta}_i$), which is a vector of sector specific abilities; a vector of idiosyncratic shocks ($\boldsymbol{\varepsilon}_{it}$), which affect sector-specific human capital (and the utility value of the Residual Sector); and a vector of sector-specific preference shocks ($\boldsymbol{\eta}_{it}$). Current and future human capital prices enter the state of a worker because I assume workers have perfect foresight. More details on this feature will be given when I discuss how expectations are formed.

[7] RAIS, the dataset used in this paper and introduced in the next section, only includes information on individuals who have worked at least once in the formal sector. Information on educational decisions is not available. For this reason, the model has workers starting at age 25, since at that age educational decisions should be complete for the vast majority of the population.

[8] New generations enter the model with age 25 and initial conditions observed in the data, including experience accumulated until then and sector of choice at age 24. The new generations do not necessarily enter the model with zero experience.

I now model each component that enters the Bellman equation (4). Variables will be indexed as follows: i: individual; a: age; s: sector; t: time (year); and $skill(i)$: skill level of individual i. Skill level can take the values 0 or 1 (unskilled or skilled).

The level of education ($Educ_i$) is divided into four categories as follows: (1) From Illiterate to Primary School Graduate; (2) From Some Middle School to Some High School; (3) High School Graduate; (4) At Least Some College.

Worker i is labeled skilled ($skill(i) = 1$) if she has education level 3 or 4 (high school graduate or higher) and unskilled ($skill(i) = 0$) otherwise (less than high school).

2.2.1 Wages

Wages are modeled in the same way as in Heckman and Sedlacek (1985), Lee (2005) and Lee and Wolpin (2006).

The wage $w^s(\Omega_{iat})$ in sector s offered to worker i of age a at time t and with state variables Ω_{iat} is given by the price of human capital in sector s at time t times the amount of human capital the worker can supply to that sector.

$$w^s(\Omega_{iat}) = \begin{cases} r_t^{0,s} h^{0,s}(\Omega_{iat}) & \text{if } skill(i) = 0 \\ r_t^{1,s} h^{1,s}(\Omega_{iat}) & \text{if } skill(i) = 1 \end{cases} \tag{6}$$

The amount of human capital worker i of age a at time t can supply to sector s depends on characteristics such as gender and education dummies, age and a vector of sector-specific experiences accumulated in each of the four productive sectors up to time $t-1$ ($Exper_{ikt}$ for $k = 1, ..., 4$).[9] It also depends on individual time-invariant and sector-specific unobservable components given by vector $\boldsymbol{\theta}_i$, and on idiosyncratic and time-varying components given by vector $\boldsymbol{\varepsilon}_{it}$, which are also unobserved by the econometrician. However, both $\boldsymbol{\theta}_i$ and $\boldsymbol{\varepsilon}_{it}$ are observed by the worker and are included in her state variables. The human capital production functions for each sector $s = 1, ..., 4$ are given by:

$$\begin{aligned} h^{0,s}(\Omega_{iat}) &= \exp\begin{pmatrix} \beta_1^s Female_i + \beta_2^s I(Educ_i = 2) + \beta_4^s (a-25) + \\ \beta_5^s (a-25)^2 + \sum_{k=1}^{4} \beta_{5+k}^s Exper_{ikt} + \theta_i^s + \varepsilon_{it}^s \end{pmatrix} \\ h^{1,s}(\Omega_{iat}) &= \exp\begin{pmatrix} \beta_1^s Female_i + \beta_3^s I(Educ_i = 4) + \beta_4^s (a-25) + \\ \beta_5^s (a-25)^2 + \sum_{k=1}^{4} \beta_{5+k}^s Exper_{ikt} + \theta_i^s + \varepsilon_{it}^s \end{pmatrix} \end{aligned} \tag{7}$$

The parameter vector $\boldsymbol{\beta}^s$ is the same for both types of human capital. I allow for workers within a specific level of skill but with a higher education level to be more productive, everything else equal. For

[9] Experience accumulated in sector k is given by the number of years a worker spent working in that sector over a 9-year window: $Exper_{ikt} = \sum_{l=1}^{9} I(s_{i,t-l} = k)$. As I discuss in Section 3, the reason why experience is computed over a 9-year window is due to the fact that data from 1986 to 1994 is used in order to compute the sector-specific experience in 1995, the first year used in the estimation sample. In order to have a definition of experience consistent for all years and generations, experience is only computed over a 9-year window.

example, everything else equal, within skill level 0, workers with education level 2 are more productive than workers with education level 1. The only difference between the two equations in (7) is in the education coefficient: β_2^s for the unskilled workers and β_3^s for the skilled workers.

It is important to call attention to the fact that the human capital production functions in (7) allow for skills acquired in sector i to be transferable to sector j. The degree of transferability is given by the parameters β_6^s to β_9^s and will be estimated.

Finally, note that the human capital production functions do not have intercepts. We cannot separately identify the intercepts in the human capital production functions and the level of the human capital prices. Consequently, I normalize the human capital intercepts to zero.

2.2.2 Value of the Residual Sector

The value of the Residual Sector $w^0(\Omega_{iat})$ for worker i of age a at time t depends on her observable characteristics (gender and education dummies, age), on that worker's unobservable time-invariant type θ_i^0, and on an idiosyncratic component ε_{it}^0, which is also unobserved by the econometrician. Everything is observed by the worker at the time the decision must be made.

$$w^0(\Omega_{iat}) = \exp\left(\begin{array}{c} \gamma_0 + \gamma_1 Female_i + \sum_{l=2}^{4} \gamma_l I(Educ_i = l) + \\ \gamma_5 (a-25) + \gamma_6 (a-25)^2 + \theta_i^0 \end{array}\right) + \varepsilon_{it}^0 \tag{8}$$

The value of the Residual Sector is not observed in the data, but can be estimated using information on wages in the different sectors, on the fraction of workers who choose the Residual Sector and on transition rates in and out of that sector. More details on identification are provided in Section 4.2.

The vector of idiosyncratic shocks ($\boldsymbol{\varepsilon}_{it}$) for the productive and Residual Sectors are independent across i, s and t and drawn from a normal distribution. The vector of idiosyncratic preferences ($\boldsymbol{\eta}_{it}$) are also independent across i, s and t but are drawn from a Gumbel distribution with mean zero.[10] Finally, the vector of individual time invariant and sector-specific abilities $\boldsymbol{\theta}_i$ is assumed to have finite support with 3 points ($\boldsymbol{\theta}_1$, $\boldsymbol{\theta}_2$ and $\boldsymbol{\theta}_3$). The probability of each of the support points (p_1, p_2 and p_3) must be estimated. Therefore, there are three types of workers in the economy, each type with fraction p_h of the population.

$$\varepsilon_{it}^s \overset{iid}{\sim} N(0, \sigma_s) \tag{9}$$

$$\eta_{it}^s \overset{iid}{\sim} Gumbel(-0.5772\nu, \nu) \tag{10}$$

$$\boldsymbol{\theta}_i \sim \{(\boldsymbol{\theta}_1, p_1), (\boldsymbol{\theta}_2, p_2), (\boldsymbol{\theta}_3, p_3)\} \tag{11}$$

It is convenient to note that the model has three sources of mobility across sectors. First, workers

[10] The reason why the components of $\boldsymbol{\eta}_{it}$ are assumed to follow a Gumbel distribution, all with the same scale parameter ν, is due to the simple analytic expressions one gets when integrating them out. This is going to be helpful when I compute the expected value of the value functions in (4). See McFadden (1981) and Rust (1994) for references on the use of the Gumbel distribution on discrete choice econometric models.

face sector-specific idiosyncratic shocks in their sector-specific human capital production functions ($\boldsymbol{\varepsilon}_{it}$) and that tends to generate two-way flows: from sector i to sector j and from sector j to sector i. Second, workers face sector-specific idiosyncratic preference shocks for sectors ($\boldsymbol{\eta}_{it}$) which will also tend to generate two-way flows. Third, variation in the human capital prices will make sectors more or less attractive to all workers, leading to net flows between sectors. These three features of the model will generate gross flows in excess of net flows, which is a stylized fact emphasized by ACM and which is also present in the data used in the current paper (see next Section).

2.2.3 Costs of switching sectors (mobility costs)

The costs of switching sectors, or mobility costs, for worker i of age a are given by equation (12), and depend on gender and education dummies, age, and the sectors of origin s and destination $s^{'}$.

$$Cost^{ss'}\left(\Omega_{iat}\right) = \exp\left(\begin{array}{c} \varphi^{ss'} + \kappa_1 Female_i + \sum_{l=2}^{4} \kappa_l I\left(Educ_i = l\right) + \\ \kappa_5(a-25) + \kappa_6(a-25)^2 \end{array}\right) \quad s \neq s',\ s' \neq 0 \qquad (12)$$

$$Cost^{ss'} = 0 \quad s = s',\ s' = 0$$

Since in the model costs of switching sectors are utility costs, the interpretation of these costs is that workers have a preference for the status quo and/or face psychological costs when switching sectors. These costs may also capture other barriers to mobility that are not included in the model such as geographic mobility costs, search and matching frictions, and/or firms' firing and hiring costs (see Kambourov (2009)).[11]

It is important to notice that the model features three distinct sources of barriers to mobility. One works directly through direct wage effects of moving: sector-specific experience may not be fully transferable across sectors. The second also works through direct wage effects and is due to the time invariant sector-specific components in $\boldsymbol{\theta}_i$ which drive permanent unobserved comparative advantage across sectors. The third works through the inability of arbitraging wage differentials, taking sector-specific experience and unobserved comparative advantage into account, i.e., mobility costs.

Note that sector-specific experience alone is not enough to simultaneously fit persistence and wage patterns found in the data. In order to match persistence of choices in the absence of costs of mobility, the model has to assign coefficients on sector-specific experience that are too large compared to how wages vary with experience in the data. The model will also need to assign very low transferability of sector-specific experience across sectors, which is also frequently inconsistent with the wage patterns found in the data.

Also, note that the parameters $\boldsymbol{\theta}_1$, $\boldsymbol{\theta}_2$ and $\boldsymbol{\theta}_3$, by themselves, are not enough to explain the persistence of sectoral choices observed in the data. In order for these parameters to be able to explain persistence in the absence of costs of mobility, we would need extremely strong comparative advantage

[11] A micro-foundation study of these costs is an important avenue for future research. In this paper costs of mobility should be interpreted purely as a measure of workers' inability to arbitrage wage differentials. It is revealed using information on wage differentials, transition rates and the structure of the model. More details on identification will be provided in Section 4.2.

across sectors: individuals very good in one sector and with rather poor performance in others. There are two reasons why this is inconsistent with the data. First, this would lead to very short spells out of an individual's comparative advantage sector, that is, high persistence in one's comparative advantage sector and very low persistence in one's comparative disadvantage sector. This is inconsistent with the patterns observed in the data: once a worker switches sectors, she usually shows persistence in the new sector as well. Second, this would cause strong sorting of workers based on unobserved comparative advantage: workers would only choose those sectors where they are very good at. This in turn will tend to cause small cross-sectional variance within sectors (after controlling for observable characteristics), which is also not consistent with the data.

2.2.4 Expectations

In order to decide in what sector to work at period t, workers must solve for $EV_{a+1,t+1}(\Omega_{ia+1,t+1}|\Omega_{iat}, s_t = s)$ and hence must make expectations about the future. I assume that expectations are taken only with respect to future idiosyncratic shocks $\boldsymbol{\varepsilon}_{it}$ and $\boldsymbol{\eta}_{it}$, which are unknown at period t. Further, workers are assumed to have perfect foresight regarding the future path of equilibrium human capital prices. Consequently, current and future equilibrium human capital prices enter their state variables in (5).[12] At this point, it is important to note that the value function is indexed not only by the age of the individual (a) but also by the year (t) when the decision is being made. The dependence on a is due to the fact that individuals are finitely lived, and the dependence on t is due to the fact that an individual of age a^* at year t_0 faces a different sequence of future equilibrium human capital prices than an individual with the same age a^* at year $t_1 \neq t_0$.

2.2.5 Aggregate Supply of Human Capital

Workers solve the Bellman Equations (4) in order to decide what sector to choose at each age a and period t. Let $d^s(\Omega_{iat})$ be an indicator variable for whether a worker with state variables Ω_{iat} chooses sector s.

$$d^s(\Omega_{iat}) = I\left\{V_{at}^s(\Omega_{iat}) \geq V_{at}^{s'}(\Omega_{iat}) \ \forall s'\right\}. \tag{13}$$

[12] It is in principle possible to relax the perfect foresight assumption by allowing workers to use past information on how equilibrium human capital prices evolved over time in order to forecast these variables in the future in the spirit of Krusell and Smith (1998) and Lee and Wolpin (2006). In my case, the disadvantage with following this route is that the sample period is relatively short (11 years of data), which will lead to very few degrees of freedom in estimating VAR's or AR(1)'s for the realized equilibrium human capital prices during the search for a fixed point between expectations and realized prices. Further, Figure (2) ahead suggests that there is very little volatility in wage differentials during the sample period. However, there are clear trends, whereby real wages in Agriculture/Mining increase relative to wages in other sectors and real wages in High-Tech Manufacturing decrease relative to wages in the other sectors. This suggests that the importance of volatility in wage differentials is of second order compared to these trends in wages. It is worthy to note that estimates of the model under perfect foresight or static expectations (where equilibrium human capital prices formed at t are thought to remain constant in the future with no uncertainty) yield very similar parameter estimates and loss functions, suggesting that the exact assumptions regarding the forecast of future wages matter little for the results. This is most likely due to the short sample period we have at hand.

The aggregate supply of human capital to sector s at time t is given by:

$$\left(H_t^{0,s}\left(\left\{\mathbf{r}_{t+k}^0\right\}_{k=0}^{35}, \widetilde{\Omega}_t\right)\right)_{Supply} = \sum_{a=25}^{60}\sum_{i=1}^{N_{at}} I\left(skill(i)=0\right) h^{0,s}\left(\Omega_{iat}\right) d^s\left(\Omega_{iat}\right) \;\; s=1,...,4 \tag{14}$$

$$\left(H_t^{1,s}\left(\left\{\mathbf{r}_{t+k}^1\right\}_{k=0}^{35}, \widetilde{\Omega}_t\right)\right)_{Supply} = \sum_{a=25}^{60}\sum_{i=1}^{N_{at}} I\left(skill(i)=1\right) h^{1,s}\left(\Omega_{iat}\right) d^s\left(\Omega_{iat}\right) \;\; s=1,...,4$$

Where N_{at} is the size of cohort born at $t-a$, and $\widetilde{\Omega}_t$ is the collection of all active (25 to 60 years old) workers' state variables at time t, excluding human capital prices. Note that the supply of human capital at time t depends not only on current human capital prices $\mathbf{r}_t^0$ and $\mathbf{r}_t^1$ but also on future human capital prices up to 35 years ahead (workers enter the market at age 25 and exit at age 60).

2.3 Labor Market Equilibrium

Controlling for the real value added in each sector $\left\{Y_t^k\right\}_{k=1}^4$ (**which is observed data from the Brazilian National Accounts and will be fixed throughout the estimation**), the equilibrium real human capital prices are determined as the solution to:

$$\left(H_t^{0,s}\left(\left\{\left(\mathbf{r}_{t+k}^0\right)^*\right\}_{k=0}^{35}, \widetilde{\Omega}_t\right)\right)_{Supply} = \alpha_t^{0,s}\frac{Y_t^s}{\left(r_t^{0,s}\right)^*} \quad s=1,...,4 \tag{15}$$

$$\left(H_t^{1,s}\left(\left\{\left(\mathbf{r}_{t+k}^1\right)^*\right\}_{k=0}^{35}, \widetilde{\Omega}_t\right)\right)_{Supply} = \alpha_t^{1,s}\frac{Y_t^s}{\left(r_t^{1,s}\right)^*} \quad s=1,...,4$$

These equations make explicit that workers have perfect foresight: aggregate supply of human capital depend on the current equilibrium human capital prices as well as on the future equilibrium human capital prices. In the estimation procedure, I am only able to recover equilibrium human capital prices from $t=1995$ to $t=2005$. Therefore, workers are assumed to have perfect foresight between 1995 and 2005. In 2005, I assume that workers have static expectations in the sense that they forecast all future equilibrium human capital prices to remain constant at the current 2005 equilibrium levels. This assumption allows me to not make assumptions regarding how cohort sizes, technology, prices and physical capital evolve over time. However, when the model is simulated, I will indeed need to impose assumptions regarding the evolution of these variables and a perfect foresight equilibrium will be computed over the entire horizon of the simulation.

Throughout the estimation, I impose that the model generates the real value added series $\left\{Y_t^k\right\}_{k=1}^4$ and the unskilled and skilled workers' wage bill series $\left\{\alpha_t^{0,s}Y_t^k\right\}_{k=1}^4$ and $\left\{\alpha_t^{1,s}Y_t^k\right\}_{k=1}^4$ (which are all observed data) with equality.

At this point, it is important to note that given the Cobb-Douglas production functions and the assumptions made on how workers form expectations, we do not need to make any assumptions regarding the mobility of physical capital in order to estimate the parameters of the model.

Given parameter values for the human capital production functions, value of the Residual Sector and for the costs of switching functions, we can compute human capital demand (right hand side of equation (15)) and human capital supply (left hand side of equation (15)) by simulating the model, and solving for the equilibrium human capital prices without the need for physical capital rental prices.

Two other observations about estimation are now timely. First, note that, since I control for $\{Y_t^k\}_{k=1}^4$, and given the assumptions on expectations, I do not need to recover neither the prices p_t^s nor the productivity terms A_t^s. Second, not only do we not have to make assumptions regarding the mobility of physical capital, but also I do not need to model how physical capital is being accumulated. Given the Cobb-Douglas assumption on the production functions and the assumptions on expectations, all the information about the human capital demand side that is relevant for estimation is contained in $\{Y_t^k\}_{k=1}^4$.

Additional structure on the model will have to be imposed when I implement the counter-factual experiments - including assumptions regarding the mobility of physical capital - but I postpone these details to Section 6.

3 Data

3.1 A Panel of Workers (1995 to 2005)

The data used in this paper comes from the *Relação Anual de Informações Sociais (RAIS)*, a matched employer-employee data set assembled by the Brazilian Ministry of Labor every year since 1986. Each year the universe of Brazilian firms are required by law to file information about both the firm as well as about each of its employees to the Ministry of Labor. These data are collected in order to fulfill two main objectives: (1) for the government to generate statistics about the labor market; and (2) to serve as the main source of information on whether a certain employee is eligible to receive the *abono salarial*, which consists of one extra minimum yearly wage payment provided by the government.

The data consist of job entries identified by both a worker ID number (*PIS*) and a firm-plant registration number (*CNPJ*). These identifiers are unique and do not change over time, which allow us to track workers over time and across firms and plants. Each job entry comes with information regarding the firm-plant pair where the worker was employed. There is information on geographic location, 5-digit level industry (CNAE classification)[13], capital ownership and other variables. At the worker level, we have information on gender, age, level of education, monthly wage, number of hours in the contract, tenure at the firm, occupation, month of accession into the job (if accession occurred during the current year), month of separation (if any) and other variables.

In order to track workers over time and across sectors, and in order to construct sector-specific experience variables, I constructed a panel of workers by first listing all the identifiers that appear in the data between 1995 and 2005. I then selected a random sample of 1% of distinct worker ID numbers at random (approximately 600,000 workers). These are the individuals that are followed in the panel. Since RAIS has data available since 1986, I used the observations from 1986 to 1994 in order to construct the experience variables that will enter the initial conditions used in the simulation as well as in the estimation of the auxiliary models used for the estimation of the structural parameters.

[13] CNAE stands for Classificação Nacional de Atividades Econômicas and is roughly equivalent to the ISIC Rev.3 classification.

Since the model assumes that a worker can supply her skills to a single sector (job) each year, I select a single job entry for each worker in each year. If a worker has multiple jobs in a given year, the job with highest hourly wage is selected. Hourly wages are computed by dividing the last observed monthly wage in the year by the number of hours in the contract. In this paper wages are actually hourly wages, since in the context of the model there is no full-or part-time decision and all workers are assumed to work full-time.

Since this is a census of the Brazilian formal labor market only, we lose track of workers who do not hold a job in the formal sector in a given year. In a given year, we are unable to observe a worker in RAIS if she is unemployed, out of the labor force, informally employed or self-employed. Because workers' ID numbers are unique, we can keep tracking them once they return to a job in the formal sector. Consequently, movements in and out of the data set are quite frequent and for a large portion of workers. In order to accommodate this feature of the data, I included a Residual Sector into the model, which represents the complement of formal sector employment. Transitions to the Residual Sector are rational and voluntary, as outlined in the model.

There are four advantages in using such data. First, we have the ability to construct a panel of workers and track them over time and across sectors. Second, by using past rounds of the data, we can recover initial conditions (sector-specific experience) for all workers, which allows us to control for them in the estimation. Third, we have a very large sample size, which will lead to high precision in the estimates. Finally, due to the sample size, conditioning on a sector, there are always workers who have accumulated experience in every other sector, generating variation that allows us to estimate the degree of transferability of sector-specific experience.

3.2 Aggregate Data

Using the Brazilian National Accounts, it was possible to construct value added series for each of the aggregate sectors used in this paper. Although data on the rental price of physical capital is not used in the estimation procedure, I will need these when I simulate the model. Aggregate capital stock series were constructed in Morandi (2004) and are available for download at *www.ipeadata.br*. Unfortunately, there are no available series that would allow for the construction of capital stock series at the industry level. Economy-wide returns to capital were calculated as: $r_t^K = \frac{Capital\ Share \times Value\ Added_t}{Capital\ Stock_t}$.

Although the Brazilian National Accounts provide information on the economy-wide wage bill, the labor share calculated as $\frac{Wage\ Bill}{Value\ Added}$ fluctuates at around 0.4. Gollin (2002) suggests that the labor income that comes from National Accounts in developing and middle income countries are most likely to be badly downward biased since they fail to correctly take into account the incomes of self-employed or informal workers. By correcting for self-employment he finds that among the countries he studies, he is able to reduce the dispersion of wage bill shares from 0.05-0.8 to 0.65-0.8. I follow this advice and impose that the economy-wide wage bill share in Brazil is equal to 0.65 and constant over time. Hence, the physical capital share used in the calculation of returns to capital is calibrated at 0.35.

In order to get sector-specific wage bill shares, the relative sectoral wage bill shares are fixed as in the data and are inflated so that the economy-wide wage bill equals 0.65 times Value Added.

All quantities are expressed in terms of 2005 R$ by deflating the nominal quantities using the *Índice*

Nacional de Preços ao Consumidor (INPC).

3.3 Some Features of the Data

The four (productive) aggregate sectors used in this paper are: 1) Agriculture and Mining; 2) Low-Tech Manufacturing; 3) High-Tech Manufacturing and 4) Non-Tradeables. In principle, the model allows for a much finer partition of the economy, but increasing the number of sectors will quickly make the estimation of the model computationally infeasible.

This paper focuses on inter-sectoral reallocation following a trade shock, and it is natural to separate the manufacturing sector into Low-Tech - a sector in which Brazil has a comparative advantage due to its abundance of low-skilled workers - and High-Tech - a sector in which Brazil has a comparative disadvantage and where import tariffs are higher during the sample period (1995 to 2005), see Kume, Piani and Souza (2000). Agriculture and Mining is also an important export-oriented sector in Brazil.

The division of Manufacturing into Low and High-Tech was based on the OECD Science Technology and Industry Scoreboard 2001 report "Towards a Knowledge Based Economy." In this report, the OECD classifies industries according to their technology intensity. I classified as Non-Tradeables all the sectors with 2-digit *CNAE* classification greater than or equal to 40, which include the following broadly-defined sectors: Retail and Wholesale Trade, Utilities, Transportation, Government and Services. Table 1 details how the 2-digit *CNAE* industries were separated into the four aggregate sectors this paper works with.

Table 1: Correspondence Between 2-digit CNAE Industries and The Four Aggregate Sectors

Agriculture/Mining	Agriculture; Forestry; Fishing; Mineral Coal Extraction; Oil Extraction; Metallic; Minerals Extraction; Non-Metallic Minerals Extraction
Low-Tech Manufacturing	Food and Beverage; Tobacco Products; Textiles; Apparel; Leather Products and Footwear; Wood Products; Paper; Cellulose; Paper Products; Editing and Printing; Rubber and Plastic Products; Non-Metallic Mineral Products; Basic Metals; Fabricated Metal Products (except machinery and equipment); Furniture; Recycling
High-Tech Manufacturing	Alcohol Production; Nuclear Fuels; Oil Refining; Coke; Chemical Products; Machinery and Equipment; Office, Accounting and Computing Machinery; Electrical Machinery and Apparatus; Radio, Television and Communications Equipment; Medical, Precision and Optical Instruments; Motor Vehicles, Trailers and Semi-Trailers; Other Transportation Equipment
Non-Tradeables	All other industries, including Utilities, Trade, Transportation, Construction, Government, Services

Figure 1 shows the employment shares across these four sectors. The shares of Agriculture and Mining vary between 5% and 6%, High Tech Manufacturing between 4% and 6%, Low-Tech Manufacturing between 14% and 16% and Non-Tradeables between 74% and 76%. The share of workers in the Residual Sector averages 40% during that period (Table 12). A closer look at these shares reveals that their importance has changed over time. The right panel of Figure 1 plots the changes in these shares with respect to 1995. We can see that the Agriculture/Mining and Non-Tradeables sectors have gained importance between 1995 and 2005, whereas the opposite happened to both manufacturing sectors. Hence, Figure 1 shows that there appears to be some reallocation taking place between these four sectors during the sample period, possibly due to the slow response to both the trade reform implemented in 1990 and Mercosur.

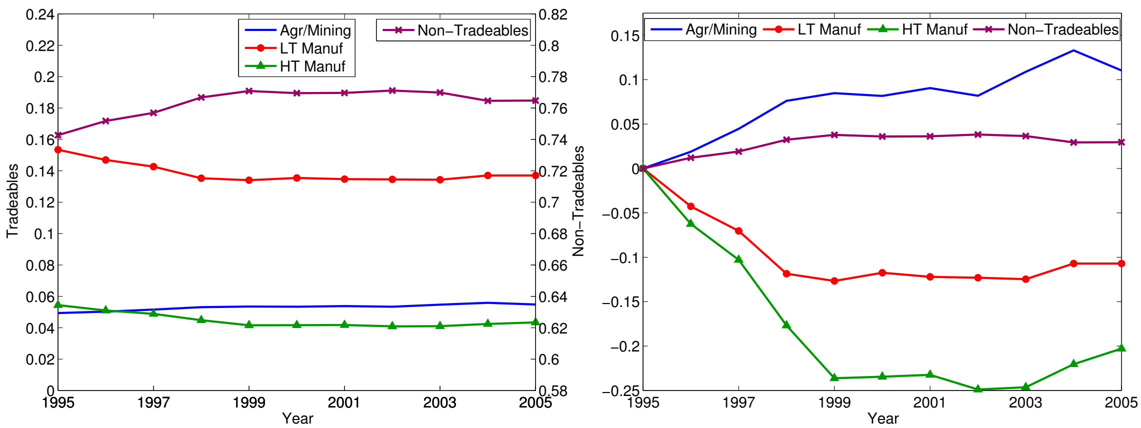


Figure 1: Left Panel: Evolution of employment shares 1995 to 2005 (Non-Tradeables: Right Axis). Right Panel: Relative changes in employment shares with respect to 1995.

Table 11 presents average hourly wages of each of the four sectors in terms of 2005 R$.[14]

Table 13.A shows the matrix of yearly flows from 1995 to 2005, averaged out. The matrix shows that, although net flows between sectors do not appear to be that large in Figure 1, gross flows are quite important, with a mass of workers entering and leaving the same sectors. We can also see the importance of the Residual Sector, with important flows into this sector coming from all other sectors. Transitions to the Residual Sector are most frequent if a worker comes from Agriculture and Mining, with 17% of workers in that sector going to the Residual Sector every year. The productive sector that appears to receive larger inflows of workers is the Non-Tradeables sector, but this is also the largest sector. What is also important to observe from this matrix is the high persistence in the sector of origin. The diagonal of the matrix has numbers between 76% and 86%, suggesting both the importance of sector-specific experience as well as costs of switching sectors, key ingredients in the model outlined in the previous section.

Figure 2 plots the evolution of wage differentials relative to the mean (after controlling for observables) across sectors from 1995 to 2005. First, note that there is a considerable dispersion in wage differentials, with High-Tech paying the most and Agriculture/Mining paying the least. Second, this dispersion has decreased between 1995 and 2005, mainly due to an upward trend in relative wages in Agriculture/Mining and a downward trend in relative wages in High-Tech Manufacturing. Third, there is very little volatility of wage differentials around these trends.

4 Estimation

In this Section, I outline the Indirect Inference method that was used in the estimation. I also discuss what features of the data will be used in the Indirect Inference estimation procedure, the so-called "auxiliary models". Finally, I discuss how the model is econometrically identified.

[14]The average exchange rate between the Brazilian Real (R$) and the US Dollar (US$) was 2.43 R$/US$ in 2005.

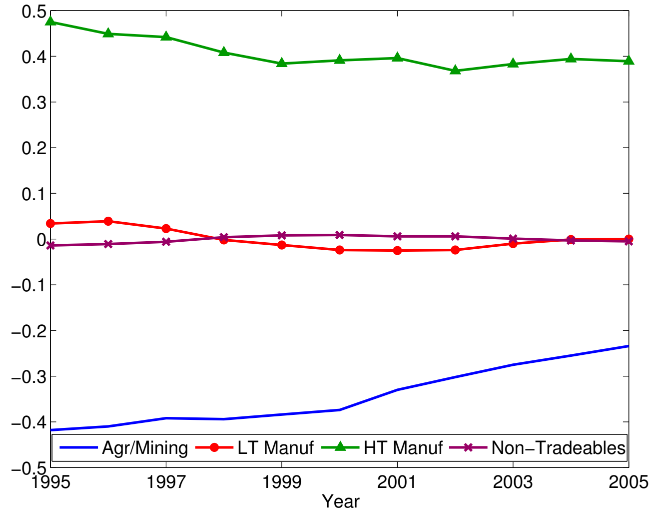


Figure 2: Evolution of wage differentials, 1995 to 2005

4.1 Indirect Inference and Initial Conditions

The estimation method that is employed in this paper is Indirect Inference (Gouriéroux and Monfort (1996)). In this method, we first choose a set of auxiliary models that provide a detailed statistical description of the data. The objective of these auxiliary models is to attempt to capture as much information as possible concerning moments and statistical relationships the researcher believes are important to be replicated or matched by the structural model. It is also important that the choice of auxiliary models allows for the structural parameters to be econometrically identified. More details on identification and on the selection of the auxiliary models are provided in Section 4.2.

Individuals have comparative advantage across sectors partly determined by the unobservable and time invariant vector $\boldsymbol{\theta}_{h(i)}$, where $h(i)$ is the type of individual i. Since most individuals are observed for the first time in 1995 and in the middle of their careers, the joint distribution of sector-specific experience is endogenous. I therefore correct for the initial conditions problem by imposing individual type probabilities to depend on the vector of sector specific experience an individual i has accumulated until she is observed for the first time at period $t_0(i)$.[15] I assume there are three types in the economy, and that their probabilities conditional on their initial vector of sector-specific experiences are given by:

[15] Another way to see the initial conditions problem is that when observed in the middle of her career, a worker's sector specific experience gives information about what is her type. Her type has partly determined her previous choices. Consequently, the probability of a worker being of type h, conditional on observed experience, is not p_h, but rather, a function of her vector of sector-specific experiences

$$\Pr\left(h(i)=2|\boldsymbol{Exper}_{it_0(i)}\right) = \frac{\exp\left(\pi_2^0+\sum\limits_{k=1}^{4}\pi_2^k Exper_{ikt_0(i)}\right)}{1+\sum\limits_{h=2}^{3}\exp\left(\pi_h^0+\sum\limits_{k=1}^{4}\pi_h^k Exper_{ikt_0(i)}\right)} \tag{16}$$

$$\Pr\left(h(i)=3|\boldsymbol{Exper}_{it_0(i)}\right) = \frac{\exp\left(\pi_3^0+\sum\limits_{k=1}^{4}\pi_3^k Exper_{ikt_0(i)}\right)}{1+\sum\limits_{h=2}^{3}\exp\left(\pi_h^0+\sum\limits_{k=1}^{4}\pi_h^k Exper_{ikt_0(i)}\right)}$$

Where $h(i)$ is the type of worker i. The parameter vectors $\boldsymbol{\pi}_2$ and $\boldsymbol{\pi}_3$ in (16) are estimated jointly with all the remaining parameters of the model. The unconditional type probabilities p_1, p_2 and p_3 can then be recovered by integrating the functions above with respect to the distribution of initial experiences. This method of correction for the initial conditions has been suggested by Wooldridge (2005).

This closes the description of the parameters that need to be estimated. Let Θ denote the collection of all the parameters of the model. Θ includes: $\boldsymbol{\beta}_1$, ..., $\boldsymbol{\beta}_4$, which are 9-dimensional parameter vectors that enter the human capital production function in each sector; σ_0, ..., σ_4, standard deviation of the value of the Residual Sector and standard deviations of sector-specific idiosyncratic shocks; $\boldsymbol{\theta}_2$ and $\boldsymbol{\theta}_3$, which are type-specific permanent unobserved heterogeneity 5-dimensional vectors (type 1 is the reference type and hence has $\boldsymbol{\theta}_1 = 0$); $\boldsymbol{\gamma}$, a 7-dimensional parameter vector that enters the value of the Residual Sector; $\boldsymbol{\varphi}$, a matrix of parameters that depend on sector of origin and destination and that enter the cost of mobility function; $\boldsymbol{\kappa}$, a 6-dimensional parameter vector that enter the cost of mobility function; $\boldsymbol{\tau}$, a 3-dimensional vector with non-pecuniary preference parameters (The Residual Sector is excluded, given that its value is estimated and the Agriculture/Mining Sector is the excluded sector to which relative utility is measured); ν, the scale parameter for the preference shocks; $\boldsymbol{\pi}_2$ and $\boldsymbol{\pi}_3$, which are 5-dimensional vectors that enter the function that relates initial conditions to type probabilities. In total, there are 94 parameters to be estimated. The discount factor ρ will be imposed throughout the estimation at 0.95.

The estimation procedure is described in detail in Web Appendices A and B.

4.2 Auxiliary Models and Identification

In constructing the Indirect Inference estimator, the researcher must choose auxiliary models that describe statistical relationships the researcher thinks her model should be able to reproduce. These models should be relatively simple, quick to estimate and provide a sufficiently rich description of statistical relationships in the data in order to allow the model to be identified.

In this paper, the statistical relationships that I will consider important to be generated by the model are (1) how wages vary over time and how they are correlated with observable characteristics, such as gender, education, age and sector-specific experiences; (2) cross-sectional wage dispersion after controlling for time dummies and observable characteristics; (3) within-individual wage volatility after controlling for time dummies and age; (4) how sectoral choices vary over time and how they are correlated with observable characteristics; (5) how transition rates between sectors vary over time and how they correlate with observable characteristics. Among those individuals who are observed in the sample for the whole sample period (those who are 25 to 50 years old in 1995) I also consider: (6) how sectoral choice probabilities in 1998, 2000 and 2005 are correlated with initial conditions such as sector where the worker was observed in 1994 (i.e., the year before the estimation sample period starts), initial sector-specific experiences and other observables; and (7) how the fraction of time worked in each sector correlates with the same observable initial conditions as in (6). Statistical relationships (6) capture 4-year (1994 to 1998), 6-year (1994 to 2000) and 11-year (1994 to 2005) persistence rates with respect to the sectors individuals were employed in 1994.

The auxiliary models used in the computation of the indirect inference loss function Q are described in Table 2. Θ is the collection of all parameters that completely describe the economy.

Table 2: Auxiliary Models Employed in Estimation

Auxiliary Model	Coefficient: Fit to Actual Data	Coefficient: Fit to Simulated Data
(1) Log wage linear regressions for each sector $k = 1, ..., 4$	$\widehat{\beta}^k$	$\left(\widehat{\beta}^k\right)^S(\Theta)$
(2) Variance of the residuals from log wage linear regressions $k = 1, ..., 4$	$\widehat{\xi^2}^k$	$\left(\widehat{\xi^2}^k\right)^S(\Theta)$
(3) Within individual log wage variance $k = 1, ..., 4$	$\widehat{\sigma^2}^k$	$\left(\widehat{\sigma^2}^k\right)^S(\Theta)$
(4) Linear probability models for sectoral choices for each sector $k = 0, ..., 4$	$\widehat{\gamma}^k$	$\left(\widehat{\gamma}^k\right)^S(\Theta)$
(5) Linear probability models for transition rates for every pair of sectors $j, k = 0, ..., 4$	$\widehat{\varphi}^{jk}$	$\left(\widehat{\varphi}^{jk}\right)^S(\Theta)$
(6) Persistence regressions $k = 0, ..., 4$; $t = 1998, 2000, 2005$	$\widehat{\psi}^{t,k}$	$\left(\widehat{\psi}^{t,k}\right)^S(\Theta)$
(7) Frequency regressions $k = 0, ..., 4$	$\widehat{\chi}^k$	$\left(\widehat{\chi}^k\right)^S(\Theta)$

Auxiliary models (1), (2), (4) and (5) share the same regressors: year dummies, gender and education dummies, age, age squared and sector-specific experience in each of the four sectors. The auxiliary models in (3) regress changes in log wages in each sector on time dummies and age, but only the variance of the residuals is recorded. The auxiliary models in (6) regress sectoral choice dummies in 1998, 2000 and 2005 on initial conditions such as sectoral dummies in 1994 (indicators of what was the sector of activity of a worker just before the start of the sample), age, gender, education and sector-specific experiences accumulated up to 1995, the first year of the sample period. The auxiliary models in (7) regress the frequency workers spent in each sector on the same initial conditions as in (6). Only individuals observed during the whole sample period (those who were 25 to 50 years old in 1995) are included in the estimation of models (6) and (7).

Due to the complexity of the model and its lack of analytical solution, it is not possible to make a purely constructive argument for identification. However, it is possible to give some intuition on what type of variation in the data allows the parameters of the model to be identified.

First, consider the human capital production functions' parameters. Due to selection based on unobservable components of wages (the time invariant component $\boldsymbol{\theta}_i$ and shocks $\boldsymbol{\varepsilon}_{it}$), it is not possible to estimate the human capital production function parameters separately, without solving the value functions and equilibrium of the model. However, the solution of the model fully takes self-selection into account so that following standard arguments as in Heckman (1979), the wage equation parameters should be identified due to the existence of an exclusion restriction. The exclusion restriction here is the sector where a worker was active in the previous period: this variable matters for the current decision of the worker, but does not enter the human capital production functions, after we control for the sector-specific experience variables. Also, the auxiliary models for transition rates work here as selection equations. The dispersion of the idiosyncratic shocks $\boldsymbol{\varepsilon}$ is pinned down by sector-specific within-individual wage variance. That is, the volatility of the human capital shocks should map to the volatility of yearly log-wage changes after controlling for observable characteristics.

The linear probability models for the decision of where to work (including the Residual Sector) help in the identification of the wage parameters, but are also crucial in identifying the parameters of the value of the Residual Sector. Fixing the parameters of the wage equation, the "employment rates" of sectors $j = 0, ..., 4$, conditioned on characteristics, help identify the value of the Residual sector parameters. These models also play an important role in identifying the preference parameters $\boldsymbol{\tau}$, since wage differentials alone cannot fully explain the distribution of workers across sectors. Since the model can only identify differences in utilities, we need to impose restrictions on $\boldsymbol{\tau}$. As previously mentioned, I impose $\tau_0 = \tau_1 = 0$. We cannot separately identify τ_0 from the level of the value of the Residual Sector parameters and we impose the Agriculture/Mining sector as our baseline sector: the remaining τ's measure the attractiveness of each sector relative to Agriculture/Mining.

The linear probability models for transition rates help to pin down the parameters in the costs of mobility function, as well as the volatilities σ_0 and ν. Sketching the expressions implied by the model for transition rates between any pair of **formal sectors** suggests that we can recover ν from the coefficients on sector-specific experiences, since the parameters of the human capital production function are identified (including the volatility of the sector-specific idiosyncratic shocks). As one increases ν, transition rates between formal sectors will be less responsive to wage differentials and hence be less responsive to sector-specific experience. Since sector-specific experiences only appear in the human capital production functions, whose parameters are identified as argued above, we are able to identify ν. The parameter σ_0 can also be recovered from the coefficients on sector-specific experiences, but now looking at transition rates from and into the Residual Sector. Finally, transition rates depend on wage differentials and on the ratio between the volatility of shocks and costs of mobility. For a given wage differential between two sectors, the higher the volatility in idiosyncratic shocks for these sectors, the higher transition rates between them will tend to be. However, the higher the costs of mobility between these two sectors, the lower the transition rates between them will tend to be. Having argued that wage differentials and volatility of shocks are identified, we are able to recover the parameters in the costs of mobility parameters.

The linear probability models for transition rates also give precise information on the sector-specific and time invariant parameters $\boldsymbol{\tau}$. Since human capital production function parameters are identified (as argued above), the overall level of transition rates from Agriculture/Mining into the Residual Sector give information on the level of the value of the Residual Sector (remember that $\tau_0 = \tau_1 = 0$ and that costs of entry into the Residual Sector are also imposed to be 0). In turn, the overall level of transition rates from Low-Tech, High-Tech and Non-Tradeables into the Residual sector also give important information on τ_2, τ_3 and τ_4.

Finally, the persistence and frequency regressions, together with sector-specific cross-sectional wage variance help to identify the parameters $\boldsymbol{\theta}_2$ and $\boldsymbol{\theta}_3$ as well as the type probability parameters $\boldsymbol{\pi}_2$ and $\boldsymbol{\pi}_3$.

The Indirect Inference loss function $Q(\Theta)$ is computed as:

$$Q(\Theta) = L_1 + L_2 + L_3 + L_4 + L_5 + L_6 + L_7 \tag{17}$$

Where

$$L_1 = \sum_{k=1}^{4} \left(\widehat{\beta}^k - \left(\widehat{\beta}^k\right)^S(\Theta)\right)' \widehat{V\left(\widehat{\beta}^k\right)}^{-1} \left(\widehat{\beta}^k - \left(\widehat{\beta}^k\right)^S(\Theta)\right)$$

$$L_2 = \sum_{k=1}^{4} \left(\frac{\widehat{\xi^2}^k - \left(\widehat{\xi^2}^k\right)^S(\Theta)}{\widehat{se\left(\widehat{\xi^2}^k\right)}}\right)^2$$

$$L_3 = \sum_{k=1}^{4} \left(\frac{\widehat{\sigma^2}^k - \left(\widehat{\sigma^2}^k\right)^S(\Theta)}{\widehat{se\left(\widehat{\sigma^2}^k\right)}}\right)^2$$

$$L_4 = \sum_{k=0}^{4} \left(\widehat{\gamma}^k - \left(\widehat{\gamma}^k\right)^S(\Theta)\right)' \widehat{V\left(\widehat{\gamma}^k\right)}^{-1} \left(\widehat{\gamma}^k - \left(\widehat{\gamma}^k\right)^S(\Theta)\right)$$

$$L_5 = \sum_{j=0}^{4}\sum_{k=0}^{4} \left(\widehat{\varphi}^{jk} - \left(\widehat{\varphi}^{jk}\right)^S(\Theta)\right)' \widehat{V\left(\widehat{\varphi}^{jk}\right)}^{-1} \left(\widehat{\varphi}^{jk} - \left(\widehat{\varphi}^{jk}\right)^S(\Theta)\right)$$

$$L_6 = \sum_{t\in\{1998,2000,2005\}}\sum_{k=0}^{4} \left(\widehat{\psi}^{t,k} - \left(\widehat{\psi}^{t,k}\right)^S(\Theta)\right)' \widehat{V\left(\widehat{\psi}^{t,k}\right)}^{-1} \left(\widehat{\psi}^{t,k} - \left(\widehat{\psi}^{t,k}\right)^S(\Theta)\right)$$

$$L_7 = \sum_{k=0}^{4} \left(\widehat{\chi}^k - \left(\widehat{\chi}^k\right)^S(\Theta)\right)' \widehat{V\left(\widehat{\chi}^k\right)}^{-1} \left(\widehat{\chi}^k - \left(\widehat{\chi}^k\right)^S(\Theta)\right)$$

$\widehat{V\left(\widehat{\beta}^k\right)}$, $\widehat{V\left(\widehat{\gamma}^k\right)}$, $\widehat{V\left(\widehat{\varphi}^{t,k}\right)}$, $\widehat{V\left(\widehat{\psi}^{t,k}\right)}^{-1}$ and $\widehat{V\left(\widehat{\chi}^k\right)}^{-1}$ are the OLS variances under homoskedasticity and hence take the standard form $\widehat{\sigma}^2\left(X'X\right)^{-1}$. X is the matrix with the data on regressors and $\widehat{\sigma}^2$ is the variance of residuals.

5 Results

5.1 Parameter Estimates

In this section, I show and interpret the parameter that were obtained estimating the model. Web Appendix C describes how standard errors were computed.

The human capital shares are illustrated in Figure 3 and are computed using industry-specific wage bill information from the Brazilian National Accounts together with information on how the wage bill is shared between skilled and unskilled workers we observe in RAIS. Due to the Cobb-Douglas assumption, these shares are obtained without solving the model, and are imposed throughout the estimation procedure.

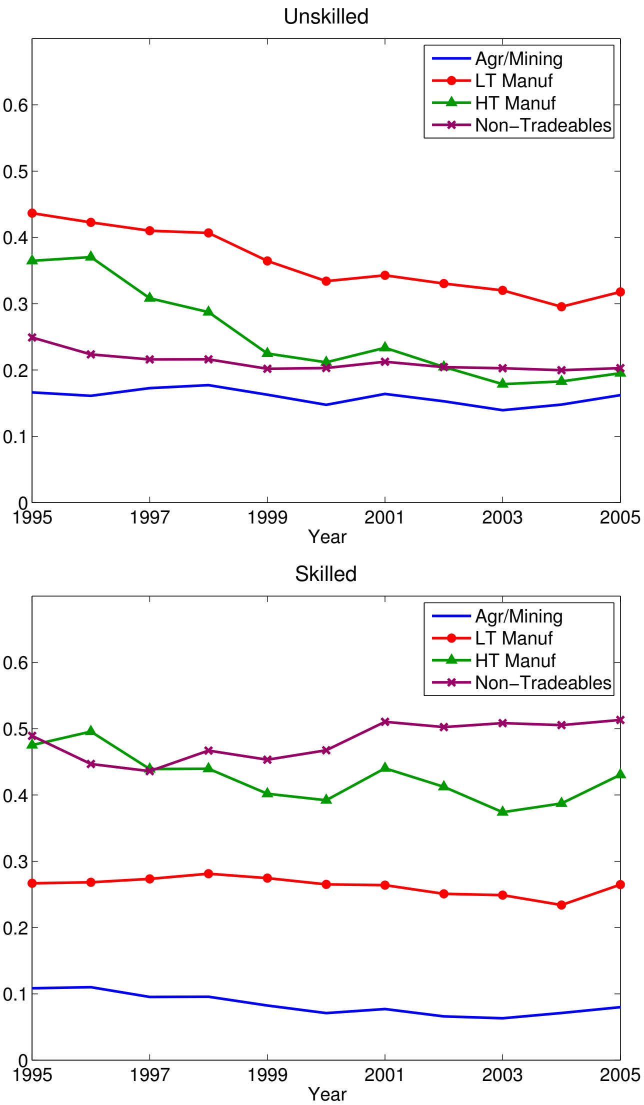


Figure 3: Evolution of human capital shares from Unskilled and Skilled workers, 1995 to 2005

Table 3 shows the human capital production functions' estimated parameters. There are two types of human capital (unskilled and skilled) but they share the same parameters. The only difference between these human capital production functions is that among the unskilled workers the education dummy is $(Educ = 2)$ (the category $(Educ = 1)$ is excluded) and among the skilled workers it is $(Educ = 4)$ (the category $(Educ = 3)$ is excluded).

The sector-specific experience coefficients indicate that sector-specific experience accumulated in sector i is somewhat transferable to sector $j \neq i$. That is, when workers switch sectors, not all experience is lost. However, sector-specific experience accumulated in sector i is **not fully transferable** to sector j, which **creates direct wage costs in switching sectors**. Nevertheless, this result also shows that models that assume the complete loss of sector-specific experience when switching sectors

Table 3: Human Capital Production Function: Parameter Estimates

	Agr/Mining	LT Manuf.	HT Manuf.	Non-Tradeables
β_1^s: *Female*	-0.4124	-0.3134	-0.3083	-0.2965
	(0.0056)	(0.0035)	(0.0044)	(0.0033)
β_2^s: $I(Educ = 2)$	0.1151	0.2721	0.2790	0.3057
	(0.0068)	(0.0043)	(0.0069)	(0.0041)
β_3^s: $I(Educ = 4)$	0.9594	0.9294	0.8119	0.9402
	(0.0077)	(0.0066)	(0.0067)	(0.0058)
β_4^s: $(age - 25)$	0.0327	0.0330	0.0402	0.0246
	(0.0011)	(0.0007)	(0.0007)	(0.0004)
β_5^s: $(age - 25)^2$	-0.0007	-0.0008	-0.0011	-0.0004
	(0.00003)	(0.00002)	(0.00002)	(0.00001)
β_6^s: $Exper_{Agr/Min}$	0.1127	0.0409	0.0189	0.0008
	(0.0016)	(0.0037)	(0.0041)	(0.0033)
β_7^s: $Exper_{LT}$	0.0187	0.0886	0.0597	0.0240
	(0.0026)	(0.0015)	(0.0018)	(0.0014)
β_8^s: $Exper_{HT}$	0.0549	0.0717	0.0977	0.0439
	(0.0024)	(0.0017)	(0.0022)	(0.0017)
β_9^s: $Exper_{NT}$	0.0568	0.0582	0.0429	0.0847
	(0.0016)	(0.0012)	(0.0015)	(0.0010)
σ^s: *SD of Shock*	0.2191	0.1735	0.1707	0.2575
	(0.0059)	(0.0033)	(0.0051)	(0.0013)

Standard errors in parenthesis.

overstate this barrier to mobility.

Interestingly, experience accumulated in High-Tech Manufacturing ($Exper_{HT}$) and experience accumulated in Non-Tradeables ($Exper_{NT}$) are quite transferable to all other sectors. On the other hand, experience accumulated in Agriculture and Mining ($Exper_{Agr/Mining}$) seems to be transferable only to Low-Tech Manufacturing. Experience accumulated in Low-Tech Manufacturing ($Exper_{LT}$) is quite transferable to High-Tech Manufacturing but only marginally useful in the other sectors.

Table 4 shows the parameters of the value of the Residual Sector. It is interesting to note that, on average, male, more educated and older workers all attach higher values to the Residual Sector. Hence, these observable characteristics, all else equal, lead to higher reservation wages. The standard deviation of idiosyncratic shocks for the value of the Residual Sector (in Table 4) is large, in the order of three times average annual wages. This high volatility is necessary for the model to be able to match frequent transitions out of the formal sector.

In order to interpret the magnitudes of the costs of mobility (whose parameters are shown in Table 5), for each observation in the data set (and unconditional on switching), I express individual costs of mobility in terms of annual average wages, conditional on the worker's characteristics (but unconditional on sector of activity). Panel A of Table 6 shows the median of costs of mobility, expressed as multiples of annual average conditional wages. For workers currently employed in the formal sector, median costs of mobility into Non-Tradeables are equal to 1.4 times annual average wages, but costs of mobility into High-Tech Manufacturing are almost twice as large and equal to 2.7 conditional annual average wages. Costs of mobility into Agriculture/Mining and Low-Tech Manufacturing are in between and equal to 1.6 and 1.9 times conditional annual average wages respectively.

Compared to the numbers obtained using the methodology developed by ACM, these costs are an order of magnitude lower. Their methodology applied to the Brazilian data I employ in this paper

Table 4: Value of the Residual Sector: Parameter Estimates

γ_0: *Intercept*	0.7058
	(0.0155)
γ_1: *Female*	-0.3385
	(0.0061)
γ_2: $I(Educ = 2)$	0.3304
	(0.0098)
γ_3: $I(Educ = 3)$	0.7456
	(0.0101)
γ_4: $I(Educ = 4)$	1.8555
	(0.0127)
γ_5: $(age - 25)$	0.0471
	(0.0013)
γ_6: $(age - 25)^2$	-0.0011
	(0.00004)
σ_0: *SD of Shock*	18.7028
	(0.2184)

Standard errors in parenthesis.

Table 5: Costs of Mobility: Parameter Estimates

	From $\Downarrow$ *To* $\Rightarrow$	*Agr/Mining*	*LT*	*HT*	*NT*
$\varphi^{Residual,s'}$:	*Residual*	3.2784	3.3092	3.4323	3.2206
		(0.0104)	(0.0096)	(0.0093)	(0.0104)
$\varphi^{Agr/Min,s'}$:	*Agr/Mining*	–	2.0708	2.4423	1.7828
		–	(0.0300)	(0.0413)	(0.0233)
$\varphi^{LT,s'}$:	*LT*	1.4267	–	2.1617	1.3655
		(0.0315)	–	(0.0246)	(0.0238)
$\varphi^{HT,s'}$:	*HT*	1.2850	1.5508	–	1.3408
		(0.0417)	(0.0264)	–	(0.0269)
$\varphi^{NT,s'}$:	*NT*	1.7585	1.8376	2.1462	–
		(0.0209)	(0.0166)	(0.0188)	–
κ_1:	*Female*	0.1300			
		(0.0044)			
κ_2:	$I(Educ = 2)$	0.0296			
		(0.0046)			
κ_3:	$I(Educ = 3)$	0.1086			
		(0.0059)			
κ_4:	$I(Educ = 4)$	0.0761			
		(0.0074)			
κ_5:	$(age - 25)$	0.0279			
		(0.0008)			
κ_6:	$(age - 25)^2$	-0.0006			
		(0.00002)			

Standard errors in parenthesis.

Table 6: Costs of Mobility

A. Costs in terms of wages		
Median Cost of Entry Into ↓	From a Formal Sector	From the Residual Sector
Agr/Mining	1.64	11.78
Low-Tech	1.88	12.15
High-Tech	2.70	13.74
Non-Tradeables	1.41	11.12
B. Costs of Switchers in terms of Wages		
Median Cost of Entry Into ↓	From a Formal Sector	From the Residual Sector
Agr/Mining	-1.67	1.53
Low-Tech	-0.50	2.84
High-Tech	0.49	2.81
Non-Tradeables	-0.26	3.02

A. $\frac{Cost^{ss'}(X_i)}{\hat{w}(X_i)}$, where $\hat{w}(X_i)$ is an estimate of the average annual wage individual with characteristics X_i gets unconditional of sector of activity.
B. $\frac{Cost^{ss_{opt}}(X_i)+\tau^{s_{opt}}-\tau^{s}+\eta_{it}^{s_{opt}}-\eta_{it}^{s}}{\hat{w}(X_i)}$ for $s \neq s_{opt}$, where s_{opt} is the sector of choice for those who switched.

produces costs of mobility in the order of 50 times annual average wages (see Dix-Carneiro (2010)). Artuç and McLaren (2010) also apply that methodology to Turkish data and obtain costs of mobility ranging from 9.5 to 23 times annual average wages. Finally, in their own paper, ACM apply their methodology to CPS data from the United States and obtain costs of mobility in the order of 6 times annual average wages in their baseline specification. The differences between the costs I obtain in my paper for Brazil and the costs obtained in ACM for the United States are quite striking since Brazil has a much more rigid labor market than the United States (Heckman and Pages (2000)).

In the methodology developed in ACM, high costs of mobility are obtained if gross flows do not respond much to wage differentials. In that case, non-trivial gross flows across sectors are rationalized by extremely high variance in the idiosyncratic preferences for sectors. Moreover, because their model assumes homogeneous workers, they estimate inter-sectoral wage differentials by computing average wages in each sector in every period. Given that taking heterogeneity (including sector-specific experience) and selection on unobservables into account is key in estimating the wage structure, the methodology is most likely producing high costs of mobility because the wage differentials they estimate in a first step may not reflect counter-factual wage differentials.

The costs of mobility from the Residual Sector are less readily interpretable. These costs are extremely high - the median is around 12 times annual average wages. These high costs are due to the fact that the model must assign a very high variance σ_0^2 to the shocks in the value of the Residual Sector (ε_{it}^0) in order to explain the very frequent movements out of the formal sector (see Table 13). Because transition rates out of the Residual Sector and into one of the formal sectors depend on the ratio between an increasing function of σ_0^2 and and increasing function of φ^{0s},[16] the model must assign

[16] To gain intuition of why this is the case, the higher the variance of ε_{it}^0, the higher transition rates out of the residual sector will be. On the other hand, the higher the costs of mobility out of the Residual Sector, the lower the transition rates from the Residual Sector and into the formal sector will be. The very frequent transitions out of the formal labor market lead to a high estimated value for σ_0^2, which in turn leads to a high estimated value for φ^{0s}. If φ^{0s} were not as high, transition rates back to the formal sector generated by the model would be much larger than the ones observed in the data.

high values to φ^{0s} in order to match the transition rates out of the Residual Sector observed in the data. These costs of mobility from the Residual Sector do not have direct analogs with other studies: First, ACM do not allow for a non-employment option; Second, dynamic studies that have estimated the value of home production in the United States such as Keane and Wolpin (1997), Lee (2005) and Lee and Wolpin (2006) do not face these extremely frequent transitions in and out of the formal labor force and hence these studies estimate a much lower variance in the shocks in the value of the home sector, which is the analog of my Residual Sector. With lower variance in the value of the home sector, they obtain much lower costs of mobility from the home sector and into a productive sector.

The median costs shown in Panel A of Table (6) are median costs that workers would face had they switched sectors and net of preference shocks. These are not actual incurred costs of mobility. Panel B of Table (6) shows median costs of mobility that switchers actually incurred during the sample period. These costs also take into account the preference parameters and shocks in each sector, so that the actual cost of switching from sector s to sector s' that worker i with characteristics X_i faces is given by $Cost^{ss'}(X_i) + \tau^{s'} - \tau^{s} + \eta_{it}^{s'} - \eta_{it}^{s}$. We can observe that median costs of switching into Agriculture/Mining, Low-Tech Manufacturing and Non-Tradeables (from a formal sector) were actually negative, which means that many of the workers who switched would be willing to switch sectors even in the event of a cut in their present value of utility (net of current non-pecuniary value and shocks). The median cost of entry into the High-Tech Manufacturing sector was of half of annual average wages. Also, median costs of entry into a formal sector from the Residual Sector look much more digestible. One intuitive look at the magnitude of the these incurred costs is: the median switcher from the Residual Sector back to the formal sector spends 2 to 3 years in school (and forgone wages) in order to gather the necessary skills to get back to work.

Figures 4 and 5 show how dispersed costs of mobility (before preference shocks) are, by plotting the nonparametric densities of these costs. These costs are dispersed only because they depend on workers' characteristics (age, gender and education). There is considerable variability in workers' abilities to arbitrage wage differentials, and a lot of that variability is explained by their demographic characteristics. Table 7 shows how costs of switching as a fraction of average conditional wages (but unconditional on sector of activity) vary with worker demographics.[17] These costs in terms of annual average conditional wages are substantially higher for women and less educated workers. However, these costs are largely insensitive to age. This last result does not necessarily mean that older workers are as able as younger workers in arbitraging wage differentials: older workers face similar costs in terms of average conditional wages, but they have a shorter period in the labor market than middle aged workers. Since workers evaluate alternative sectors in terms of their expected present value, it would be more accurate to express costs of mobility in terms of the present value of staying in the current sector. The second column of Table 7 does exactly that, and finds that older workers actually face higher costs of mobility than younger workers, and that the age gradient is quite steep. All else

[17] Average conditional wages are obtained by first obtaining the best linear predictor of log wages conditional on gender, education, age and experience; and then taking the exponential. Since costs of mobility are also an exponential of a linear function of these variables, the cost of switching as a fraction of average conditional wage is an exact function of gender, education, age and experience.

equal, older workers move less across sectors than younger workers.[18]

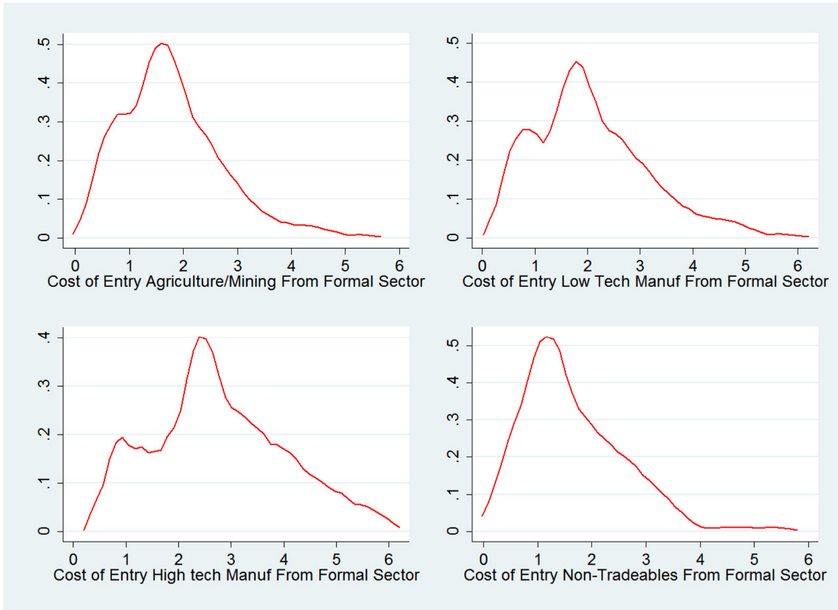


Figure 4: Non-parametric Density of Costs of Mobility - Any Formal Sector as Origin

Table 8 displays the Non-Pecuniary preference parameters. The reference sector is Agriculture/Mining, $\tau_1 = 0$. The model must assign a lower utility to the High-Tech Manufacturing sector in order to rationalize the existence of the high wage premium paid in that sector together with the rate at which people choose that sector.

Table 9 shows the time-invariant unobserved comparative advantage components. Recall that the model features three types of workers. Note that type II is a "good" type with absolute advantage in all the sectors and type III is a "bad" type with absolute disadvantage in all sectors, type I being an intermediate type. Interestingly, the pattern of comparative advantage across types is quite different, with type III being relatively much worse in High-Tech Manufacturing than type II, for example. Finally, estimates on Table 10 show that the higher the initial experience in Non-Tradeables, the higher the probability that the individual has type III, and the higher the initial experience in High-Tech Manufacturing, the higher the probability that the individual has type II. Integrating these probabilities across all individuals' initial conditions on experience, I obtain that the unconditional distribution of types in the economy is as follows: 22% type I, 28% type II and 50% type III.

5.2 Goodness of Fit

Tables 11, 12 and 13 compare unconditional wage, sectoral choice and transition rate moments in the data and those generated by the model. The model reproduces the unconditional moments reasonably well.

[18]However, older workers have less persistent choices. This is mostly due to the fact that they are more likely to move to the Residual sector, since they attach a higher value to that sector than younger workers.

Figure 5: Non-parametric Density of Costs of Mobility - Residual Sector as Origin

Table 7: Correlates of Costs of Switching Expressed in Terms of Wages or in Terms of Expected Present Value of staying in the Current Sector

	log Costs In Terms of	
	Wages	Present Value
$Female$	0.44	0.41
	–	[0.000]
$I(Educ = 2)$	-0.18	-0.22
	–	[0.001]
$I(Educ = 3)$	-0.50	-0.43
	–	[0.001]
$I(Educ = 4)$	-1.38	-1.34
	–	[0.001]
$(age - 25)$	0.001	-0.013
	–	[0.000]
$(age - 25)^2$	-0.00004	0.00199
	[0.000]	[0.000]
$Exper_{Agr/Mining}$	-0.04	0.02
	–	[0.000]
$Exper_{LT}$	-0.07	0.00
	–	[0.000]
$Exper_{HT}$	-0.13	0.00
	–	[0.000]
$Exper_{NT}$	-0.07	-0.03
	–	[0.000]
Observations	1,189,953	1,189,953
R-squared	1.000	0.989

Random sample of 50,000 individuals followed over time.
First Column: Dependent variable is $log\left(\frac{Cost^{ss'}(X_i)}{\hat{w}(X_i)}\right)$, where $\hat{w}(X_i)$ is an estimate of X_i gets unconditional of sector of activity.
Second Column: Dependent variable is $log\left(\frac{Cost^{ss'}(X_i)}{PV(X_i)}\right)$, where $PV(X_i)$ is the expected present value that individual with characteristics X_i gets if she chooses to remain in the current sector.the average annual wage individual with characteristics.

Table 8: Non-Pecuniary Preference Parameter Estimates

τ_2: *LT*	0.2459
	(0.0183)
τ_3: *HT*	-0.6332
	(0.0342)
τ_4: *NT*	0.3115
	(0.0171)
ν: *Scale Parameter of Shock*	2.0964
	(0.0222)

Standard errors in parenthesis.

Table 9: Type/Sector Matching Parameters

	Type II	*Type III*
θ_h^0: *Residual*	0.8454	-0.8609
	(0.0171)	(0.0243)
θ_h^1: *Agr/Mining*	0.5201	-0.6995
	(0.0181)	(0.0113)
θ_h^2: *LT*	0.6733	-0.6715
	(0.0108)	(0.0118)
θ_h^3: *HT*	0.5842	-0.8471
	(0.0094)	(0.0206)
θ_h^4: *NT*	0.7934	-0.6110
	(0.0098)	(0.0110)

Standard errors in parenthesis.

Table 10: Type Probability Function

	Type II	*Type III*
π_h^0: *Intercept*	0.0985	0.3102
	(0.0306)	(0.0311)
π_h^1: $Exper_{Agr/Min}$	0.0233	0.2409
	(0.0253)	(0.0271)
π_h^2: $Exper_{LT}$	0.0134	0.0820
	(0.0133)	(0.0129)
π_h^3: $Exper_{HT}$	0.1190	0.0498
	(0.0221)	(0.0200)
π_h^4: $Exper_{NT}$	0.0357	0.1261
	(0.0127)	(0.0115)

Standard errors in parenthesis.

Table 11: Wages 1995-2005: Data vs. Model

A. Average Hourly Wage (2005 R$) 1995-2005		
Sector	Data	Model
Agr/Mining	4.37	3.51
Low-Tech	5.74	5.72
High-Tech	12.11	12.31
Non-Tradeables	8.20	8.13
B. Average Log Hourly Wage (2005 R$) 1995-2005		
Sector	Data	Model
Agr/Mining	0.99	0.96
Low-Tech	1.36	1.39
High-Tech	2.06	2.22
Non-Tradeables	1.59	1.62

Table 12: Sectoral Choices (%) 1995-2005: Data vs. Model

	Data	Model
Residual	39.05	40.15
Agr/Mining	3.33	3.58
Low-Tech	8.34	8.30
High-Tech	2.77	2.50
Non-Tradeables	46.51	45.47

Table 13: Transition Rates (%) 1995-2005: Data vs. Model

	Residual	Agr/Min	LT Manuf	HT Manuf	Non-Tradeables
A. Data					
Residual	79.44	1.71	2.74	0.62	15.50
Agr/Mining	17.13	76.52	2.06	0.49	3.80
Low-Tech	14.10	0.79	79.50	0.72	4.89
High-Tech	10.58	0.58	2.13	81.59	5.12
Non-Tradeables	12.24	0.26	0.86	0.32	86.32
B. Model					
Residual	80.52	1.65	2.68	0.45	14.69
Agr/Mining	18.37	77.68	0.97	0.13	2.86
Low-Tech	14.42	0.76	79.41	0.62	4.79
High-Tech	9.30	0.80	2.47	82.04	5.38
Non-Tradeables	12.57	0.32	0.82	0.31	85.97

Figure 6 plots the coefficients of the auxiliary models in the data vs. the coefficients of the auxiliary models in the simulated data. The regression weights each observation with the inverse of the standard error of the respective coefficient estimated using the actual data. A perfect fit would lead to all coefficients on top of the 45° line.

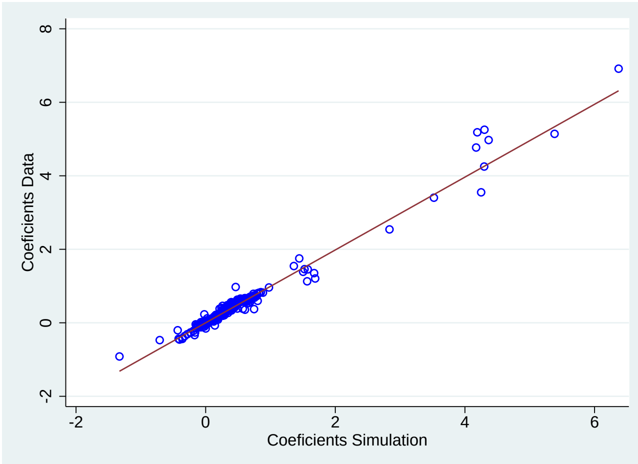
The Web Appendix D shows how well the model replicates conditional wage, choice and transition rate moments. Overall, the model is able to reasonably generate important unconditional and conditional moments in the data.

6 Counter-factual Experiments

In this section, I use the model as a laboratory in order to analyze the dynamics of the labor market following a counter-factual trade liberalization episode. I focus on the following issues: (1) Quantify the speed of adjustment with which the labor market readjusts as a response to trade liberalization; (2) Investigate the impact of assumptions regarding the mobility of physical capital on the transition path; (3) Quantify welfare losses for workers initially employed in the adversely affected sector, and determine how these losses correlate with demographic characteristics; (4) Quantify welfare adjustment costs; (5) Analyze the impact of different labor market policies on aggregate welfare and on welfare losses of workers initially employed in the adversely affected sector; (6) Attempt to quantify the relative importance of costs of mobility to sector-specific experience in explaining the slow adjustment.

The general procedure will be to:

1. Generate a stable economic environment. All the parameters of the model will be fixed over time, as will the stock of physical capital and the characteristics of the upcoming generations of workers.



	$\hat{\beta}_{Data}$
$\hat{\beta}_{Sim}$	0.9910
	(0.003)
Constant	0.000
	(0.000)
Observations	1,022
R^2	0.988

Figure 6: Goodness of Fit - Indirect Inference coefficients obtained in the **actual** data plotted versus those obtained in the **simulated** data. A perfect model fit would lead to all the points over the 45° line. The regression shown in the right hand side is weighted by the inverse of standard errors of the coefficients obtained with the **actual** data.

Simulate the model long enough so that the distorted-trade steady state is reached.

2. Shock the economy with a trade liberalization episode. The trade liberalization episode will consist of an unanticipated once-and-for-all negative shock in the price of the High-Tech Manufacturing sector (the import-competing sector) of 30% (a smaller shock of 10% will also be simulated and discussed in Section 6.7). This negative shock is interpreted as being induced by a decrease in the tariffs imposed in that sector. The prices of Agriculture/Mining and of Low-Tech Manufacturing will be kept constant but the prices of Non-Tradeables will adjust endogenously. This is a standard small open economy assumption. The prices of tradeables are all determined in international markets and the domestic economy is assumed to be small enough to have no impact on these prices.

3. Analyze the outcome of interest.

The next sub-section goes over some additional features that must be incorporated to the model when carrying out and analyzing the simulations. These features were irrelevant in estimation. The Web Appendix E provides the details of how I proceed with the simulations of the counter-factual experiments. In particular, it explains how the productivity terms and total stock of physical capital used in the simulations are determined.

6.1 Closing the Model For the Simulations

6.1.1 Utility for Consumption

As mentioned in Section 2.2, workers must immediately consume their wages since there is no saving nor borrowing. Consumption of Agriculture/Mining, Low-Tech Manufacturing, High-Tech Manufacturing and Non-Tradeables output generates utility following a Cobb-Douglas utility function $U(\mathbf{C}) = \left(\prod_{k=1}^{4} C_k^{\mu^k}\right)$. These assumptions imply that the price index at time t is given by $\mathbf{P}_t = \prod_{k=1}^{4} (p_t^k)^{\mu^k}$.[19] The

[19] The indirect utility of a worker who receives nominal wage w_t is given by $\frac{w_t}{\mathbf{P}_t}$.

Cobb-Douglas shares used in the simulation were obtained from the Brazilian National Accounts and can be seen on Table 14.

Table 14: Expenditure Shares

Agriculture/Mining	0.09
LT Manuf	0.06
HT Manuf	0.09
Non-Tradeables	0.76

6.1.2 Capital Owners

Capital owners were not mentioned in the model outline of Section 2. However, I need to detail their participation in the economy in order to endogenize the price of Non-Tradeables and to define aggregate welfare. In the experiments, the total stock of physical capital is fixed over time and hence no investment decisions are modeled.

Capitalists receive payments for the rental of their capital and proceed to consumption. They enjoy the same Cobb-Douglas utility of consumption, with the same expenditure shares as workers. Their indirect utility at time t is given by: $\frac{\textit{Total Capital Income}_t}{\prod_{k=1}^{4} p_{kt}^{\mu_k}} = \sum_{k=1}^{4} r_t^{K,k} K_t^k$. Where $r_t^{K,k}$ is the real rental price of capital in sector k.

6.1.3 Market Clearing for Non-Tradeables

In the simulations, the prices of Agriculture/Mining and of Low-Tech Manufacturing will be kept constant, but the price of Non-Tradeables will adjust endogenously. All Non-Tradeable output must be consumed domestically. Hence (in nominal terms):

$$Y_t^4 = p_t^4 C_t^4 \tag{18}$$

Given the Cobb-Douglas utility functions, we have the following chain of equalities (in nominal terms):

$$p_t^4 C_t^4 = \mu^4 \left(\textit{Wage Bill} + \textit{Capital Income} \right) = \mu^4 \left(\sum_{k=1}^{4} Y_t^k \left(\mathbf{p}_t \right) \right) = Y_t^4 \left(\mathbf{p}_t \right) \tag{19}$$

The last equality pins down p_t^4 as a function of p_t^1, p_t^2, and p_t^3. μ^4 is the expenditure share on Non-Tradeables.

6.1.4 Aggregate Welfare

Total welfare at a given point in time is obtained summing total real capital income $\sum_{k=1}^{4} r_t^{K,k} K_t^k$ to total real wages paid in the economy, sector-specific utilities, total enjoyed value of the Residual Sector and costs of mobility incurred.

6.2 Simulations: Perfect Physical Capital Mobility

For the simulations presented in this sub-section, physical capital is assumed to be **perfectly mobile** and efficiently allocated across sectors. Figure 7 shows the main results of the simulation.[20] All prices are normalized to 1 in the pre-shock, distorted-trade steady state. The shock in the price of High-Tech Manufacturing occurs at year 1, when that price drops from 1 to 0.7. The prices of Agriculture/Mining and Low-Tech Manufacturing are set to 1 throughout (small open economy assumption). The price of Non-Tradeables is determined in equilibrium and gradually adjusts to its new steady state value.

Human capital prices in the adversely affected sector drop sharply with the shock. The price of human capital prices from unskilled workers face a sharp decline the same year the shock occurs and then slowly declines further until stabilizing. On the other hand, human capital prices for skilled workers follow a sharp decline on the very short run but slowly recovers over time. The reason for this recovery is due to the fact that unskilled workers face higher costs of mobility than skilled workers, and hence move out of the sector in a slower pace.

The labor market adjusts relatively quickly. 80% of the reallocation is completed after 3 years and 95% of it is completed after 6 years.[21] There is a sizeable adjustment in the labor market. Employment in High-Tech Manufacturing drops to virtually zero in the new steady state. The price shock in this sector is large, causing both workers and capital to be reallocated elsewhere. This extreme result occurs only because physical capital is perfectly mobile. The intuition behind this result is that the price in High-Tech drops, driving wages in that sector down, making some workers leave the sector. With less human capital in the sector, the marginal product of capital decreases, inducing capital to be allocated elsewhere. That decreases wages in High-Tech further, making additional workers leave, and so on and so forth. Additionally, the costs of switching into the High-Tech sector are the highest. As long as the human capital prices in that sector were high, it was worthwhile for workers to incur the costs and to switch there. However, with declining wages in that sector, many workers leave and fewer enter, if at all.

The level of real value added and aggregate welfare are normalized to 1 before the shock. The long term gain in real value added is of 3.8%, but the economy goes through some delay in reaching the new steady state (80% of the transition is completed only after 8 years). It takes longer for real value added to stabilize than the headcount of workers across sectors. There are at least two reasons why this is the case. First, even after the allocation of workers have come close to the one in steady state, workers keep accumulating experience in their new sectors (which is more valuable than the experience they previously accumulated elsewhere), so that the steady state distribution of sector-specific experience takes a little bit longer to kick in. This contributes to a slower evolution of real value added. Second, as this transition related to the accumulation of sector-specific experience is happening, physical capital is

[20] Some of the Real Value Added and Welfare plots in Figures 7, 8 and 9 show a saw-like shape due to numerical error. The smaller the gains, the larger is the zoom, so that numerical errors are more apparent.

[21] The measure of cumulative reallocation used in order to quantify the speed of adjustment is given by:

$$\text{Cumulative Reallocation}_t = \frac{1}{2}\sum_{s=0}^{4} |Emp_t^s - Emp_0^s| \tag{20}$$

Where $t = 0$ is the last year before the shock and Emp_t^s is total employment (headcount) in sector s at year t.

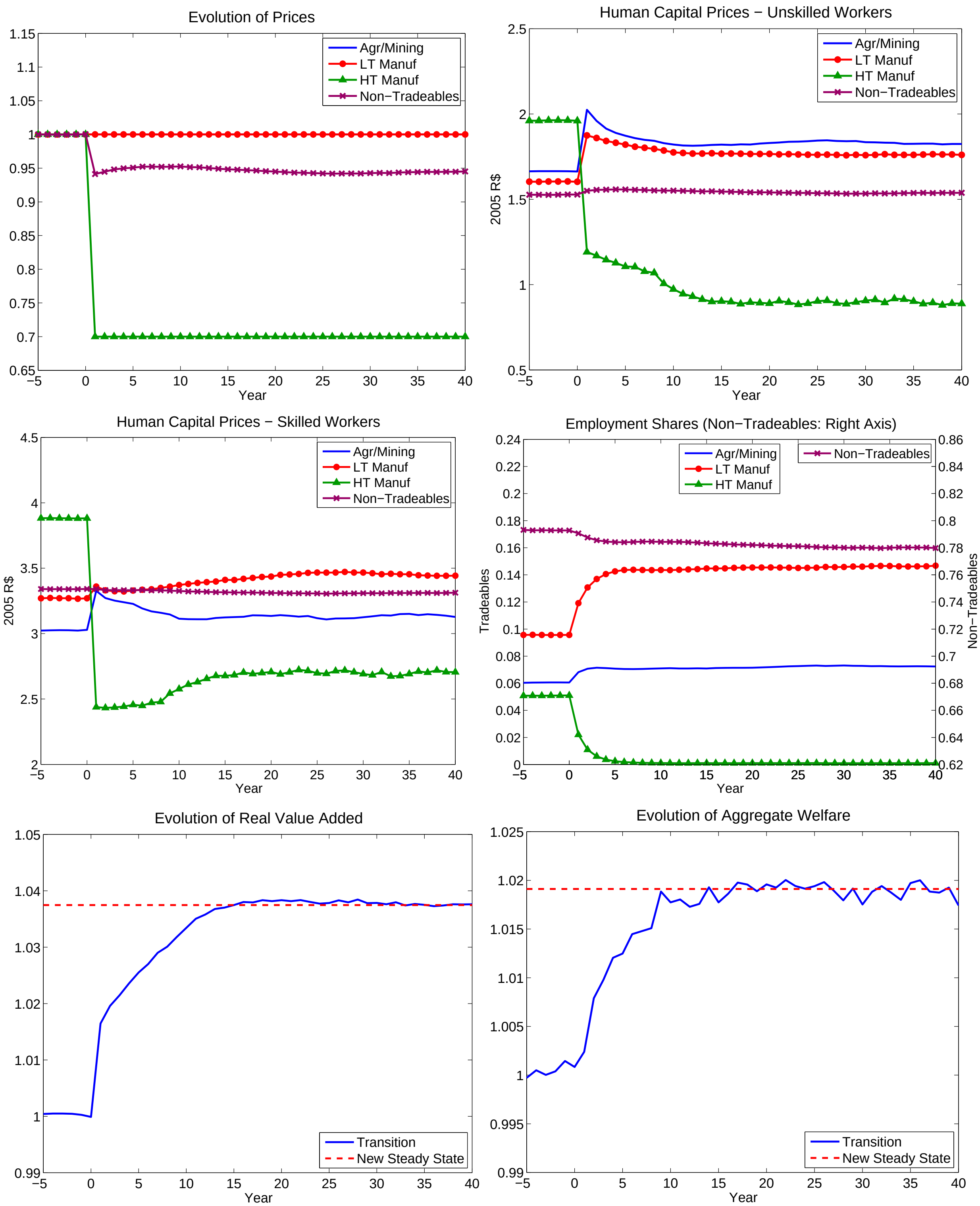


Figure 7: Dynamics under **Perfect Capital Mobility** following the adverse price shock in the High Tech Manufacturing sector illustrated in the left upper panel. The price in the Non-Tradeables sector adjusts in equilibrium. The evolution of human capital prices, employment shares, real value added and aggregate welfare following the shock are subsequently displayed in that order.

also being reallocated and its marginal productivity gradually increases. Long term aggregate welfare gains are of 1.9%. The welfare gains are smaller than the gains in real value added since, every year, a sizeable portion of the economy chooses the Residual Sector. The value of the Residual Sector is not affected by prices, and hence this dilutes the gains from liberalization for the economy as a whole.

6.3 Simulations: No Physical Capital Mobility

Figure 8 shows the dynamics of the labor market following the price shock in High-Tech Manufacturing when physical capital sector-specific and hence immobile.

The perverse spiral that occurs when capital is perfectly mobile is absent here. The drop in the High-Tech Manufacturing price first drives real human capital prices down in that sector since workers are not perfectly mobile. However, the exodus of workers out of the adversely affected sector pushes human capital prices up in that sector. That slows down and limits the mobility of workers out of that sector. The long-run real human capital prices are quite similar to the pre-shock levels, which give incentives for the new young generations to keep choosing the High-Tech Manufacturing sector. So, contrary to the case where capital is perfectly mobile, Figure 8 shows that the High-Tech Manufacturing sector does not die out in the long run. Adjustment of the labor market is also relatively fast, but the magnitude of adjustment is smaller than with perfect capital mobility. As in the case where capital is perfectly mobile, 80% of the reallocation of workers takes 3 years and 95% of the reallocation is completed after 6 years. Since capital cannot reallocate across sectors, the gains from the trade shock are rather modest. The long-term gain in real value added is of 0.2% and the long-term gain in aggregate welfare is of 0.3%.

It is interesting to note that aggregate real value added overshoots in the short run. The rental price of capital increases in all sectors with the exception of the High-Tech Manufacturing Sector. In the aggregate, physical capital income increases by 2% in the long run. On the other hand, aggregate real wage payments gradually decline, but this decline is slower than the increase in capital income producing the overshooting in real value added in the short run. The decline in real wage payments is caused by a decline in total wage payments to skilled workers.

6.4 Simulations: Imperfect Physical Capital Mobility

In this section, physical capital is assumed to be imperfectly mobile for illustration purposes. There are many different ways to impose frictions on the mobility of physical capital. Moreover, since these frictions were not estimated, assuming numbers for the magnitude of these frictions is inevitably arbitrary. Consequently, this section should be viewed as a numerical exercise on how imperfect physical capital mobility may interact with frictions in the labor market in generating slow transitional dynamics.

In my benchmark simulation, I assume that 10% at most of each sector's capital can change sector every year. Therefore, physical capital is perfectly mobile in the long run, but not in the short run. Figure 9 shows the dynamics under this assumption. In the short run, real human capital prices in High-Tech Manufacturing behave as in an economy with immobile capital, with an initial fall and

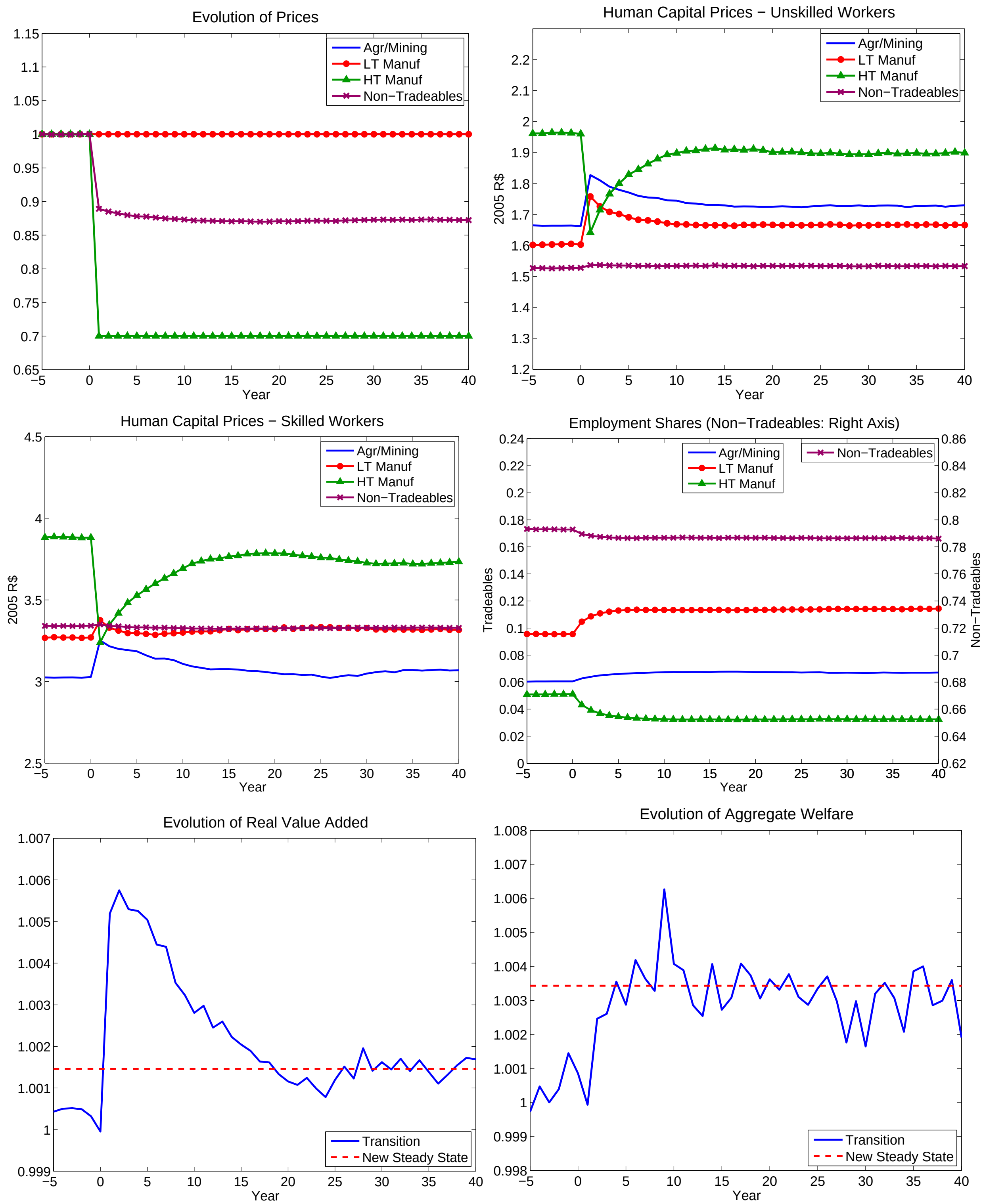


Figure 8: Dynamics under **No Capital Mobility** following the adverse price shock in the High Tech Manufacturing sector illustrated in the left upper panel. The price in the Non-Tradeables sector adjusts in equilibrium. The evolution of human capital prices, employment shares, real value added and aggregate welfare following the shock are subsequently displayed in that order.

subsequent recovery. But in the long run, as capital flees the adversely affected sector, the economy behaves as it would in an economy where capital is perfectly mobile. The adjustment of the labor market is much slower, compared to those in Sections 6.2 and 6.3. 80% of the reallocation of High-Tech Manufacturing is completed only after 16 years. 95% is completed after 39 years. The slow mobility of capital interacts with barriers to labor mobility amplifying the duration of the transition.

I have also experimented with different degrees of physical capital mobility. Simulations where physical capital was allowed to flow away from a sector at the maximum rates of 5%, 20%, and 30% a year were also simulated. The dynamics look very much like those in Figure 9. However, the slower capital changes sectors, the slower the reallocation of the labor market is. When physical capital is only allowed to flow away from a sector at the rate of 5% a year at most, it takes 32 years for labor reallocation to be 80% complete and 87 years for it to be 95% complete. When physical capital is allowed to flow away from a sector at the rate of 30% a year at most, it takes 6 years for labor reallocation to be 80% complete and 10 years for it to be 95% complete.

These different patterns in dynamics according to the degree of mobility of physical capital show that rigorously modeling physical capital accumulation and its degree of mobility together with workers' barriers to mobility is a very important direction for future research.

Even if physical capital presents a high degree of industry specificity, analyzing the dynamics of transition under the assumption of fixed capital is not appropriate, due to the depreciation of existing capital and reduced incentives of investing in adversely affected industries. Although this paper does not model investment decisions, it suggests that a model with sector-specific capital, depreciation and endogenous investment decisions will lead to transitions similar to those illustrated in this section.

6.5 Welfare Losses and Adjustment Costs

Table 15 shows welfare losses for workers who were employed in High-Tech Manufacturing - the adversely affected sector - prior to the adverse price shock, that is at time $t = 0$. These are losses in terms of the present value of welfare, which are computed over the **actual transition path** and are relative to the welfare path that would have resulted in the absence of the shock. Welfare losses are computed for different demographic groups and under different assumptions regarding the mobility of physical capital. All demographic groups in the other sectors gain from the shock (or at least do not lose), so the losers are clearly identified.

Table 15: Welfare Changes (in %) of Workers Who Were Employed in HT Manufacturing The Year Before The Shock

	Perfect Capital Mobility	No Capital Mobility	Imperfect Capital Mobility
Overall	-8.9	-5.3	-8.0
By Demographics			
Old/Unskilled	-6.4	-3.8	-5.0
Old/Skilled	-10.7	-6.8	-8.5
Young/Unskilled	-5.4	-3.8	-5.3
Young/Skilled	-10.3	-6.0	-9.8

Shock of 30% in the price of High-Tech Manufacturing
Imperfect mobility of capital: rate of 10% per year

Under perfect capital mobility, the welfare losses for the group as a whole is 8.9%. Within age

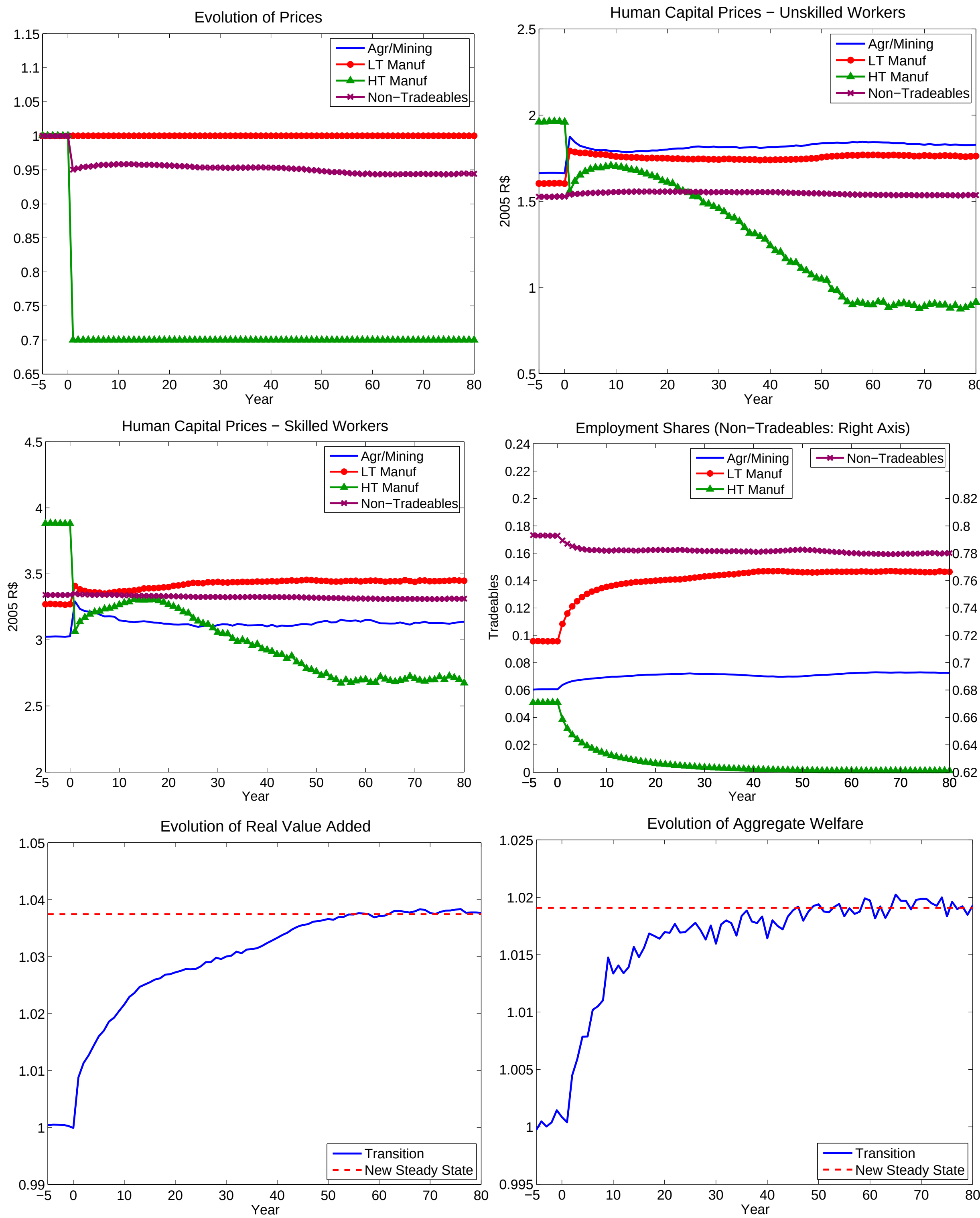


Figure 9: Dynamics under **Imperfect Capital Mobility** (rate of 10% per year) following the adverse price shock in the High Tech Manufacturing sector illustrated in the left upper panel. The price in the Non-Tradeables sector adjusts in equilibrium. The evolution of human capital prices, employment shares, real value added and aggregate welfare following the shock are subsequently displayed in that order.

categories, skilled workers are more adversely affected than unskilled workers. Since skilled workers face lower costs of mobility than unskilled workers (both in terms of wages and present values), this last result deserves explanation. In steady state, persistence in the High-Tech Manufacturing Sector is much higher among skilled than among unskilled workers - a fact consistent with what is observed in the data. For example, among the Young/Skilled workers initially employed in the High-Tech Manufacturing Sector, the steady state 5-year persistence rate prior to the shock is of 84%. This persistence rate is much lower for the Young/Unskilled workers, which is of 62%. That is, 38% of those Young/Unskilled initially employed in High-Tech would no longer be there in 5 years, even in the absence of shock (22% in excess compared to the Young/Skilled). These 38% of Young/Unskilled workers are consequently likely to benefit from a negative price shock in High-Tech Manufacturing, since they would have switched sectors regardless of occurrence of the shock, but now they face lower prices for consuming High-Tech Manufacturing output. In the aggregate, both skilled and unskilled face welfare losses, but the unskilled face lower losses due to their lower persistence in the High-Tech Manufacturing sector.[22] Conditional on skill category, older workers (45 to 59 years old in the year before the shock) lose almost as much in terms of welfare than younger workers (25 to 39 years old in the year before the shock). Actually, if I regress the change in welfare due to the shock on education dummies, age, age squared and experience accumulated in High-Tech, it turns out that older workers actually slightly benefit from the shock, but that workers with many years of experience in the sector suffer substantial losses. Since older workers in the sector tend to have substantial sector-specific experience in that sector, older workers (without controlling for experience) appear to lose more from the shock. The reason why, after controlling for experience, older workers actually benefit from the shock in High-Tech is as follows. As I noted above with unskilled workers, older workers also show less persistence in High-Tech Manufacturing (after controlling for experience in that sector). Lower persistence in that case comes from the fact that older workers attach a higher value to the Residual Sector.

Under immobile capital or imperfectly mobile capital, Figures 8 and 9 show that human capital prices in the adversely affected sector see an immediate drop as a response to the shock but they also go through a short-run recovery. That explains why workers employed in High-Tech Manufacturing right before the shock suffer smaller losses under these assumptions for the mobility of physical capital than under perfect mobility.

I now define and compute adjustment costs. Let $W_{DT}(\infty)$ be the steady state aggregate welfare before the shock (DT standing for distorted trade) and $W_{FT}(\infty)$ the steady state aggregate welfare after the shock (FT standing for free trade).

If the transition were immediate, then the present value of the gains would be:

$$G = \frac{1}{1-\rho}\left(W_{FT}(\infty) - W_{DT}(\infty)\right) \tag{21}$$

However, the transition path of welfare is usually below $W_{FT}(\infty)$, as can be seen in Figures 7 and

[22] The mechanism through which the model generates less persistence among unskilled workers is through the complementarity of experience and education (they are both inside an exponential in the human capital production function), so that the opportunity cost of switching sectors or switching to the Residual Sector is lower for less educated workers.

9, implying that long run quantitative models of trade that only compare the initial and final value of aggregate welfare may be substantially over estimating the gains from openness.

Let W_A be aggregate welfare over the adjustment path at time t. Adjustment costs are defined by:

$$AC = \frac{1}{1-\rho} W_{FT}(\infty) - \sum_{t=0}^{\infty} \rho^t W_A(t) \tag{22}$$

Table 16 shows that, under perfect capital mobility, adjustment costs eat up about 16% of the gains in aggregate welfare. Under imperfect capital mobility (10% mobility per year), these numbers are much larger: 31%. Assuming physical capital mobility of only 5% per year, these costs can reach up to 42%. Finally, adjustment costs are only 8% under no capital mobility.

Table 16: Adjustment Costs

	Long Term Gain (%)	Adjustment Cost (%)
Perfect Capital Mobility	1.9	16.3
Imperfect Capital Mobility	1.9	30.7
No Capital Mobility	0.3	8.3

Shock of 30% in the price of High-Tech Manufacturing
Imperfect mobility of capital: rate of 10% per year

In conclusion, if capital is assumed to be immobile, adjustment costs are low, but long term gains from trade are much lower than those when capital can be reallocated. On the other hand, if capital can be reallocated (either perfectly or imperfectly), adjustment costs become large. Further, the slower capital is allocated, the higher the adjustment costs are.

6.6 Labor Market Policies

I now use the framework developed in this paper in order to analyze the impact some advocated labor market policies may have on the labor market. I focus on analyzing the potential these policies have in compensating the losers and on their impact on the costs of adjustment as defined in equation (22). **Perfect mobility of physical capital will be assumed throughout.**

The first policy consists of a retraining program. The other policy is a moving subsidy that partly or entirely covers the costs that workers face in switching sectors (before the preference shocks). The aim is to focus on the impact of these policies without introducing distortions into the economy, so they are assumed to be financed through lump sum transfers. In light of the competitive equilibrium nature of the model and the welfare theorems, the second policy cannot be welfare improving, but may have attractive implications for compensation. The first policy can, in principle, be welfare improving since the government introduces a new retraining technology, which was otherwise unavailable to workers.[23]

[23] A retraining program could in principle be added to the estimated model if we had data on educational and/or mid-career training decisions. Unfortunately, these data are not available in RAIS, so I have to assume that a retraining program is a monopoly of the government and is otherwise not available for workers to take up.

6.6.1 Retraining Program

I assume that a retraining program works as follows: workers spend a year retraining in the classroom and this yields x years of sector-specific experience in the target sector. I experiment with $x = 2$ and $x = 3$. Eligible workers face three additional options: retrain to enter Agriculture/Mining, retrain to enter Low-Tech Manufacturing or retrain to enter Non-Tradeables. Retraining lasts one year, workers do not produce while being retrained and get a transfer from the government in the value of $w^0(X_i)$[24], the individual value of the Residual Sector net of the idiosyncratic shock ε_{it}^0.[25] However, after a year of retraining they enter the sector for which they retrained with $x = 2$ additional years of sector-specific experience in the chosen sector. In other words, one year of retraining for a sector is worth two years of sector-specific experience in that sector, but workers must stay out of the formal labor market for a year. This policy is labeled "Retraining 1." I also experiment with a retraining program where one year of retraining yields $x = 3$ years of sector-specific experience in the target sector. This policy is labeled "Retraining 2."

Workers still need to incur a cost of switching into a retraining program. For example, if a worker decides for retraining in sector s, she incurs the cost of moving into s. However, after the year spent retraining, she will have access to the sector she retrained for with no cost. Eligible workers are those employed at High-Tech Manufacturing at year $t = 0$, right before the adverse price shock. A worker loses eligibility if and only if she chooses to switch directly to one of the remaining sectors (without retraining) or once she takes up a retraining program for any sector. Eligible workers keep their eligibility if they switch to the Residual Sector.

The retraining program is implemented for 5 years, that is, eligible workers can take up the retraining program until $t = 5$, and they are aware of that.

Since I cannot know the cost of such a retraining program, I assume that it costs the transfer $w^0(X_i)$ plus the discounted difference between the expected continuation value in the new sector under retraining and the expected continuation value in the same sector without retraining:

$$w^0(X_i) + \rho\left(EV_{a+1,t+1}\left(\Omega_{ia+1,t+1}|\Omega_{iat}, s_t = \text{retraining for } s\right) - EV_{a+1,t+1}\left(\Omega_{ia+1,t+1}|\Omega_{iat}, s_t = s\right)\right)$$

In other words, the program costs what it is worth.

It is important to note that the type of retraining program considered here works by adding value to eligible workers' human capital and at the same time giving incentives for them to quickly switch sectors - leaving their decadent initial sector of employment. However, a retraining program may also reduce the cost of entry into different sectors. For example, in the real world workers may need to have some type of certificate in order to be considered for a highly specialized job. Unfortunately, this potentially important role for retraining is not considered in this section. The main reason is due to the fact that I do not have a micro-foundation for costs of mobility and consequently cannot know how this role of retraining will affect entry costs. On the other hand, the moving subsidy programs

[24] $X_i = (Female_i, Educ_i, age_{it})$

[25] The fact that this value is net of the idiosyncratic shock ε_{it}^0 is not important for the results. This assumption is made only because the government transfers this value based only on the observable characteristics of workers (gender, age, education).

described below play a similar role as a retraining program that only removes barriers to entry, without affecting human capital.

6.6.2 Moving Subsidy

Under this program, eligible workers are compensated with the mobility cost $Cost^{ss'}(X_i)$ they incur when switching sectors if the destination sector is **not** the High-Tech Manufacturing sector. Eligible workers are those employed in High-Tech Manufacturing at year $t = 0$, right before the adverse price shock. Eligibility is lost after a worker is compensated once or after the program expires. If an eligible worker switches to the Residual Sector, she does not lose eligibility. This policy is labeled "Moving Subsidy 1." A policy labeled "Moving Subsidy 2" works in exactly the same way, with the only difference that only half the mobility costs is compensated. Both policies are implemented for 5 years, and workers are aware of that.

6.6.3 Results

Results of these policies are shown in Tables 17 and 18.

Table 17: Welfare Adjustment Costs in (%) Under Different Labor Market Policies

No Policy	16.3
Retraining Policy 1	18.3
Retraining Policy 2	18.0
Moving Subsidy 1	23.4
Moving Subsidy 2	17.7

Shock of 30% in the price of High-Tech Manufacturing
Perfect Physical Capital Mobility.

Table 18: Welfare Changes (in %) of Workers Who Were Employed in HT Manufacturing The Year Before The Shock - Different Labor Market Policies

	No Policy	Retraining 1	Retraining 2	Moving Subsidy 1	Moving Subsidy 2
Overall	-8.9	-7.7	-5.6	-0.9	-6.1
By Demographics					
Old/Unskilled	-6.4	-6.3	-4.6	+9.0	-1.3
Old/Skilled	-10.7	-9.4	-6.8	-0.7	-7.5
Young/Unskilled	-5.4	-5.3	-4.9	+4.0	-1.9
Young/Skilled	-10.3	-8.1	-5.8	-5.3	-8.4

Shock of 30% in the price of High-Tech Manufacturing
Perfect Physical Capital Mobility.

The main results that arise are that: (1) The moving subsidy policies are better at compensating unskilled workers than at compensating skilled workers, who are the ones who lose the most; (2) The retraining policies are better at compensating skilled workers than unskilled workers, which is expected given the complementarity between education and experience that the human capital production functions generate; (3) The moving subsidy that compensates mobility costs has better compensation properties than any of the other simulated policies, although at the expense of higher welfare adjustment costs. It is also interesting to compare the policies "Retraining 2" and "Moving Subsidy 2."

Both generate similar welfare adjustment costs (18% and 17.7% respectively), so that their burden on the economy are roughly equal, and they lead to similar compensation at the aggregate level (eligible workers lose 5.6% and 6.1% respectively instead of 8.9% under "No Policy"). However, the "Moving Subsidy 2" program overwhelmingly favors the unskilled workers. The main conclusion from this exercise is that there is no clear ranking between these policies. If the sole objective of the government is to compensate the losers broadly defined as "those initially employed in the High-Tech Manufacturing Sector" then the moving subsidy that compensates mobility costs is the best policy, but it comes at the expense of higher welfare adjustment costs.

6.7 Additional Remarks

The adverse price shock of 30% may in part be explaining the large and sometimes fast response of the labor market to trade reform. For that reason, I also experimented with a shock of 10% in the price of High-Tech Manufacturing. We still obtain large employment price elasticities and reallocation times are almost the same as with the 30% shock. The exception is under perfect capital mobility. In that case, a 10% adverse shock in High-Tech leads to 80% of the labor market reallocation being completed only after 12 years. But even in that case, the response of the labor market is substantial (the price elasticity in that sector is around 8, but the sector does not die out as with the 30% shock).

Another natural question to ask is what type of barrier is more important in explaining sluggish labor market adjustment: is it sector-specific experience, or is it costs of mobility? Answering this question is not trivial. One cannot simply remove costs of mobility from the model and ask how the dynamics of transition compare with an economy with costs of mobility. The pre-shock steady state equilibrium without costs of mobility will look completely different, with an over-inflated High-Tech Sector and a much more compressed wage structure. Nevertheless, I conduct an experiment where I gradually decrease costs of mobility and compare the speed of adjustment under these different cost structures. Under perfect capital mobility and an adverse price shock of 10%, 80% of the reallocation is completed after 12 years under the actual structure of costs, 9 years after all costs are reduced by 20% and 4 years after all costs are reduced in 50%.[26] This result, together with the fact that sector-specific experience is quite transferable across sectors, suggests that sector-specific experience is not the main barrier to mobility across sectors.

Finally, how do the labor market responses obtained in this paper compare to those reported in papers that empirically studied the response of the labor market to trade reform or other trade shocks? Revenga (1992) finds 5-year wage and employment elasticities with respect to import prices in the US of 0.4 and 1.7 respectively. In her paper, she argues that small wage gaps are enough to trigger large employment responses in the United States, due to its very flexible labor market and the supposedly small costs workers face in switching sectors. On the other hand, Goldberg and Pavcnik (2007) survey several studies analyzing the response of the labor market to trade reform in developing countries and a robust finding is that there is little inter-sectoral reallocation of labor following trade reform. The

[26] The reason why I investigate the role of sector-specific experience vs. costs of mobility in explaining the delay in adjustment with perfect capital mobility and a 10% adverse shock is because I wish to isolate other barriers to adjustment by allowing capital to flow freely, and I wish to analyze a case where adjustment is particularly slow, which is the case when the shock is smaller.

authors then argue that labor markets in developing countries are much more rigid, and that in these countries workers may face high costs of mobility. Two observations are now timely. First, Table 19 shows that 5-year elasticities under No Capital Mobility or Imperfect Capital Mobility (10% per year) are remarkably similar to the ones Revenga (1992) obtained for the United States. So the model is capable of generating sensible responses of the labor market to trade reform. Second, my results show that (large) costs of mobility are not enough to explain the lack of reallocation following trade reform that characterized the experience of developing countries. Possible explanations for the lack of reallocation following trade reform in developing countries that would reconcile the results obtained here with the empirical evidence include: low pass-through from tariffs to prices, faster productivity growth in adversely affected sectors and slow and limited mobility of physical capital across sectors.

Table 19: 5-year Price Elasticities of Wages and Employment in High-Tech Manufacturing

	Perfect Capital Mobility	No Capital Mobility	Imperfect Capital Mobility
Wage	1.3	0.3	0.5
Employment	3.2	1.1	1.9

Shock of 30% in the price of High-Tech Manufacturing
Perfect Physical Capital Mobility.

7 Conclusion

At the heart of most arguments in favor of trade liberalization is the claim that it will induce a reallocation of resources towards sectors in which countries have comparative advantage. Nevertheless, this reallocation of resources takes time and is costly. As a result, it is perhaps surprising that there is relatively little work attempting to model, measure and understand the implications of these costs and delay, not only for the welfare of individual workers but also for the economy as a whole.

Also, international trade theory predicts that trade liberalization generates winners and losers, but their identity crucially depends on what assumptions the researcher is willing to make regarding the mobility of resources across sectors. Cases typically considered in theoretical models usually assume two extreme cases: there is either perfect mobility or no mobility of resources across sectors. In a model where resources are imperfectly mobile across sectors with the degree of mobility being estimated from the data, who are the winners and losers that arise in this context?

This paper sheds light on these issues estimating a structural dynamic equilibrium model of the labor market within a small open economy with a non-tradeable sector and a non-employment option. The model is estimated using matched employer-employee data from Brazil and yields median costs of switching sectors that range from 1.4 to 2.7 times annual average wages, depending on what sector a worker is considering to enter. In addition, the distribution of these costs has a large dispersion within the population. For example, female and less-educated workers face substantially higher costs of switching sectors in terms of average conditional wages. Even though the costs of switching as a fraction of average conditional wages are largely insensitive to age, when expressed as a fraction of expected present values they increase steeply with age, implying that is much harder for older workers to arbitrage wage differentials. Moreover, in line with previous research by Neal (1995), this paper finds that sector-specific experience is imperfectly transferable across sectors, leading to additional barriers to mobility.

The estimated model was then used as a laboratory for counter-factual trade liberalization experiments. My findings indicate that: (1) The duration and magnitude of the transition are very sensitive to assumptions regarding the mobility of physical capital. (2) There is a large labor market response following trade liberalization but the transition may take several years. If capital is perfectly mobile or immobile, 95% of the reallocation of workers is completed only after 5 years. Under the assumption of imperfect capital mobility, and depending on its degree of mobility, this duration can be an order of magnitude longer. (3) Workers employed in High-Tech Manufacturing prior to the shock face substantial losses in welfare, especially those with higher educational attainment. (4) Adjustment costs - defined as the fraction of the potential gains from trade that are lost due to the slow and costly adjustment - may be as large as 16% to 42% depending on the degree of mobility of capital. (5) A moving subsidy that covers switching costs performs better than a retraining program in compensating the losers, although at the expense of higher welfare adjustment costs. (6) These last two labor market policies also have distinct implications for redistribution within the target population. Finally, (7) Costs of mobility appear to be more important than sector-specific experience in explaining the slow adjustment of the labor market.

The analyses in this paper show that high costs of inter-sectoral mobility are not inconsistent with large employment and small wage long-run price elasticities: following a shock wages can recover in the short to medium run due to a sluggish adjustment of physical capital. They also show that a model with costs of mobility, sector-specific experience and complete pass-through from tariffs to prices is not able to explain the lack of reallocation following large-scale trade reform in developing countries, as surveyed by Goldberg and Pavcnik (2007). Plausible alternative explanations for this lack of reallocation include incomplete pass-through from tariffs to prices, faster productivity growth in the adversely affected sectors and frictions in the mobility of physical capital across sectors. Assessing these alternative explanations are important directions for future work.

The different patterns in dynamics according to the degree of mobility of physical capital show that rigorously modeling physical capital accumulation and its degree of mobility together with workers' barriers to mobility is a very important direction for future research. This will require a deeper understanding of what should we understand by physical capital, what is its depreciation rate, how does it vary across industries, how much of it can be re-used in other sectors and at what rate can it be transferred.

This paper leaves unexplained what constitutes the costs workers face in switching sectors, apart from direct wage costs due to the accumulation of sector specific-experience and the presence of comparative advantage due to observable and unobservable components. An understanding of what constitutes these costs is of great importance. What features under the control of governments enter these costs and how important are they? To what extent these costs of mobility are explained by labor market regulations (e.g. firing costs), geographical mobility costs, search and matching frictions and imperfections in the credit market? Answering some of these questions will be very informative for governments willing to open their markets to foreign competition on what type of reforms may maximize the gains from trade.

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A Appendix - Solving The Bellman Equation

Given the parameter set Θ that fully parametrizes the economy (see Section 4.1), the distribution of initial conditions across the population, and real value added series for each sector, we can simulate individual choices and compute the sector-specific equilibrium human capital prices as described in Section 2.3.

The distribution of initial conditions is given by the joint distribution of gender, education, age and sector-specific experiences as found in the data in the first sample period, 1995. From 1996 onwards, I need to include the initial conditions of entering generations (those who are 25 years old) and keep track of the decisions generated by the model of the older generations.

In order to simulate the individual decisions for the parameter set Θ, I must first solve the Bellman equation given by (3) and (4). The Bellman equation is solved by backward recursion, starting at the terminal age $A = 60$ and terminal period T ($T = 2005$ in the estimation) and going back until the next to initial age of 26 is reached. Some difficulties arise in the solution of (3)-(4). First, in order to compute expectations, I must integrate the value function - which is a nonlinear and non-separable function of the state variables, including the human capital shocks - with respect to all idiosyncratic shocks (those affecting the human capital production functions and those affecting preferences for sectors). The multidimensional integrals with respect with the human capital idiosyncratic shocks do not have a closed form solution and hence must be approximated. Second, remember that the returns to skill $\left\{r_t^{0,k}\right\}_{k=1}^4$ or $\left\{r_t^{1,k}\right\}_{k=1}^4$ (current and future) are included in the state variables and these are continuous variables. Consequently, I have a large state space with continuous variables.

In order to deal with these problems in a way that still makes estimation feasible, I approximate the solution of the Bellman equation using similar methods as in Keane and Wolpin (1994), Rust (1994 and 1997), and the algorithm for computing the perfect foresight equilibrium as in Lee (2005). The method described in Lee (2005) is an iterative procedure for obtaining a fixed point between the sequence of human capital prices workers use in making decisions and those that arise in equilibrium. In short, for a fixed value of Θ, it imposes a simple way workers form expectations regarding future human capital prices in the first iteration (workers have static expectations - at each point in time workers forecast that future human capital prices will persist indefinitely with no uncertainty at the equilibrium prices that are currently formed). This will lead to an equilibrium sequence of human capital prices that arises under this static expectation assumption. The second iteration imposes that workers use these new equilibrium human capital prices in order to forecast future human capital prices, which leads to a new sequence of equilibrium prices that is the input of a third iteration. This iteration is repeated until convergence of the equilibrium sequence. See Lee (2005) for further details. I describe in the following paragraphs how the value functions are computed fixing a sequence of human capital prices workers use in forecasting the future.

Consider a worker with gender g, education level e, type h, age a at period t. Suppose that this worker chose to work at sector s in the previous period $t-1$ ($d_{t-1} = s$). That worker starts period t with sector-specific experience given by the vector **Exper** and faces current human capital prices for her skill level given by the vector $\mathbf{r}$. Further, that worker assumes that the future sequence of human capital prices she faces is given by $\left\{\mathbf{r}^*_{t+k}\right\}_{k=1}^{60-a}$, and that's fixed. Let $EMAX_{a,t}(g,e,h,s,\mathbf{Exper},\mathbf{r},\left\{\mathbf{r}^*_{t+k}\right\}_{k=1}^{60-a}) = E_{\boldsymbol{\varepsilon},\boldsymbol{\eta}}V_{a,t}(g,e,h,\mathbf{Exper},\mathbf{r},\left\{\mathbf{r}^*_{t+k}\right\}_{k=1}^{60-a},\boldsymbol{\varepsilon},\boldsymbol{\eta}|d_{t-1}=s)$ denote the expected value this worker gets at age a and time t, before the idiosyncratic shocks are revealed and before the age a choice is made.

Let

$$\Delta = \left\{ \left(exper^1,...,exper^4,r^1,...,r^4\right) \mid \sum_{s=1}^{4} exper^s \leq 9 \; ; \; \underline{r} \leq r^s \leq \overline{r} \right\}$$

$\underline{r}$ and $\overline{r}$ are lower and upper bounds for prices of human capital. For each age a, period t, gender g, education level e, type h and sector s, and given a sequence of future human capital prices $\left\{\mathbf{r}^*_{t+k}\right\}_{k=1}^{60-a}$ I approximate $EMAX_{a,t}\left(g,e,h,s,\left\{\mathbf{r}^*_{t+k}\right\}_{k=1}^{60-a},.\right)$ defined on Δ with the following backward recursion procedure.

Repeat the following algorithm for all $g \in \{Male, Female\}$, $e \in \{1,2,3,4\}$, $h \in \{1,2,3\}$, and $s \in \{0,1,2,3,4\}$.

1) Start with terminal simulation period $t = T$ and $a = A = 60$. Draw $N = 1500$ points at random

$$\left\{\boldsymbol{\delta}^n \equiv \left(exper^{1,n},...,exper^{4,n},r^{1,n},...,r^{4,n}\right)\right\}_{n=1}^{N} \in \Delta.$$

For each n, approximate $EMAX_{A,T}\left(g,e,h,s,\boldsymbol{\delta}^n\right)$ by first drawing idiosyncratic shocks $\boldsymbol{\varepsilon}$ and for each of these shocks integrate over $\boldsymbol{\eta}$. The distributional assumption regarding $\boldsymbol{\eta}$ yields a convenient closed-form solution for the integral over that variable (see McFadden (1981) and Rust (1994)). I then use Monte Carlo integration over 500 draws of vector $\boldsymbol{\varepsilon}$. In the terminal period T of the simulation ($T = 2005$ in the estimation procedure), I impose that the workers assume the period T equilibrium human capital prices will persist forever in the future (static expectations).

2) Approximate $EMAX_{A,T}\left(g,e,h,s,.\right)$ by fitting a complete second-order polynomial regression of $EMAX_{A,T}\left(g,e,h,s,\boldsymbol{\delta}^n\right)_{n=1}^{N}$ on $\left\{ \begin{array}{c} 1, exper^{1,n},...,exper^{4,n},r^{1,n},...,r^{4,n}, \\ r^{1,n}I\left(r^{1,n}>c^1\right),...,r^{4,n}I\left(r^{4,n}>c^4\right) \end{array} \right\}$

3) Follow the same approximation procedures and approximate $EMAX_{a,T}\left(g,e,h,s,.\right)$ for $a =$ 59,...,26 adopting static expectations and using equations (3) and (4). The use of static expectations here is only due to the fact that this is the terminal period. Otherwise, workers would have used the remaining future human capital prices that were fixed before the procedure.

4) Use equations (3) and (4) and repeat this procedure for $T-1$, with the additional detail that workers now assume that at T, human capital prices are given by the imposed value of $\mathbf{r}_T = \mathbf{r}^*_T$.

5) Repeat the whole procedure for $T-2, T-3, ..., 1$.

Ideally, $c_1,...,c_S$ should be chosen so as to obtain the best possible fit, but in this paper, I set $c_s = \frac{\underline{r^s}+\overline{r^s}}{2}$ in order to save computational time. I get, nevertheless, very good fit for the polynomial regressions ($R^2 > 0.97$ for all a, t, g, e, h, s).

B Appendix - Estimation Procedure

Here is how I proceed with the estimation.

1. Obtain the time varying human capital shares α_t^s using the skill level specific wage bills and value added Y_t^s for each sector $s = 1, ..., 4$. Remember that I impose the economy-wide skill share to be equal to 0.65, so the total wage bill must be corrected upwards.

2. Impose the inter-temporal discount factor to $\rho = 0.95$.

3. Estimate the auxiliary models with data from the panel of workers. Let $\widehat{\delta}$ denote the estimates of these models all stacked up in a single vector. This vector will be fixed throughout the estimation procedure.

4. Extract initial conditions from the panel of workers. The initial conditions consist of the empirical joint distribution of age, gender, education level and sector-specific experiences as found in the data. In 1995, I will have initial conditions for individuals aged 25 to 60 years old and after that, from 1996 to 2005, I will only have initial conditions for entering generations at the age of 25 (the age of entry into the model). 1,000 individuals for each cohort and skill level (skilled or unskilled) are sampled from the data, and adequately weighted by the size of their corresponding cohort and skill level. These are the individuals who will be used for simulating the model.

Steps 5 to 11 are embedded in an optimization routine.

5. Start with a set of structural parameters Θ, or obtain it through an optimization algorithm.

6. Algorithm for computing the perfect foresight equilibrium. If first iteration of that algorithm, solve for the Bellman equations using static expectations. If not first iteration, impose future human capital prices as those obtained in the previous iteration of the perfect foresight algorithm, and solve for the Bellman equations.

7. For $t = 1995, ..., 2005$ compute, by simulating the economy parametrized by Θ, the equilibrium vectors of human capital prices $\left\{r_t^{0,k}\right\}_{k=1}^4$ and $\left\{r_t^{1,k}\right\}_{k=1}^4$ that satisfy:

$$H_t^{0,s} = \sum_{a=25}^{60}\sum_{i=1}^{1000} N_{at}^0 h_{iat}^{0,s} d^s\left(\left\{r_t^{0,k}\right\}_{k=1}^4, \widetilde{\Omega}_{iat}\right) \quad s = 1, ..., 4$$

$$H_t^{1,s} = \sum_{a=25}^{60}\sum_{i=1}^{1000} N_{at}^1 h_{iat}^{1,s} d^s\left(\left\{r_t^{1,k}\right\}_{k=1}^4, \widetilde{\Omega}_{iat}\right) \quad s = 1, ..., 4$$

$$r_t^{0,s} = \alpha_t^{0,s}\frac{Y_t^s}{H_t^{0,s}} \quad s = 1, ..., 4$$

$$r_t^{1,s} = \alpha_t^{1,s}\frac{Y_t^s}{H_t^{1,s}} \quad s = 1, ..., 4$$

Where N_{at}^{skill} is the relative size of cohort with age a at year t and skill level $skill$, and d^s is a dummy for whether sector s is chosen, as function of the state variables. $\widetilde{\Omega}_{iat}$ is the state space of individual i of age a at time t, excluding current human capital prices but including the future human capital prices in the initially imposed sequence in step 6.

The economy is simulated by sequentially drawing the individual idiosyncratic shocks and computing the equilibrium human capital prices.

Save $\left\{(\mathbf{r}_t^*)^j\right\}_{t=1995}^{2005}$, the equilibrium sequence of human capital prices obtained in this step. Check for convergence of this sequence, comparing it to the sequence obtained in the previous iteration of the fixed point algorithm.

8. In case of convergence, go to 9. Otherwise, go back to 6.

9. Estimate the auxiliary models with the data that is simulated in step 7. Let $\widehat{\delta}^S(\Theta)$ denote the estimates of these models stacked up.

10. Compute the Indirect Inference loss function:

$$Q(\Theta) = \left(\widehat{\delta} - \widehat{\delta}^S(\Theta)\right)' \Omega \left(\widehat{\delta} - \widehat{\delta}^S(\Theta)\right) \tag{23}$$

$Q(\Theta)$ is a measure of the distance between $\widehat{\delta}$ and $\widehat{\delta}^S(\Theta)$. Ω is a positive definite weighting matrix.

11. Use an optimization routine to guess a new set of structural parameters Θ and go back to 5 until Q is minimized.

The procedure described above is illustrated in Figure 1.

C Appendix - Standard Errors

The Indirect Inference estimator is defined by:

$$\widehat{\Theta} = \arg\min_{\Theta} \left(\widehat{\delta} - \widehat{\delta}^S(\Theta)\right)' \widehat{\Omega} \left(\widehat{\delta} - \widehat{\delta}^S(\Theta)\right)$$

Where $\widehat{\Omega}$ is a positive definite matrix with $\Omega = p\lim \widehat{\Omega}$

Since the model is assumed to be correctly specified:

$$\delta_0 \equiv p\lim \widehat{\delta} = \delta(\Theta_0)$$

Define

$$\widetilde{g}^S(\Theta) \equiv \widehat{\delta} - \widehat{\delta}^S(\Theta)$$

$$\widetilde{g}^S(\Theta_0) = \widehat{\delta} - \delta_0 + \delta_0 - \widehat{\delta}^S(\Theta_0)$$

$$\begin{aligned}
\sqrt{N}\widetilde{g}^S(\Theta_0) &= \sqrt{N}\left(\widehat{\delta} - \delta_0\right) + \sqrt{N}\left(\widehat{\delta}^S(\Theta_0) - \delta_0\right) \\
&= \sqrt{N}\left(\widehat{\delta} - \delta_0\right) + \frac{\sqrt{N^S}}{\sqrt{S}}\left(\widehat{\delta}^S(\Theta_0) - \delta_0\right) \\
&\Rightarrow N\left(0, AVAR\left(\widehat{\delta}\right) + \frac{1}{S} AVAR\left(\widehat{\delta}^S(\Theta_0)\right)\right)
\end{aligned}$$

The first order condition to the minimization problem is:

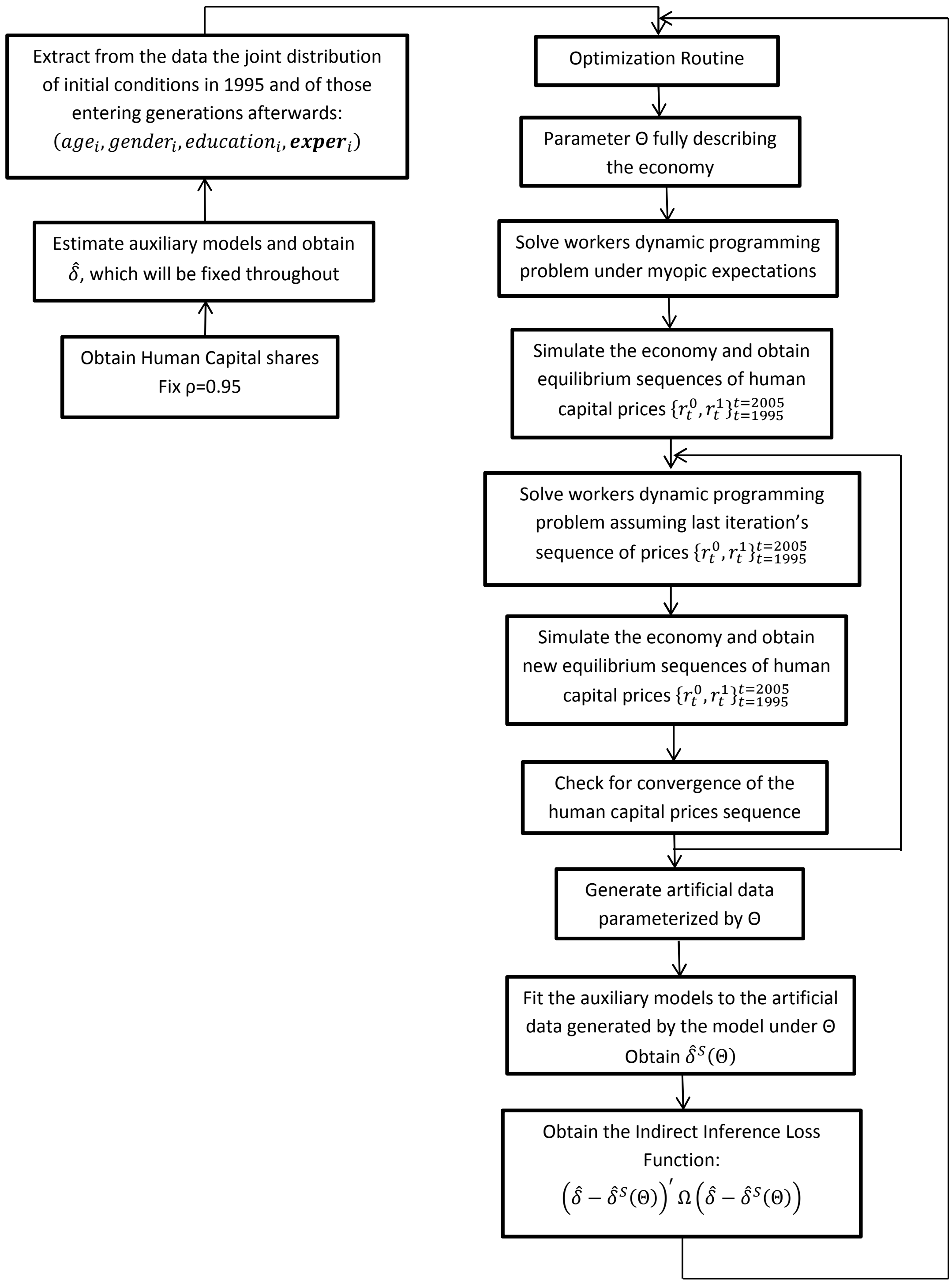

Figure 1: Estimation procedure

$$\frac{\partial \widetilde{g}^S\left(\widehat{\Theta}\right)}{\partial \Theta}\widehat{\Omega}\widetilde{g}^S\left(\widehat{\Theta}\right)=0$$

The mean value theorem applied to $\widetilde{g}^S\left(\widehat{\Theta}\right)$ gives:

$$\left(\frac{\partial \widetilde{g}^S\left(\widehat{\Theta}\right)}{\partial \Theta}\right)'\widehat{\Omega}\left(\widetilde{g}^S\left(\Theta_0\right)+\left(\frac{\partial \widetilde{g}^S\left(\overline{\Theta}\right)}{\partial \Theta}\right)\left(\widehat{\Theta}-\Theta_0\right)\right)=0$$

Where $\overline{\Theta}\in\left[\Theta_0,\widehat{\Theta}\right]$.

$$\sqrt{N}\left(\widehat{\Theta}-\Theta_0\right)=\left[\left(\frac{\partial \widetilde{g}^S\left(\widehat{\Theta}\right)}{\partial \Theta}\right)'\widehat{\Omega}\left(\frac{\partial \widetilde{g}^S\left(\Theta_0\right)}{\partial \Theta}\right)\right]^{-1}\left(\frac{\partial \widetilde{g}^S\left(\overline{\Theta}\right)}{\partial \Theta}\right)'\widehat{\Omega}\sqrt{N}\widetilde{g}^S\left(\Theta_0\right)$$

Taking the limit $N\to\infty$ (which implies $S\times N\to\infty$, for S fixed), we have:

$$\frac{\partial \widetilde{g}^S\left(\widehat{\Theta}\right)}{\partial \Theta}\xrightarrow{p}E\left[\frac{\partial g\left(\Theta_0\right)}{\partial \Theta}\right]\equiv G_0$$

$$\sqrt{N}\left(\widehat{\Theta}-\Theta_0\right)\Rightarrow N\left(0,\left(G_0'\Omega G_0\right)^{-1}G_0'\Omega\left[AVAR\left(\widehat{\delta}\right)+\frac{1}{S}AVAR\left(\widehat{\delta}^S\left(\Theta_0\right)\right)\right]\Omega G_0\left(G_0'\Omega G_0\right)^{-1}\right)$$

Consequently:

$$Var\left(\widehat{\Theta}-\Theta_0\right)\approx\left(G_0'\Omega G_0\right)^{-1}G_0'\Omega\left[\frac{AVAR\left(\widehat{\delta}\right)+\frac{1}{S}AVAR\left(\widehat{\delta}^S\left(\Theta_0\right)\right)}{N}\right]\Omega G_0\left(G_0'\Omega G_0\right)^{-1}$$

Plugging estimates for the above quantities:

$$\widehat{AVAR\left(\widehat{\delta}\right)}=N\times\widehat{Var\left(\widehat{\delta}\right)}$$
$$\widehat{AVAR\left(\widehat{\delta}^S\left(\Theta_0\right)\right)}=S\times N\times\widehat{Var\left(\widehat{\delta}^S\left(\Theta_0\right)\right)}$$

$$\widehat{Var\left(\widehat{\Theta}-\Theta_0\right)}=\left(\frac{\partial \widetilde{g}^S\left(\widehat{\Theta}\right)}{\partial \Theta}\widehat{\Omega}\frac{\partial \widetilde{g}^S\left(\widehat{\Theta}\right)}{\partial \Theta}\right)^{-1}\left(\frac{\partial \widetilde{g}^S\left(\widehat{\Theta}\right)}{\partial \Theta}\right)'\widehat{\Omega}\left[\widehat{Var\left(\widehat{\delta}\right)}+\widehat{Var\left(\widehat{\delta}^S\left(\Theta_0\right)\right)}\right]\times$$
$$\widehat{\Omega}\left(\frac{\partial \widetilde{g}^S\left(\widehat{\Theta}\right)}{\partial \Theta}\right)\left(\frac{\partial \widetilde{g}^S\left(\widehat{\Theta}\right)}{\partial \Theta}\widehat{\Omega}\frac{\partial \widetilde{g}^S\left(\widehat{\Theta}\right)}{\partial \Theta}\right)^{-1}$$

Although $\widehat{Var\left(\widehat{\delta}\right)}$ can be computed using the *GMM* equations that define $\widehat{\delta}$, the size of the problem makes the asymptotic variance have a very cumbersome expression. For this reason, $\widehat{Var\left(\widehat{\delta}\right)}$ will be computed by bootstrap.

Since the model is assumed to be correctly specified, $\widehat{Var\left(\widehat{\delta}^S(\Theta_0)\right)}$ can also be computed by bootstrap with the original data. The procedure is as follows: 1) extract 1000 individuals per generation and skill level from 1995 to 2005. 2) Repeatedly draw these individuals with replacement. 3) For each drawn sample j, fit $\widehat{\delta}^j = \left(X^{j\prime}WX^j\right)^{-1} X^{j\prime}WY^j$, where W is a weighting matrix that corrects for the sampling scheme.

C.1 Weighting Matrix

$$\widehat{W} = \begin{bmatrix} \widehat{V\left(\widehat{\beta}\right)}^{-1} & 0 & 0 & 0 \\ 0 & \widehat{V\left(\widehat{\gamma}\right)}^{-1} & 0 & 0 \\ 0 & 0 & \widehat{V\left(\widehat{\varphi}\right)}^{-1} & 0 \\ 0 & 0 & 0 & \widehat{V\left(\widehat{\sigma^2}\right)}^{-1} \end{bmatrix}$$

C.2 Computation of $\mathbf{G}_0$

1) For each component n of Θ, sample 20 points $\widehat{\Theta}+\varepsilon_n e_n$, where $|\varepsilon_n|$ is small and compute $\widehat{\delta}^S\left(\widehat{\Theta}+\varepsilon_n e_n\right)$.
2) Fit a second order polynomial of $\left\{\widehat{\delta}^S\left(\widehat{\Theta}+\varepsilon_n e_n\right)\right\}$ on $\left\{\widehat{\Theta}_n+\varepsilon_n\right\}$.
3) Obtain an approximation for $\left.\frac{\partial\delta}{\partial\Theta_n}\right|_{\Theta=\widehat{\Theta}}$ by looking at the derivative of the polynomial at $\widehat{\Theta}_n$.

D Appendix - Goodness of Fit

The Indirect Inference method is very similar to the Simulated Method of Moments. Suppose we had a single auxiliary model, $y = X\beta + \varepsilon$ and let the weighting matrix be $X'X$. The Indirect Inference loss function becomes:

$$\begin{aligned} Q(\Theta) &= \left(\widehat{\beta} - \widehat{\beta}^S(\Theta)\right)' X'X\left(\widehat{\beta} - \widehat{\beta}^S(\Theta)\right) \\ &= \left(X\widehat{\beta} - X\widehat{\beta}^S(\Theta)\right)'\left(X\widehat{\beta} - X\widehat{\beta}^S(\Theta)\right) \\ &= \left(\widehat{E}[y|X] - \widehat{E}[y(\Theta)|X]\right)'\left(\widehat{E}[y|X] - \widehat{E}[y(\Theta)|X]\right) \end{aligned} \tag{24}$$

Where $\widehat{E}$ denotes the best linear predictor operator and $y(\Theta)$ is the data generated by the model under parameter Θ.

In that case, Indirect Inference matches best linear predictors. Since the weighting matrix used in the Indirect Inference procedure described in Section 4.1 is block diagonal, with the blocks given by the standard variance of residuals times the inverse of the cross-product matrix, I use that intuition in investigating the goodness of fit of the model in Figures 2, 3 and 4. Each of these figures plots the best linear predictor in the data vs. the best linear predictor under the model conditional on time dummies, gender, education, age and experience for each individual observed in the data set. Figure 2 investigates log-wage fit, Figure 3 investigates sectoral choice fit and Figure 4 investigates transition rate fit. Overall, the model is able to match reasonably well best linear predictors in the data.

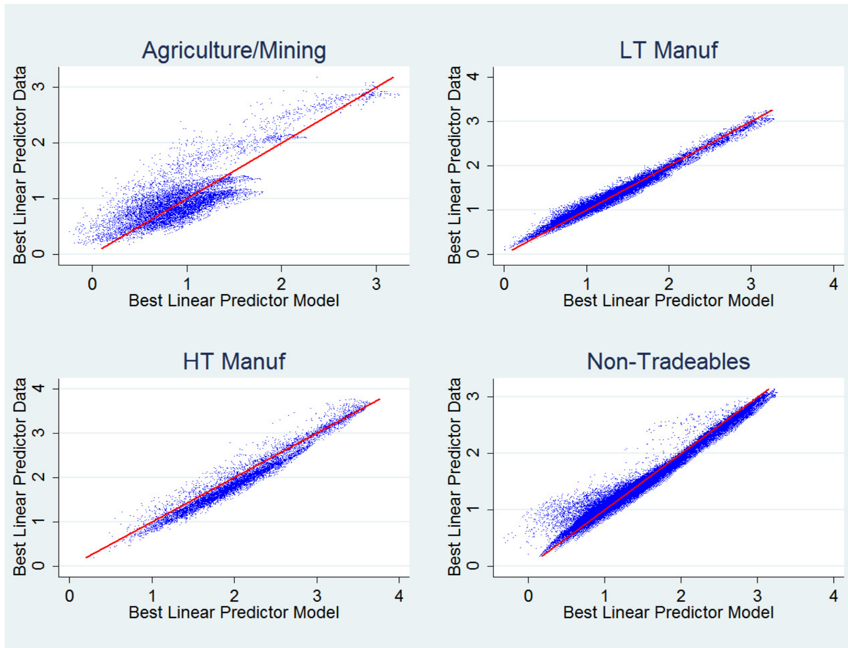

Figure 2: Goodness of Fit - Log Wage Regressions. The vertical axis displays the best linear predictors of log wages in the data. The horizontal axis displays the best linear predictors of log wages implied by the model. The distribution of the conditioning variables is extracted from the data. A perfect model fit would lead to all the points over the 45° line.

E Appendix - Steady State

The economy is simulated as follows:

1. The productivity terms $z_t^s \equiv p_t^s A_t^s$ $(s = 1, ..., 4)$ are recovered for $t = 2005$, the last period in the sample. In order to do that, we need to make an assumption on how physical capital is allocated. Since the economy-wide rental price of capital is what we can recover from the data, I assume efficient allocation, that is, marginal product of physical capital is equalized across sectors and equal to the rental price of physical capital in the data. It follows that:

$$K_{2005}^s = \frac{\left(1 - \alpha_{2005}^{0,s} - \alpha_{2005}^{1,s}\right) Y_{2005}^s}{r_{2005}^K} \quad s = 1, ..., 4$$

z_{2005}^s is is recovered as a residual of equation (1) for $s = 1, ..., 4$:

$$z_{2005}^s = \frac{Y_{2005}^s}{\left(H_{2005}^{0,s}\left(\widehat{\Theta}\right)\right)^{\alpha_{2005}^{0,s}} \left(H_{2005}^{1,s}\left(\widehat{\Theta}\right)\right)^{\alpha_{2005}^{1,s}} \left(K_{2005}^s\right)^{1-\alpha_{2005}^{0,s}-\alpha_{2005}^{1,s}}}$$

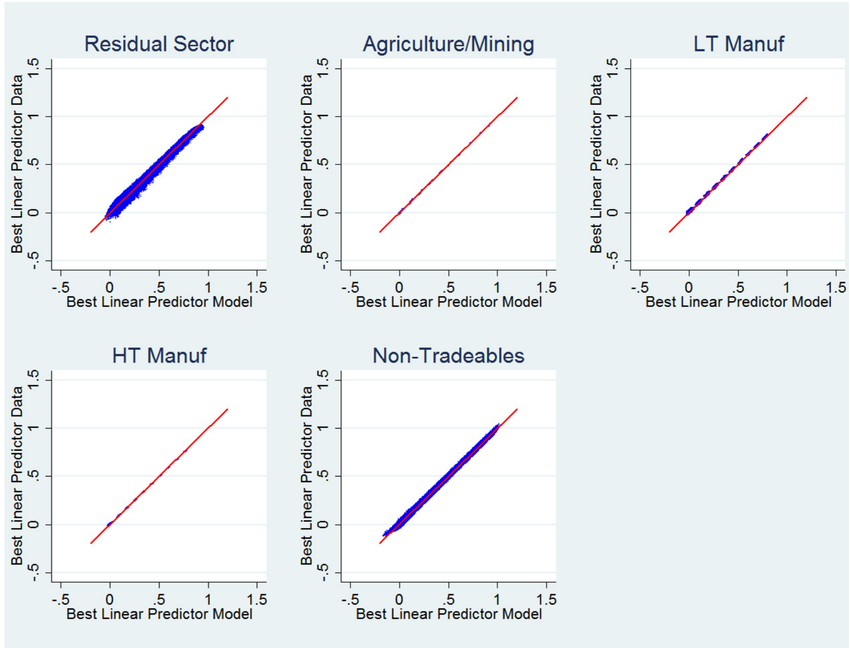

Figure 3: Goodness of Fit - Sectoral Choice Regressions. The vertical axis displays the best linear predictors of choices in the data. The horizontal axis displays the best linear predictors of choices implied by the model. The distribution of the conditioning variables is extracted from the data. A perfect model fit would lead to all the points over the 45° line.

Where $\widehat{\Theta}$ is the vector of estimated parameters.

2. Initially set $A^s_{2005} = z^s_{2005}$ $(s = 1, ..., 4)$. Prices of all sectors (except Non-Tradeables) are set to 1 in 2005 and throughout the simulation. The price of Non-Tradeables is determined in equilibrium.

For the simulations, $A^s_t = A^s_{2005}$ $(s = 1, ..., 4)$ for all t, productivity will be fixed over time. Analogously, the human capital shares will be fixed at their 2005 value.

3. Entering generations all look alike. The distribution of gender and education is given by the distribution of the cohort born in 1980 (last generation to enter the estimation, in 2005). The new generations enter the simulation with zero experience.

4. As a result of the previous step, the composition of the population will change as compared to 2005, since the entering generations will look different from the entering generations used in estimation. In particular, they will be more educated (the 1980 cohort is more educated than, say, the 1960 cohort). Consequently, the simulated economy will be richer in human capital than the economy used in estimation. I allow for the capital stock to accompany the growth in human capital. Hence, the economy-wide rental price of capital will be fixed to r^K_{2005} and the capital stock will be determined so that the marginal product of capital in each sector equals r^K_{2005}. Simulate this economy until the economy reaches a steady state. After the steady state is reached, the capital stock is fixed at the steady state level.

5. The steady state price for Non-Tradeables is then normalized to 1. The value of A^4_t is reset so that z^4_t satisfies (19).

6. Once the steady state is reached, the economy is shocked with a once-and-for-all tariff reduction that decreases the domestic price of High-Tech Manufacturing by 30%. That is, the new domestic price

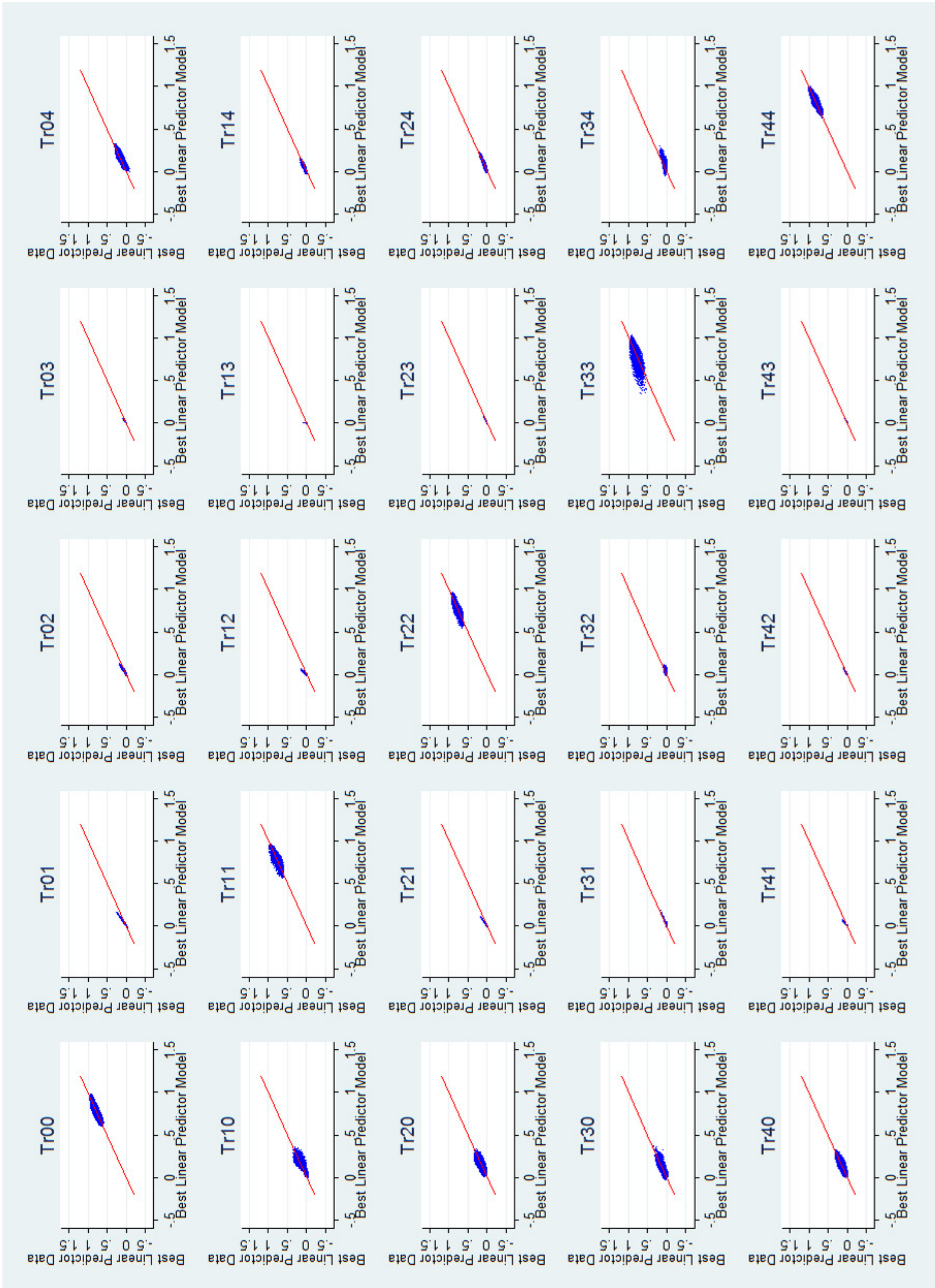

Figure 4: Goodness of Fit - Transition Rates Regressions. The vertical axis displays the best linear predictors of 1-year transition rates in the data. The horizontal axis displays the best linear predictors of 1-year transition rates implied by the model. The distribution of the conditioning variables is extracted from the data. A perfect model fit would lead to all the points over the 45° line.

of High-Tech Manufacturing is now of 0.7 and persists forever.

7. Price of Non-Tradeables and physical rental prices adjust endogenously to the shock. How the latter will adjust will depend on the assumptions made regarding the mobility of physical capital.