Trade Shocks, Firm-Level Investment Inaction, and Labor Market Responses*

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Abstract

When an export opportunity arrives, the gains from trade can only be materialized if the economy adjusts. In particular, in order to expand and meet new markets, firms must tune their capital stock by investing in product lines, machines and equipment. This process is costly and imperfect. Firms face convex and fixed investment costs, as well as investment irreversibility costs. These costs generate regions of firm inaction. When a trade shock occurs, some firms will be moved out of this inaction region and invest. But many other firms will remain in the inaction region, especially if the costs of adjustment are high. As a consequence, the economy reacts partially and gradually. This process, in turn, has implications for labor demand, employment and wages. To explore these issues with a dynamic model featuring a multi sector-economy with worker's mobility costs, heterogeneous firms and costly capital adjustment. We fit this model to plant-level panel data and household survey data from Argentina. We estimate the structural capital and labor adjustment cost parameters and we use them in counterfactual simulations. Under firm investment inaction in the presence of capital adjustment costs, the impacts of trade shocks can be very different from those derived from alternative models of capital mobility.

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1 Introduction

When an export opportunity arrives, the gains from trade can only be materialized if the economy adjusts. In particular, in order to expand and meet new markets, firms must tune their capital stock by investing in product lines, machines and equipment. This process is costly and imperfect, and, in fact, industry adjustment may be fully hindered. This, in turn, has implications for labor demand, employment and wages. In this paper, we study the role of costly capital adjustment on the dynamic response to a trade shock of investment, capital, employment and wages. It is noteworthy that the treatment of capital adjustment costs is succinct in the related trade literature. Artuç, Chaudhuri and McLaren (2010) assume fixed capital and Dix-Carneiro (2010) works out an example with arbitrary costs.[1]

Firms face different types of costs of capital adjustments. There are convex costs that induce firms to smooth investment over time. There are also non-convex, fixed, costs that create occasional investment bursts instead. And there are irreversibilities of investment when installed capital can be sold at a fraction of the purchasing prices. Overall, these costs generate regions of investment (and disinvestment) inaction. When a trade shock occurs, some firms will be moved out of this inaction region and invest. The economy thus adjusts. But many other firms will remain in the inaction region, especially if the costs of adjustment are high. As a consequence, the economy reacts partially and gradually. If the trade shock is large, or if a given trade shock arrives in a setting with lower costs, then the adjustment will be fuller and quicker.

To explore this theme, we formulate a dynamic structural model of trade with worker's intersectoral search and firm's capital accumulation decisions. Our framework combines the labor supply model with workers' mobility costs of Artuç, Chaudhuri and McLaren (2010) with the labor demand model with capital adjustment costs of Cooper and Haltiwanger (2006). The labor supply side is characterized by a rational expectations optimization problem of workers facing mobility costs and time-varying idiosyncratic shocks. The labor demand side is characterized by the rational expectations intertemporal profit maximization problem of firms facing costs for adjusting their capital stock and time-varying technology shocks.

[1]In contrast, imperfect labor mobility has been extensively studied. A branch of the literature focuses on workers' moving sectoral costs (Artuç, Chaudhuri and McLaren, 2010; Artuç, 2009; and Dix-Carneiro, 2010) and workers' sector-specific experience (Coşar, 2010; Dix-Carneiro, 2010; Davidson and Matusz, 2004; Davidson and Matusz, 2006; and Davidson and Matusz, 2010). Another set of explanations focuses on firm behavior and includes firing and hiring costs (Kambourov, 2009; Dix-Carneiro, 2010) and market search frictions (Coşar, 2010; and Coşar, Guner and Tybout, 2010). All these studies conclude that large adjustment costs may lead to large unrealized gains from trade.

We fit our model to plant-level panel data and household survey data from Argentina. We use the firm-level data to identify the technology and capital adjustment costs parameters that define labor demand. We use the panel component of the household survey data to identify the labor mobility costs parameters. We recover the structural parameters that characterize the frictions faced by both workers and firms. We then combine all these estimates to characterize the stationary steady-state of the economy. Finally, we use the estimated parameters and the solution of the equilibrium to simulate counterfactual adjustments of investment, capital, labor allocations and wage distributions across sectors after a trade shock.

Our findings show that the costs of adjustment matter. A positive shock to the Food & Beverages sector, whose domestic price increases, triggers a gradual increase of the capital stock. To cover 75-95 percent of the transition to the new steady state takes between five and nine years. In turn, this also triggers a relatively sluggish response of the labor market. Real wages increase at first in Food and Beverages but decline elsewhere. Workers gradually reallocate towards Food and Beverages, and wages in the sector start to decline (while real wages in all other sectors slightly recover). As the price shock becomes larger, the economy responds more and, in addition, it becomes proportionately more responsive. This is because higher price changes make a larger proportion of firms to move out of the inaction region. As expected the economy adjusts much more abruptly and quickly in the absence of adjustment costs. These costs generate short-run firm investment inaction for 4-5 years following a trade shock. These results are magnified when the trade shock is bigger. Finally, we find heterogeneous firm-level investment responses. High-technology firms respond more than low-tech firms. They also respond proportionately more when the price shock is larger. This is because the inaction region is smaller for these firms. With reduced costs of capital adjustment, this heterogeneity dissipates.

The paper is organized as follows. In section 2, we discuss the theoretical model of firm and worker behavior in the presence of capital adjustment costs and labor mobility costs. In section 3, we discuss the data, the estimation strategy and the main results. In section 4, we compute the stationary rational expectations equilibrium of the model and we estimate the effects of trade liberalization on labor market by performing counterfactual simulations. Finally, section 5 concludes.

2 The Model

In this section, we develop the structural model that we use to explore how the economy adjusts to a trade shock in the presence of factor adjustment costs. Firms face capital adjustment costs, as in Cooper and Haltiwanger (2006), and workers face labor mobility costs, as in Artuç, Chaudhuri, and McLaren (2010).[2] The dynamic optimization problem of the firms delivers a set of supply functions for outputs and a set of demand functions for labor in each of the sectors, given the goods prices and the costs of adjusting capital. The behavior of firms is described in section 2.1. Workers maximize utility. They choose a consumption bundle, given their income and the goods prices, and they choose a sector of employment, given the costs of mobility. Their behavior is described in section 2.2. The equilibrium of the economy is discussed in section 2.3.

2.1 Firms: Labor Demand and Output Supply

Our model of firm behavior is based on Cooper and Haltiwanger (2006). The purpose of the model is to derive labor demand and output supply functions of different sectors in the presence of costly capital adjustment. There are J sectors in the economy, a manufacturing (traded) sector and a large non-manufacturing/non-tradable sector. The manufacturing sector is, in turn, composed of J_m exportable and importable sub-sectors.[3] Each sector is composed of a continuum of firms.

In a given sector j, production technology is Cobb-Douglas:

$$(1) \quad Q^j_{ft}(\widetilde{A}^j_{ft}, K^j_{ft}, L^j_{ft}) = \widetilde{A}^j_{ft} K^{\alpha^j_k}_{ft} L^{\alpha^j_l}_{ft},$$

where $\widetilde{A}^j_{ft}$ is an idiosyncratic productivity shock faced by firm f in sector j at time t, K^j_{ft} is the

[2] Alternatively, we could assume that firms face both capital and labor adjustment costs as in Bloom (2009), while workers can move freely across sectors. We prefer our setting for various reasons. First, note that we cannot have both labor adjustment costs on the firm side and labor mobility costs on the workers side. This is because Artuç, Chaudhuri, and McLaren (2010) is a discrete choice model, and any worker who chooses a sector must get a job in that sector. This is not guaranteed with hiring and firing costs on the firms side, for instance. In Coşar (2012), firms and workers interact through a matching process. Second, faced with a choice, we adopt Artuç, Chaudhuri, and McLaren (2010) because it has become a leading model of trade with imperfect labor mobility. This model can explain large inter-industry wage differentials and can create bilateral flows of ex-ante homogenous workers across sectors. Both features are observed in the Argentine data used to estimate the model below. Only large differences in labor hiring and firing costs across sectors could explain the same phenomenon. Our data, however, are not rich enough to identify sector-specific labor adjustment costs. Furthermore, while we can estimate the parameters of Artuç, Chaudhuri, and McLaren (2010) model, our data are not rich enough either to estimate the parameters of a matching function. Research embedding the three sources of factor adjustment costs is therefore pending.

[3] In the implementation of the model in section 3, J_m=5, namely Food and Beverages; Apparel, Leather and Textiles; Nonmetallic Minerals; Primary Metals and Fabricated Metal Products; Other Manufactures. There are thus $J = 6$ sectors in the economy.

capital stock and L_{ft}^j is the labor input. Firms differ in $\widetilde{A}$, so that the productivity shocks are a source of firm heterogeneity (as in Melitz, 2003). Different levels of technology trigger firm-level heterogeneous investment decisions. This determines the demand for labor, thus affecting wages and labor allocations. α_k^j and α_l^j are estimable parameters.

We assume that all manufactures are tradable. The country is small and faces exogenously given international prices p^{j*}. The government sets trade taxes at the rate $\tau^j > 0$, in the case of imports, or $\tau^j < 0$, in the case of exports. Domestic prices faced by producers are $p^j = p^{j*}(1+\tau^j)$. In the non-manufacturing sector, prices are endogenously determined. In each industry, we assume that products are homogenous and that firms compete perfectly. We assume decreasing returns to scale due to fixed factors such as "managerial capacity," as in Friedman (1962). Since firms are heterogeneous in productivity and prices are exogenous, this is important to prevent the most productive firms to completely sweep the market.[4]

Investment becomes productive with a one period lag. Capital accumulation is given by:

$$(2) \quad K_{f,t+1}^j = (1-\delta)K_{ft}^j + I_{ft}^j,$$

where I_{ft}^j denotes gross investment and δ is the capital depreciation rate.

For a given level of the capital stock (which is predetermined at t), firms choose labor to maximize instantaneous profits (see Appendix A.1). Operating profits π_{ft}^j, i.e, the maximized short run profits with respect to the labor input for given capital stock and factor prices, are given by:

$$(3) \quad \pi_{ft}^j(A_{ft}^j, K_{ft}^j; w_t^j; \tau^j) = \varphi(w_t^j, \tau^j)A_{ft}^j K_{ft}^{\theta^j},$$

where $\varphi(w_t^j)$ is a function of the nominal wage paid by firms in sector j at time t (w_t^j) and A_{ft}^j is a "profitability shock," which combines productivity shocks ($\widetilde{A}_{ft}^j$) and shocks to international prices (p^{j*}). The parameter θ^j comprises technology parameters and is thus an estimable parameter.[5]

The decision of the firm is to choose optimal investment in order to maximize intertemporal discounted operating profits. This intertemporal maximization problem is characterized by two key

[4] It is theoretically straightforward to work with a monopolistic competition model as in Melitz (2003). However, the assumption of fixed international prices seems more realistic for a small Argentine manufacturing sector. In addition, the monopolistic competition model requires a larger number of unknown parameters, such as elasticities of substitution, number of varieties, and so on, that can complicate the already complex estimation method. See Coşar (2012) and Coşar, Gunar, and Tybout (2011) for monopolistic competition models.

[5] See appendix A.1 for details on the derivation of equation (3) as well as on the functional forms corresponding to $\varphi(w_t^j)$, A_{ft}^j and θ^j.

elements of the model: the evolution of the profitability shocks and the nature of the costs of capital adjustment. As is standard in the literature, we assume that the natural log of A follows a Markov process with transition function χ. The estimable parameters associated with the profitability shocks, i.e., the moments of the first order autoregressive Markov process, is denoted by Θ_a.

To model capital adjustment costs, we adopt the specification in Cooper and Haltiwanger (2006), which includes three types of costs: fixed adjustment costs, quadratic adjustment costs, and partial investment irreversibilities:

$$(4)\, G^j_{ft}(K^j_{ft}, I^j_{ft}, A^j_{ft}) = FK^j_{ft}\, 1[I^j_{ft} \neq 0] + \frac{\gamma}{2}(I^j_{ft}/K^j_{ft})^2 K^j_{ft} + p_b I^j_{ft}\, 1[I^j_{ft} > 0] + p_s I^j_{ft}\, 1[I^j_{ft} < 0],$$

where $1[I^j_{ft} \neq 0]$ is an indicator variable equal to one if investment is non-zero, and $1[I^j_{ft} > 0]$ and $1[I^j_{ft} < 0]$ are indicator variables equal to one if investment is strictly positive and negative respectively. The first term captures fixed adjustment costs, which are independent of the investment level and are paid whenever investment (or disinvestment) takes place. In (4), F measures the magnitude of fixed capital adjustment costs in terms of the average level of capital at the plant-level. F is an estimable parameter. This component is related to non-convexities in the functional form of the cost of adjustment. Cooper and Haltiwanger (2006) argue that these costs capture indivisibilities in capital, increasing returns to the installation of new capital and increasing returns when restructuring the production activity. We assume that these costs are proportional to the level of capital at the plant level. Note that these costs become more relevant as the firm grows larger. In addition, they can be avoided by choosing zero investment.[6]

The second term in (4) captures the quadratic adjustment costs, which are measured by the estimable parameter γ. These are variable costs that increase with the level of the investment rate. Variable costs are higher when the investment rate changes rapidly. We assume these costs are proportional to the level of capital at the plant-level. These costs are motivated by the observation in Dixit and Pindyck (1994) who argue for the existence of increasing costs in the incorporation new capital, in the reorganization of production lines and in worker's training. These costs can be

[6]Fixed costs can also be modeled as proportional to the level of sales at the plant-level. See for example Bloom (2009), Cooper and Haltiwanger (2006), Caballero and Engel (1999). In particular, Caballero and Engel (1999) estimate a model where fixed costs are random. These modeling assumptions on fixed costs imply a decrease in firm's productivity during investment periods. Thus, large investments are less costly during periods of low profitability as adjustment costs are low. This does not necessarily imply a negative correlation between investment and profitability shocks, since there is a gain to investment in high profitability states if there is enough serial correlation in the profits to the shocks. We do not incorporate this fixed costs specification into the model because it generates noise in the measure of profitability shocks. In particular, it is necessary to disentangle capital adjustment costs from low productivity realizations.

avoided by choosing zero investment.

Finally, the last two term in (4) captures partial irreversibilities related to transactions costs and capture reselling costs, capital specificity and asymmetric information (as in the market for lemons). These costs are incorporated into the model by assuming a gap between the buying p_b and selling price p_s of capital so that $p_b > p_s$. The presence of irreversibilities generates a region of inaction for the firm. Following a negative shock firms may hold on capital in order to avoid reselling losses; conversely, in periods of high profitability, firms may choose not to increase the capital stock as much in anticipation of eventual future costs of selling that capital. In the estimation, we let $p_b = 1 \geq p_s$. The selling price p_s is thus an estimable parameter.

The firm's problem is to maximize the present discounted flow of operating profits net of adjustment costs, by choosing the investment level (I^j_{ft}) in each period. The Bellman equation is:

$$(5) \quad V^j_{ft}(A^j_{ft}, K^j_{ft}; w^j_t) = \max_{I^j_{ft}} (\pi^j_{ft}(A^j_{ft}, K^j_{ft}; w^j_t) - G^j_{ft}(A^j_{ft}, K^j_{ft}, I^j_{ft}) + \beta_0 E_t V^j_{f,t+1}(A^j_{f,t+1}, K^j_{f,t+1}; w^j_t)),$$

where $\beta_0 \in (0,1)$ is a discount factor, E_t is the expectation operator conditional on information available at time t, and $E_t V^j_{f,t+1}(A^j_{f,t+1}, K^j_{f,t+1}; w^j_t; \tau^j) = \int V^j_{f,t+1}(A^j_{f,t+1}, K^j_{f,t+1}; w^j_t; \tau^j)\chi(a, da_{t+1})$.

The solution to the Bellman equation leads to the following policy function:

$$(6) \quad I^j_{ft} = g(K^j_{ft}, A^j_{ft}; w^j_t),$$

which is a function of the state variables of the firm (K, A) and the nominal wage rate (w) (as well as the trade tax τ).

We can now derive the firm labor demand and total aggregate demand. Recalling that variable inputs can be adjusted without costs, the labor demand for a firm with state variables (K, A) is:

$$(7) \quad L^d(K^j_{ft}, A^j_{ft}; w^j_t; \tau^j) = \frac{\alpha^j_l}{(1-\alpha^j_l)} \frac{\pi^j_{ft}(K^j_{ft}, A^j_{fj}; w^j_t; \tau^j)}{w^j_t}$$

Aggregate labor demand at time t in sector j is therefore given by:

$$(8) \quad N^j_t = \int\int L^d(K^j_{ft}, A^j_{ft}; w^j_t; \tau^j)\, \mu^j(dK \times dA),$$

where $\mu^j(dK \times dA)$, the cross-section steady-state distribution of (K, A), satisfies:

$$(9) \quad \mu^j(\Lambda \times Z) = \int 1_{g(K,A;w;\tau)\in\Lambda} \chi(A, Z) \mu_j(dK \times dA),$$

for all sets Λ and Z.

At time t, the capital stock is predetermined. Given K and the realization of the profitability shock, profit maximization delivers optimal levels of labor demand, as well as, given the costs of adjustment, the optimal level of investment. This determines the supply of goods. For manufacturing, since goods are tradable goods and prices are exogenously determined, firms sell all their output at those prices. Instead, prices for non-manufactures must clear the market. The model also delivers an aggregate labor demand in each sector. Wages must adjust to equate demand and supply.

2.2 Workers: Labor Supply and Output Demand

To characterize the behavior of workers, we follow the labor mobility costs model of Artuç, Chaudhuri, and McLaren (2010) and Artuç (2012). The economy is populated by a continuum of homogeneous workers with measure $\bar{L}$. The utility function of a worker is assumed to be Cobb-Douglas. The demand for traded good j is D_t^j at prices $p^{j*}(1 + \tau^j)$. The demand for non-tradable goods is D_t^o, which must equal supply at equilibrium prices. The indirect utility function of the worker is $v(p, \iota) = \iota/\vartheta(\mathbf{p})$, where $\mathbf{p}$ is a J dimensional vector price, ι is income, and ϑ is a linear-homogeneous consumer price index.

All individuals are risk neutrals, have rational expectations, and share a common discount factor $\beta_1 < 1$.[7] In each period of time, each individual works in one of the j sectors (the J_m manufacturing sectors or the non-traded sector) in the economy. A worker $l \in [0, \bar{L}]$ in sector j at time t produce in sector j and earn the market wage for that sector. Instantaneous utility u_t^j at time t is defined as

$$(10) \quad u_t^j = w_t^j + \eta^j,$$

where w_t^j is the observed sector specific wage common to all agents working in sector j, and η^j is the unobserved sector specific iid utility shock also common to all agents. This shock acts as a sector compensating differential.

At the end of the period, the worker has the option of moving to another sector at a cost. Workers

[7] Note that β_1 could in principle be different from β_0, the discount factor of the firms.

can move within manufacturing sectors and also between tradable and non-tradable sectors. The mobility costs have two components, a common component and an idiosyncratic component. The common cost of moving from sector j to sector k is C^{jk}. These costs are the same for all periods and publicly known. We assume that $C^{jj} = 0$ for all j.

For worker l, the idiosyncratic benefit of being in sector j in period t is ε^j_{lt}. These benefits are independently and identically distributed across individuals, sectors and dates. As it is standard in discrete choice models, we assume that ε is distributed iid extreme value type I with location parameter $-\nu\gamma$, scale parameter ν, and cdf $F(\varepsilon) = \exp(-\exp(-\varepsilon/\nu - \gamma))$, where $E(\varepsilon) = 0$, $Var(\varepsilon) = \pi^2\nu^2/6$ and γ is the Euler's constant.

The total cost for worker l of moving from sector j to k can be expressed as $\varepsilon^j_{lt} - \varepsilon^k_{lt} + C^{jk}$. Workers know the values for ε^j_{lt} for all j before making the moving decision (in period t). The costs C^{jk}, the variance of the idiosyncratic utility shocks ν, and the compensating differentials η^j are estimable parameters. In the estimation, we impose some restrictions on C^{jk} due to data constraints. In particular, we will assume a common cost C^m within the manufacturing sectors and a cost C^{nm} for movements between manufacturing and non-manufacturing sectors. The parameter set is therefore $\Theta_C = \{C^m, C^{nm}, \nu, \eta^j\}$.

The worker's problem is to maximize the expected discounted value of being in a sector (net of mobility costs), by choosing in each period the sector of employment. This decision is based on the current labor allocation vector L_t across sectors, on the current aggregate labor demand vector N_t across sectors (which depends on the current distribution of state variables K and A), and on the vector of idiosyncratic shocks ε_{lt}. Let $U^j_l(L, N, \varepsilon)$ be the maximized value of being in sector j given the current allocation of labor L; the aggregate labor demand N, and the idiosyncratic shock ε. Denote by $W^j_l(L, N)$ the expectation of $U^j(L, N, \varepsilon)$ with respect to the vector ε. Thus, $W^j_l(L, N)$ can be interpreted as the expected value of being in sector j, conditional on L and N, but before the worker learns her value of ε. The individual optimizing behavior can be expressed as:

$$(11)\quad U^j_l(L_t, N_t, \varepsilon) = \widetilde{w}^j_t + \eta^j + \max_k\{\varepsilon^k_{lt} - C^{jk} + \beta_w E_t[W^k_l(L_{t+1}, N_{t+1})]\},$$

where $\widetilde{w}^j_t$ is the real wage. Note that the expectation on (11) is taken with respect to aggregate labor demand, N_{t+1}, conditional on all information available at time t. The next period aggregate labor demand, N_{t+1}, is determined by the distribution of the state variables A and K. On the other hand, L_{t+1}, the next period labor supply, is derived from the current allocation L_t and the workers' decision rules.

To derive the evolution of labor supply, we need to take the expectation of (11) with respect to the agent-specific shocks, and then write the choice-specific value function as (dropping the agent superscript l for notational convenience):

$$(12)\quad W_t^j(L_t, N_t) = \widetilde{w}_t^j + \eta^j + E_t \max_k \left\{ \beta_w E_t[W_l^k(L_{t+1}, N_{t+1})] - C^{jk} - \varepsilon_t^k \right\}.$$

Rearranging, we get

$$(13)\quad W_t^j(L_t, N_t) = \widetilde{w}_t^j + \eta^j + \beta_1 E_t W_{t+1}^j + E_t \max_k \{\varepsilon_t^k + \bar{\varepsilon}_t^{jk}\},$$

where

$$\bar{\varepsilon}_t^{jk} = [E_t W_{t+1}^k - E_t W_{t+1}^j] - C^{jk}.$$

Then, the choice-specific values can be written as

$$(14)\quad W_t^j = \widetilde{w}_t^j + \eta^j + \beta_1 E_t W_{t+1}^j + \Omega_t^j,$$

where the option value, Ω_t^j, is the extra utility generated by being able to change sectors. As moving costs C increase, the option value decreases, and it diminishes to zero when the moving cost goes to infinity. Artuç (2012) shows that

$$(15)\quad \Omega_t^j = \nu \log \sum_k \exp\left((E_t W_{t+1}^k - E_t W_{t+1}^j - C^{jk}) \frac{1}{\nu} \right).$$

Let m_t^{jk} be the fraction of agents who switch from sector j to sector k. This can be interpreted as gross flows from j to k, or the probability of choosing k conditional on j. The total number of agents moving from j to k is equal to $y_t^{jk} = L_t^j m_t^{jk}$, where L_t^j is the number of agents who are in j at time t. Under the extreme value distributional assumption, the gross flow m_t^{jk} can be written as

$$(16)\quad m_t^{jk} = \frac{\exp\left(\left(E_t W_{t+1}^k - E_t W_{t+1}^j - C^{jk} \right) \frac{1}{\nu} \right)}{\sum_{i=1}^{J} \exp\left(\left(E_t W_{t+1}^i - E_t W_{t+1}^j - C^{ij} \right) \frac{1}{\nu} \right)}.$$

The transition equation governing the allocation of labor between sectors is thus given by:

$$(17)\quad L^j_{t+1} = \sum_{k \neq j} m^{kj}_t L^k_t + m^{jj}_t L^j_t.$$

This shows that, on aggregate, the individual decisions at time t determine the labor supply to each sector j at time $t+1$.

2.3 Equilibrium

Here, we describe the stationary competitive equilibrium for the economy. All tradable sectors face exogenous prices, with domestic prices equal to international prices plus trade taxes. Equilibrium prices for non-tradable goods must equate domestic supply to domestic demand. We assume competitive spot labor markets in every sector j, both within manufactures and in the non-tradable sector. As a consequence wages in each sector are determined by the interaction between labor supply and demand.

The timing of events can be summarized as following:

$$(18)\quad \overset{t}{\Longrightarrow} \begin{array}{ccccc} \text{Workers} & \xrightarrow{\varepsilon^j_{lt},\ \varepsilon^k_{lt}} & & m^{jj}_t, m^{jk}_t & \overset{t+1}{\Longrightarrow} L^j_{t+1} \\ & \searrow & & \nearrow & \\ & & \left.\begin{array}{c} L^j_t \\ N^j_t \end{array}\right\} \Rightarrow w^j_t & & \\ & \nearrow & & \searrow & \\ \text{Firms} & \xrightarrow[\{K^j_{ft}\},\{A^j_{ft}\}]{} & & \{I^j_{ft}\} & \overset{t+1}{\Longrightarrow} N^j_{t+1} \end{array} \qquad \forall k \neq j\ .$$

The current labor supply, together with the aggregate labor demand in each sector, determines wages through spot labor market clearing. Then, given each firm's current profitability shock, the capital stock, and the equilibrium wage paid in the sector, firms choose investment in period t. These decisions determine the following period's $(t+1)$ labor demand for each sector. On the other hand, each worker observes the allocation of wages between sectors and her idiosyncratic shock ε and decides whether to remain in her current sector or move. In the aggregate, these decisions determine the following period's labor supply.

A stationary equilibrium for this economy is defined as a set of value functions V^j for firms in the manufacturing and non-tradable sectors; a set of policy functions $I^j = g(K, A; w^j; \tau^j)$; a set of value functions W^j for workers; a set of distribution functions μ^j; aggregate quantities N_t^j and L_t^j; a price for non-tradable goods p_o; and a vector of constant wages w^j for all sectors such that:

1. The value function V^j and the policy function $I^j = g(K, A; w; \tau)$ solve the firm's problem (5) for each firm;

2. The distribution μ is invariant (self-preserving); i.e. $\mu' = \mu$ in equation (9).

3. The value function W^j, the vector of wages w^j, and the price p_o solve the workers' problem (14) for all j.

4. The labor market in each sector clears; i.e, there is a vector of wages w^j such that:

$$\int\int L^d(K_{ft}^j, A_{ft}^j; w_t^j; \tau^j)\ \mu^j(dK \times dA) = \bar{L}_t^j \quad \forall j \tag{19}$$

5. The product market in the non-tradable sector clears; i.e, there is a price p^o such that $p^o Q^o = p^o D^o = \lambda_o(Y)$, where λ_o is the expenditure share on non-tradable goods and Y is the total income in the economy (including the value of output and any tax revenue).

The details of the numerical calculation of the equilibrium are given in section 4.

3 Estimation

In this section, we discuss how we estimate the different components of the theoretical model. The model is fully characterized by a parameter vector $\Theta = (\alpha_l, \alpha_k; \Theta_a; F, \gamma, p_s; \Theta_C; \beta_0, \delta, \beta_1)$, which comprises parameters related to the firm's and worker's decision problems. We estimate the parameters associated with each of these problems separately, relying on different methodologies. We begin with firm choices in section 3.1, and we move to worker choices in section 3.2.

3.1 Firms

The estimation of the firm's problem requires panel data with detailed information on the investment decision of the firms. In particular, to fit the capital adjustment cost model, we need data on purchases of new capital as well as on sales of installed capital. We estimate the model using an Argentine manufacturing survey, the Encuesta Nacional Industrial (National Industrial Survey), which meets these requirements. Note that the ENI covers only the manufacturing sector.[8]

We use a balanced panel from the ENI consisting of 568 Argentine manufacturing plants for the period 1994-2001. The ENI dataset provides information on gross revenue, costs, intermediate inputs, employment, consumption of energy and fuels, inventory stock, and both gross expenditures and gross sales of capital.[9] Information on gross capital sales is important in order to estimate the role of partial irreversibility in the capital adjustment costs structure. Table 1 presents some summary statistics on gross revenue, value added, capital stock, investment, intermediate materials (all of them expressed in constant 1993 pesos), and labor (production workers). The highest capital stock is in Fabricated Metals, followed by Nonmetallic minerals, Others, and Food and Beverages. The capital stock in Apparel and Textiles is in contrast low. In terms of employment of production workers, the largest sectors are Nonmetallic Minerals and Fabricated Metals, followed Food and Beverages, Apparel and Others.

The firm's model is defined by a parameter vector $\Theta_f = (\alpha_l, \alpha_k; \Theta_a; F, \gamma, p_s; \beta_0, \delta)$, which describes the curvature of the production function, the structure of the stochastic process governing the profitability shocks, the capital adjustment costs function, the intertemporal discount factor, and the depreciation of capital. Since the firm's problem does not have a closed form solution, we recover the main parameters of interest with a simulated method of moments estimator, as in Cooper and Haltiwanger (2006) and Bloom (2009).[10] In principle, all the parameters of the model could be estimated simultaneously with this method but this strategy puts a heavy burden on the data and requires huge computing power. To simplify the estimation, we follow Cooper and Haltiwanger (2006) and combine different strategies to recover different parameters.

To begin with, we set the depreciation rate δ at 9.91% (for all firms) and we assume a firm discount factor (β_0) of 0.95, common to all firms in all sectors.

To estimate the production function parameters, we follow Olley and Pakes (1996). Since many firms report zero investment, we use materials as a proxy (Levinsohn and Petrin, 2003). Also, since there are relatively few firms in each sector, we estimate a common set of technology parameters for all firms. Results are reported in column 1 of Table 2. The labor coefficient is 0.5892 and the capital

[8] See below for the non-manufacturing sector strategy.

[9] For a discussion of these variables, see Appendix A.2.

[10] See Ruge-Murcia (2007, 2012) for a comparative analysis of different methods to estimate dynamic stochastic general equilibrium models.

coefficient is 0.1420 which are both statistically significant. The implied value of θ is 0.3457.[11] As already explained, the model exhibits decreasing returns to scale because of the presence of fixed factors.

The ENI surveys firms in the manufacturing sector, and we do not have comparable data to estimate the parameters of technology for the non-tradable sector. However, it is important to include this sector in the analysis because it accounts for almost 80 percent of employment in Argentina. To do this, we calibrate, rather than estimate, the parameters of the production function. We set the values α_l, α_k and the mean of the profitability shock (A) to minimize a quadratic loss function. In particular, for any set of parameter values for the non-traded sector, we compute the aggregate steady state level of capital as well as the predicted employment level (given the observed sectoral wages). Then, the loss function matches the predicted sectoral employment, the predicted ratio of non-manufacturing to manufacturing capital, and the predicted shares of labor and capital in revenue with their observed counterparts. Information on aggregate capital by sector and the capital share of revenue come from the National Institute of Statistics and Census of Argentina (INDEC) input-output matrix for the year 1997, while information on employment and wages come from our dataset.

The calibrated parameters for the non-manufacturing sector are displayed in column 2 of Table 2. The labor coefficient is 0.3402 and the capital coefficient is 0.1153. There are also strong decreasing returns to L and K in the non-manufacturing sector, with an implied value for θ of 0.0884.

The structure of the profitability shock A^j_{ft} is a fundamental piece in the estimation of the adjustment costs parameters. As in Cooper and Haltiwanger (2006), we model profitability shocks for firm f through the interaction of an aggregate shock (b_t) and an idiosyncratic shock (e_{ft}):

$$(20) \quad \ln A^j_{ft} = b_t + e_{ft}.$$

We measure the left-hand side with $\varphi(w^j_t, \tau^j)A^j_{ft}$ from equation (3) using data on firm's profit (π^j_{ft}), capital (K^j_{ft}), and the estimate of the production function (θ). This implies that shocks to wages are assumed to affect the profitability of the firm (even when wages are deterministic in the model). In turn, trade taxes are assumed to be fixed across time (but any random variation is also assumed to be part of the aggregate profitability). We compute b_t as the mean (by year) of $\ln A^j_{it}$ and the idiosyncratic component (e_{ft}) is given by the difference between these two quantities. To simplify,

[11] These results are comparable to those obtained by Pavcnik (2002) for Chile, for example.

these parameters are also common to all firms.

We model b_t as a first order, two-state, Markov process with symmetric transition matrix. To create sufficient serial correlation, we set the diagonal elements of the transition matrix to 0.8 (Cooper and Haltiwanger, 2006). The states of the shock are set in order to reproduce the standard deviation of the process observed in the data.

We assume that e_{ft} follows a first order autoregressive Markov process given by:

$$(21) \quad e_{ft} = \mu_e + \rho_e e_{f,t-1} + \zeta_{ft},$$

where $\zeta_{it} \sim N(0, \sigma_e)$ and ρ_e is the first order autocorrelation coefficient. Moments σ_e and ρ_e are critical for understanding key moments associated with the investment rate, such as investment bursts or investment inaction. These parameters determine the risk that firms face: a higher degree of autocorrelation and a lower variance of the innovation allow firms to make better forecasts of future profitability shocks. In consequence, they determine the firms' optimal policies for a given structure of adjustment costs, and the benefits of reallocation of inputs across firms. Additionally, at the macro level, these parameters affect total factor productivity, and may affect business cycle dynamics (Gourio, 2008).

We estimate equation (21) using ordinary least squares. The second panel of Table 2 reports an estimate of the moments for the idiosyncratic component of the profitability shock. Idiosyncratic shocks to the firm seem to be highly autocorrelated. From the plant-level data, ρ_e is estimated at 0.8853 for the full sample. We also estimate large variance for the innovations of the idiosyncratic shock process, with a standard deviation (σ_e) of 0.6652.[12] We adopt these parameters for firms in the non-manufacturing sector as well.

We estimate the capital adjustment costs parameters with the simulated method of moments (SMM), which minimizes the distance between actual and simulated moments in the data (McFadden, 1989; and Pakes and Pollard, 1989). For a given vector of parameters $\Theta_{f,K} = (F, \gamma, p_s)$ we solve the dynamic problem and obtain the policy functions that are used to generate a simulated version of the data. After eliminating the first 100 periods from the simulated data (so that the simulation is independent of the initial conditions), we calculate a set of simulated moments $\Psi^s(\Theta_{f,K})$. The estimated parameter vector $\widehat{\Theta}_{f,K}$ minimizes the weighted distance between the actual (Ψ^d) and

[12] Note that these parameters are needed to numerically generate the shocks to profits. To reproduce both the set of aggregate and idiosyncratic profitability states as well as the transition matrices, we follow the methodology developed by Tauchen and Hussey (1991). See Appendix A.3.

simulated moments ($\Psi^s(\Theta)$). Formally:

(22) $$\widehat{\Theta}_{f,K} = \arg\min_{\Theta_{f,K}} \; [\Psi^d - \Psi^s(\Theta_{f,K})]' W [\Psi^d - \Psi^s(\Theta_{f,K})]$$

where W is a weighting matrix. In particular, we use the optimal weighting matrix given by an estimate of the inverse of the variance-covariance matrix of the actual moments. Lee and Ingram (1991) show that the efficient choice of W is given by the inverse of the variance-covariance matrix of $[\Psi^d - \Psi^s(\Theta_f)]$. In addition, under the null hypothesis, the variance-covariance matrix of the simulated moments converges to $\frac{1}{n}\Upsilon$, where Υ is the variance-covariance matrix of the actual moments and $n = N/T$, where N is the length of the simulated data and T the length of the actual data. Therefore, since Ψ^d and $\Psi^s(\theta_f)$ are independent by construction, $W = [(1 + 1/n)\Upsilon]^{-1}$. We use bootstrapping with replacement on actual data to generate the variance-covariance matrix of the actual moments (Υ). Bootstrapping is done by sampling firms instead of observations, so that when one firm is picked all observations of that firm enter into the bootstrap draw.[13]

Since the function $\Psi^s(\Theta_{f,K})$ is not analytically tractable, the minimization is performed using numerical techniques. We use a simulated annealing algorithm for minimizing the criterion function. We use this algorithm because of the discretization of the state space and the potential presence of local minima and discontinuities in the criterion function across the parameter space.[14]

The identification of the parameters and the efficiency of the SMM estimator depend crucially on the appropriate choice of moments to match, moments that must be informative about the underlying structural parameters (the informativeness principle). The literature has established that a combination of moments which describe both the cross-section and time series behavior of the investment rate works well in practice. To explore which moments to use, Table 3 provides some insights about the behavior of investment rates at the plant-level in the Argentine ENI panel data. About 29.17 percent of all (plant-level) observations exhibit inaction (an investment rate less than 1 percent in absolute value). In addition, only 4.48 percent of all plants entail negative investment rates (an investment rate less than -1 percent). We also observe episodes of intense adjustment of the capital stock. Investment rates exceeds 20 percent in about 13.57 percent of all plants ($spike^+$), while 2.71 percent of them exhibit an investment rate less than -5 percent ($spike^-$). These findings illustrate the highly asymmetric feature of investment rates at the micro level. Figure 1 summarizes

[13]We perform 1000 replications in order to construct the variance-covariance matrix of the actual moments.

[14]See appendix A.3 for a detailed discussion about the SMM and its practical implementation in our dataset.

these observations.

Based on these features of the data and on the guidelines in the literature (Cooper and Haltiwanger, 2006; Bloom, 2009; Caballero and Engel, 2003; Cooper, Haltiwanger and Power, 1999), we select four fairly standard moments to match. The serial correlation of investment rates ($corr(i, i_{-1})$) and the correlation between the investment rate and the profitability shock ($corr(i, a)$) have both been shown to be very sensitive to the structure of the capital adjustment costs. To capture the fact that the investment rate distribution at the plant-level is asymmetric with a fat right tail, we include the positive and negative spikes rates.

Table 4, panel A, presents our estimates for all three forms of capital adjustment costs along with the standard errors of these estimates.[15] We also report both the observed moments and simulated moments that we match, as well as a measure of fit for the model (the distance function, denoted by $\Gamma(\Theta_f)$). Due to small sample sizes, we estimate a common set of adjustment cost parameters for all firms in all sector.

The estimated adjustment costs imply large fixed cost, large reselling costs, and large quadratic costs. All the parameters estimated are found to be significantly different from zero. We estimate a fixed cost equal to $F = 0.1451$. This is a substantial cost since it implies that the fixed cost of adjustment is about 14.5 percent of the average plant-level capital value. The estimated coefficient for the quadratic adjustment cost parameter (γ) equals 0.1132. Using the quadratic adjustment cost function and a steady state investment rate equal to the depreciation rate ($I/K = \delta = 0.0991$), the estimated parameter implies an adjustment cost relative to the average plant-level capital of 0.056 percent. Finally, our estimate of the transaction costs ($p_s = 0.9143$) implies that resale of capital goods would incur a loss of about 8.6 percent of its original purchase price.

Our estimates of capital adjustment costs parameters for Argentina can be directly compared with those in Cooper and Haltiwanger (2006) for the U.S. Our model is based on theirs, and we use the same specifications. As expected, Cooper and Haltiwanger (2006) estimate smaller fixed costs (F=0.039), smaller partial irreversibilities ($p_s = 0.975$), and smaller quadratic adjustment costs (γ=0.049). This implies that capital is more flexible in the U.S. than in Argentina. These differences, as well as the magnitudes of the estimates, are, however, sensible and plausible.[16]

[15] Appendix A.3 describes the methodology used to compute standard errors.

[16] Bloom (2009) and Bond, Soderbom and Wu (2008) report larger values for the partial irreversibility cost, with capital reselling losses of 47 and 16.9 percent respectively. Both papers also find larger values for the quadratic adjustment cost parameter (2.056 in Bloom, 2009; 1.985 in Bond, Soderbom and Wu, 2008). In turn, the fixed costs parameter F, which is estimated in terms of annual sales (instead of average capital) ranges from 0.3 percent (Bond,

3.2 Labor Mobility Costs

To estimate $\Theta_C = \{C^m, C^{nm}, \nu, \eta^j\}$, the labor mobility cost parameters, we follow the two-step procedure developed by Artuç (2012). In the first step, we estimate the expected values associated with workers choices and, in the second step, these estimated expected values are plugged in a Bellman equation to construct a linear regression to retrieve the parameters.

To see how this works, recall that the total number of workers who move from sector j to k is equal to $y_t^{jk} = L_t^j m_t^{jk}$. Using (16), we get:

(23)

$$\log\left(L_t^j m_t^{jk}\right) = \frac{1}{\nu}E_t W_{t+1}^k - \frac{C^{jk}}{\nu} - \frac{1}{\nu}E_t W_{t+1}^j + \log\left(L_t^j\right) - \log\left\{\sum_{i=1}^{J}\exp\left(\left(E_t W_{t+1}^i - E_t W_{t+1}^j - C^{ij}\right)\frac{1}{\nu}\right)\right\}.$$

This equation is estimable, but there are two problems with it. The right hand side includes the expected values $E_t W_{t+1}^j$ for all j, which are unknown. Also, the logarithmic specification is problematic when the flows m_t^{jk} are zero, or small. We deal with these problems separately. First, note that the terms on the right can be grouped into a set of terms that are related to the sector of origin (j), a set of terms related to the sector of destination (k), and terms that depend on the costs C^{jk}/ν. Thus, let

$$\lambda_t^k = \frac{1}{\nu}E_t W_{t+1}^k + \Lambda_t,$$

$$\delta_t^{jk} = -\frac{C^{jk}}{\nu},$$

and

$$\alpha_t^j = -\frac{1}{\nu}E_t W_{t+1}^j - \log\left\{\sum_{i=1}^{J}\exp\left(\left(E_t W_{t+1}^i - E_t W_{t+1}^j - C^{ij}\right)\frac{1}{\nu}\right)\right\} + \log(L_t^j) - \Lambda_t,$$

where Λ_t is an unidentified constant common to all $j = 1, .., J$ (because workers' decisions depend only on the difference between values rather than on the actual values). Now, (23) becomes:

(24) $$\log\left(y_t^{jk}\right) = \alpha_t^j + \lambda_t^k + \delta_t^j.$$

Soderbom and Wu, 2008) to 1.3 percent of annual sales (Bloom, 2009). Note that these results are not directly comparable to ours because of these and other differences in specification—e.g., both papers estimate additional parameters to the capital adjustment costs parameters.

Next, we write this as a regression model. As we argued before, because of data limitations, we need to impose some restrictions on C^{jk}.[17] We set $C^{jj} = 0$, and we estimate a cost of mobility within manufactures, C^m, and a cost of mobility between manufactures (any sector) and non-manufactures, C^{nm}. To deal with the zeros and low-value flows, we write the model in levels:

$$(25) \quad \hat{y}_t^{jk} = \exp\left(\alpha_t^j + \lambda_t^k + C^m 1[j,k \in J] + C^{nm} 1[j \text{ or } k \in J]\right) + v_t^1,$$

where α_t^j is interpreted as a sector of origin dummy, λ_t^k is a sector of destination dummy, $1[j,k \in J]$ is an indicator dummy equal to 1 if j and k, $j \neq k$, are both in manufactures, $1[j \text{ or } k \in J]$ is an indicator dummy equal to 1 if j is a manufacturing sector and k is the non-manufacture sector, or vice-versa, with $j \neq k$, and v_t^1 in an error term. The error term has a non-standard distribution (which could in principle be derived from the model). Because of this, and because the flows m^{jk} are created by a (dynamic) discrete choice model, we can estimate this equation with a Poisson pseudo maximum likelihood estimator (Gourieroux, Monfort and Trognon, 1984; Cameron and Trivedi, 1998).

For our purposes, the Poisson pseudo ML regression provides estimates of C^m/ν and C^{nm}/ν (on top of estimates of workers' values). In the second step of Artuç procedure, we separately identify ν and η^j using the Bellman equation for the workers' problem (14). Multiplying (14) by $1/\nu$ and taking expectations, we get:

$$(26) \quad E_t\left[\frac{1}{\nu} W_{t+1}^j - \frac{1}{\nu}\left(\widetilde{w}_{t+1}^j + \eta^j\right) - \frac{\beta_1}{\nu} E_{t+1} W_{t+2}^j - \frac{1}{\nu} \Omega_{t+1}^j\right] = 0.$$

Using the definition of λ_t^j and λ_{t+1}^j, and noting that $\omega_t^i = \Omega_t^i/\nu = -\lambda_t^i - \alpha_t^i + \log(L_t^i)$, we get:

$$(27) \quad \lambda_t^j - \Lambda_t = E_t\left[\frac{1}{\nu}\left(\widetilde{w}_{t+1}^j + \eta^j\right) + \beta_1 \lambda_{t+1}^j - \beta_1 \Lambda_{t+1} + \omega_{t+1}^j\right].$$

Using a similar expression for sector i to net out Λ_t, we finally get:

$$(28) \quad \lambda_t^i - \lambda_t^j = E_t\left[\frac{1}{\nu}\left(\widetilde{w}_{t+1}^i + \eta^i - \widetilde{w}_{t+1}^j - \eta^j\right) + \beta_1\left(\lambda_{t+1}^i - \lambda_{t+1}^j\right) + \left(\omega_{t+1}^i - \omega_{t+1}^j\right)\right].$$

[17] The procedure is in fact amenable to the estimation of a large number of mobility costs, data permitting. Artuç (2012), for instance, uses U.S. data to estimate 416 different sector-specific and time-varying mobility costs (16 sectors and 26 years).

We can now write this as a linear regression equation

$$(29) \quad \left(\lambda_t^i - \lambda_t^j\right) - \beta_1\left(\lambda_{t+1}^i - \lambda_{t+1}^j\right) - \left(\omega_{t+1}^i - \omega_{t+1}^j\right) = \frac{1}{\nu}\left(\widetilde{w}_{t+1}^i + \eta^i - \widetilde{w}_{t+1}^j - \eta^j\right) + v_t^2,$$

where v_t^2 is an error term. The structural parameters can be estimated using Generalized Method of Moments with lag wage differences as instruments (as in Artuç, Chaudhuri, and McLaren, 2010). Since the error terms are correlated across sectors within years, we cluster the observations to calculate the standard errors.

We estimate the data using the panel sample of the Encuesta Permanente de Hogares (EPH). The database contains information on individual wages, employment sector, demographic characteristics and other standard variables in labor force surveys. Part of the EPH is a panel and we can use it to track labor employment flows and wages to estimate (24) and (29). Table XX shows the average flow of workers across our six sectors in the sample period, 1996-2007. DESCRIBE.

The estimates of the labor mobility costs are in panel B of Table 4. Our estimate of C^m is 2.07 and of C^{nm} is 1.41. This means that, on average, a worker wishing to switch sectors within the manufacturing sector would pay a mobility cost equivalent to 2.07 times his annual wage earnings. The costs needed to switch from manufactures to non-manufactures (or vice-versa) is lower, around 1.41 times the value of the annual wage income. We also estimate a fairly high variance of the idiosyncratic costs, $\nu = 0.78$.

Our estimates are much lower than those reported in Artuç (2012), using the same specification and U.S. data. He estimates 416 values of C, ranging from 5.098 to 9.299. Artuç and McLaren (2012) also use U.S. data on sectoral and occupational mobility, and report values closer to ours, with estimates of C as low as 0.99 and as high as 1.54 (with ν=0.257). Using different regression specifications, Artuç, Chaudhuri, and McLaren (2010) estimate an average moving cost of 6.565, and a value of ν of 1.884.[18] Artuç and McLaren (2010) estimate the model for Turkey for the period 2004-2006, also obtaining high average moving costs ranging from 9.50 to 22.89.

4 Firm-Level Investment Inaction and Trade Shocks

We now use the model and the estimated parameters to simulate the dynamic implications of various trade shocks. We explore the impacts on sectoral capital, employment, and wages. We also

[18] In all these paper, the authors impose, as we do, a value for the discount factor of 0.97.

investigate firm-level heterogeneous responses in investment. We simulate the responses to trade shocks that affect the price of Food and Beverages.

4.1 Computational Issues

To simulate the model, we need to solve for the initial steady stead, the post-shock steady state, and the full transition. The process involves a number of computational issues that we have to discuss. A major technical problem arises because of the costs of factor adjustment, and in particular because of the non-convexities in investment due to the fixed costs. Workers face large common costs of moving, C, but they also receive sector-specific utility shocks that act as additional moving costs/benefits. As a result, workers make heterogeneous decisions (even though they are homogenous ex-ante) and end up in different sectors. Likewise, firms face the same costs of adjusting capital, but they are heterogeneous because they receive different productivity shocks. As a result, firms choose different investment levels and end up with different levels of capital.

The main challenge in the solution is the fixed cost of investment. Due to the large F, firms stay dormant for some time and then choose large investment bursts. Investment becomes cyclical, a feature that is not consistent with the smooth aggregate behavior that we need for the stationary equilibrium. To circumvent this, we make firms heterogeneous and asynchronous. This means that firms need to make different investment choices and they need to make them at different time periods.[19] We do this by allowing for technology shocks. Firms receive shocks of different magnitudes at different times and thus their behavior becomes both heterogeneous and asynchronous.

The equilibrium can be characterized as follows. Firms need to choose optimal investment and solve the Bellman equation (5). Workers need to choose sectors and solve the Bellman equation (14). Finally, given the aggregate capital stock K and the labor allocation, wages need to clear labor supply and labor demand. These conditions need to hold for each of the six sectors of the economy. We advance the following algorithm to solve for the autarky steady state. In what follows, for any variable X, the variable $X^{(a)}$ means the guess in iteration number (a), and $\widehat{X}^{(a+1)}$ means the number (value) implied by $X^{(a)}$ using the equations from the model. The goal is to reach a fixed point where $\widehat{X}^{(a+1)} = X^{(a)}$.

[19] Both features are important. Consider the case where firms are ex-ante heterogeneous in the capital stock and let a positive trade shock (i.e., a price increase) take place. Firms want to expand. Since firms are heterogeneous in K, some of them may invest right away, but others will let K depreciate and invest in bursts at a later date. Eventually, however, firms will converge to the new their equilibrium capital and their investment behavior will become synchronized after that. This is incompatible with a stationary equilibrium.

We conjecture initial values for firms f in sector j, $V_f^{j,(a)}$, and initial values for the workers in sector j, $W^{j,(a)}$, $a = 0$ being the initial guess. We also guess, for each sector, the aggregate capital stock $K^{j,(a)}$, the labor allocation $L^{j,(a)}$, and the wage $w^{j,(a)}$. These conjectures need to be updated until convergence. This is done as follows. Given the values for firms and workers, wages, capital levels, and labor allocations, we solve for the level of the technology A^j at the sector level, on average.[20] Given $A^{j,(a)}$, $K^{j,(a)}$ and $L^{j,(a)}$, we calculate the equilibrium wage $\widehat{w}_j^{(a+1)}$ using the production function. Given the calculated wages and the guessed $W^{j,(a)}$, we update W using equation (14), $\widehat{W}^{j,(a+1)} = \widehat{w}^{j,(a+1)} + \beta_1 W^{j,(a)} + \Omega^j$. (To calculate the option value Ω^j, which is a function of the guessed values, $W^{j,(a)}$, we use equation (15)). Finally, using the guessed values $W^{j,(a)}$ for all sectors, we calculate the flows $m^{jk,(a)}$ with (16) and this allows us to calculate the labor supply vector $\widehat{L}^{(a+1)}$ with (17).

To end, we need to update the capital stock. In doing so, we need to account for the fact that the steady-state for an individual firm does not exist because of the non-convexities in investments. We work with 100 hypothetical firms. For each of them, we guess an initial capital stock $k_f^{j,(a)}$ and an initial value $V_f^{j,(a)}$, where $f = 1, 2, .., 100$ is the firm index. We also take draws from the idiosyncratic technology shocks from (21). Note that, in theory, the average of the firms k^j is the aggregate stock K^j.

Given the guessed aggregate capital $K^{j,(a)}$ and the 100 element vector $k^{j,(a)} = [k_1^{j,(a)} k_2^{j,(a)}, ..., k_{100}^{j,(a)}]'$, we solve the Bellman equation (5) for each of the firms. This is done as follows. Given the state b the firm is (high or low in the Markov process) and the idiosyncratic technology shock, we determine the firm's productivity level, A. Given A, we calculate instantaneous profits for every possible capital level on a k-grid. We do the same for the capital adjustment cost function G in (4). Then, given the firm current productivity level, we calculate the probability of being on the high productivity state and on the low productivity state and, using these probabilities, we calculate the expected value V^j, which is a vector of all possible capital grids as well. Then, we maximize with respect to k_f^j, and this determines $\widehat{k}_f^{j,(a+1)}$. Using (5), we can then calculate $\widehat{V}_f^{j,(a)}$ for each firm.

Once we calculate all the implied variables $\widehat{X}^{j,(a+1)}$, i.e., $\widehat{K}^{j,(a+1)}$, $\widehat{V}^{j,(a+1)}$, $\widehat{W}^{j,(a+1)}$, $\widehat{L}^{j,(a+1)}$,

[20]This means that the absolute level of technology and capital stock are arbitrary. As we explain below, what matters instead is the proportional change.

and $\widehat{w}^{j,(a+1)}$, we update the guess at the end of the iteration (a) as follows:

$$X^{j,(a+1)} = \rho \widehat{X}^{j,(a+1)} + (1-\rho) X^{j,(a)},$$

where ρ is a small positive number (we set it equal to 0.1). This is done to facilitate computational convergence of the algorithm.[21] Note that the firms' decision vector contains discrete variables, therefore we set it directly equal to the optimal response for the next iteration, i.e. $k_f^{j,(a+1)} = \widehat{k}_f^{j,(a+1)}$.

Note that the updated K will fluctuate a lot in the beginning. To deal with this, we initially iterate the procedure for about 2000 times, until K becomes stable, and then iterate again 500 more times. The last 500 iterations are very close to the steady-state solution. We thus have a series of optimal capital $k^{j,(2001)}$ to $k^{j,(2500)}$ for 100 firms in each sector j, which we claim represent their true behavior. By following a firm from $(a) = 2001$ to $(a) = 2500$, we can track its investment and capital adjustment cycle during the (aggregate) steady state. The evolution of the capital stock for different firms in the aggregate steady state is plotted in Figure **??**. The upper panel plots investment (left) and capital (right) for four high-productivity firms, while the bottom panel reports two low-productivity firms. There are firm-specific investment bursts cycles of different magnitude, and the firm-level capital fluctuates in a saw-like pattern. This is because there is no firm steady state. Aggregate K, however, does not fluctuate.

The solution for the transition is similar to the solution for the steady state. Rather than conjecturing the aggregate steady state variables, we conjecture series for the aggregate variables, $\{K_t^{j,(a)}\}$, $\{V_t^{j,(a)}\}$, $\{W_t^{j,(a)}\}$, $\{L_t^{j,(a)}\}$, and $\{w_t^{j,(a)}\}$ for $t = 1, 2, ..., T$ (where T is the transition length). The updating of these guesses involves the whole series but, apart from that, works as in the solution for the steady state. With the sequences $\{K_t^{j,(a)}\}$ and $\{L_t^{j,(a)}\}$, we calculate $\{\widehat{w}_t^{j,(a+1)}\}$; we calculate workers' values $\{\widehat{W}_t^{j,(a+1)}\}$ with $\widehat{W}_t^{j,(a+1)} = \widehat{w}_t^{j,(a+1)} + \beta_1 W_t^{j,(a)} + \Omega_t^j$; with these values, we calculate the updated flows $\{\widehat{m}_t^{jk,(a+1)}\}$, and then the updated labor supply $\{\widehat{L}_t^{j,(a+1)}\}$.

To update the capital stock and the transition path for the firms, we randomly draw 100 firms from the steady state solution. This is equivalent to randomly picking an iteration from the steady state solution (from $a = 2001$ to $a = 2500$) and recovering, for each firm f, its capital stock k_f^j and its productivity level (high or low). In this process, we pick firms at different points in the investment cycle. For each firm, we guess a sequence of capital choices $\{k_f^{j,(a)}\}$. By solving the Bellman equation (5), we update these sequences $\{\widehat{k}_f^{j,(a+1)}\}$ and the sequences for the firms' values

[21] For example, this avoids hitting the boundaries of the k-grid.

$\{\widehat{V}_t^{j,(a+1)}\}$. As before, we update the guessed variables using the current guesses and the implied variables, $\{X_t^{j,(a+1)}\} = \rho\{\widehat{X}_t^{j,(a+1)}\} + (1-\rho)\{X_t^{j,(a)}\}$.

4.2 Responses to Trade Shocks

We study the transitional dynamics in response to a positive trade shocks to the Food & Beverages sector, whose domestic price thus increase. We begin with the impacts of a price increase of 10 percent on capital, employment and real wages. Results are displayed in Figure 2. The general equilibrium effects in other sectors are discussed in the Appendix. The immediate implication of higher prices is an increase in profitability for firms in the sector. Firms want to expand and choose to invest. However, since capital adjustment is costly, their stock of K is gradually increased. Three forth of the adjustment of the capital stock takes place within five years following the trade shock, and 95 percent of the transition is covered in 9 years. The capital stock increases by 5.6 percent initially (Year two), by 17.9 percent in Year 5; by 22.6 percent in Year 10, and by 23.3 percent in the new steady state (see Table 5).

Real wages increase at first in Food and Beverages (but decline elsewhere). In F&B, this is because the initial investment burst increases labor productivity and thus labor demand. Firms must thus pay higher wages to their workers. This increase in nominal wages dominates the increase in the price index and real wages go up as a result. (In all other sector, nominal wages are initially not affected, but real wages drop due to higher prices.) As wages change, workers reallocate towards Food and Beverages. Note that, because of the idiosyncratic utility shocks, not all workers move at once or even in the same direction. The flows towards F&B, however, increase. As workers move, wages adjust again. As a result, the real wage in F&B starts to decline (and the real wages in all other sectors slightly recover). The real wage in Food and Beverages increases on impact by 5.8 percent, and starts declining gradually after. In the new steady state, real wages are only 2.5 percent higher than in the initial equilibrium. See Table 7. This happens even though firms keep expanding capital for a few years. because of the continuous inflow of workers. Employment increases gradually, by 7.4 percent in Year 2, 15.6 percent in year 10, and 15.8 percent in steady state (Table 6).

We also explore responses to trade shocks of varying sizes. In Tables 5, 7, and 6, we report the impacts (on capital, wages, and employment, respectively) of price increases of 5, 10, 20 and 30 percent. As expected, the economy adjusts more when the trade shock is larger. For example, while, as we just showed, a price increase of 10 percent induces an increase in capital of 5.6 percent in Year 2 and of 23.3 percent in steady state, the responses to a price increase of 30 percent are 19.6 and 72.8 percent, respectively. Real wages increase, on impact, by 16.4 percent; then, wages continuously decline and, in the steady state, they are only 7 percent higher (so that the decline after Year 1 is of about 9.4 percentage points).

Note that as the price shock becomes larger, the economy becomes proportionately more responsive. This can be seen by comparing the elasticity of capital to the price shock. For a 10 percent price shock, for instance, the elasticity is 0.56 in Year 2, 1.51 in Year 4, 2.26 in Year 10, and 2.33 in steady state. For a 30 percent positive price increase, the elasticity of capital is 0.65 in Year 2, 1.67 in Year 4, 2.37 in Year 10, and 2.43 in steady state. This is because, in a given year of the transition, a higher price change provides incentives to invest to a larger proportion of firms. In other words, at higher prices, more firms will cross the threshold and invest, thus increasing the aggregate capital stock.

To further explore the role of firm-inaction and capital adjustment costs, we simulate a counterfactual shock where the trade shock takes place in the absence of both fixed costs of investment. With $F = 0$, firm-level investment inaction is not an optimum. Consequently, we expect a smoother and quicker response of firm-level capital accumulation and aggregate capital. To build the counterfactual experiment, we run, for a given price change, two simulations, one with both lower costs and changed prices, and another with lower costs and no price change. We do this to control for the fact that a decrease in adjustment costs necessarily brings firm responses in capital that we want to keep constant. More concretely, in what follows, we study the difference between the levels of the variables in the two simulations.

Results for capital are reported in Table **??**. We compare the response to a positive price change under the baseline (characterized by investment inaction) and the counterfactual (no-inaction) scenarios, and we report the (proportional) difference in those responses. For a given price change, the economy responds much more during the early years of the transition. For a 10 percent price increase, the response of the capital stock in Year 2 is 75.5 percent larger when we eliminate the fixed costs F. In year 3, it is 45.7 percent larger. In steady state, it is only 1.8 percent larger. To interpret the result, it is important to note that we are controlling for the impact of lower costs themselves on the optimal capital. That is, the economy is converging to different steady states.[22]

[22] Capital is higher when adjustment costs are lower. Our result is about the interaction between the trade shock and the lower costs, not about the level effect of those lower costs.

The result implies a long-term response of capital to price that is only marginally stronger in the absence of fixed costs. However, the response during the first (few) years of the transition is much stronger. This means that the economy adjusts much more abruptly and quickly in the absence of adjustment costs. In other words, the fixed costs generate short-run firm investment inaction for 4-5 years following a trade shock.

This has implications for employment and wages (Tables **??** and **??**). For a 10 percent price increase, the steady state response of employment is only 1.4 percent higher with no F. In the short-run, the responses are slightly stronger (6.6 percent more in Year 2, 6.4 percent more in Year 4) but never as pronounced as the response of the capital stock. Real wages also react more in the short-run. In Year 2, for example, real wages are 10.5 percent higher in the absence of fixed capital adjustment costs. These additional gains in wages are cut by more than half in Years 4 and 5 and are subsequently eliminated entirely in the long-run. As capital and labor adjust, there would be no discernible *additional* gains in real wages for an economy that faces a positive trade shock with lower investment inaction costs.

The other main finding of the paper emerges from the comparison of the differential response of capital at different price shocks. The economy reacts less during the first 4-5 years when the shock becomes larger, but react more after that. In Year 2, as we just showed, the response of capital is 75.5 percent higher in the absence of "inaction" costs when the price shock is 10 percent, but it is 48.8 percent higher when the price shock is 30 percent. In Year 3, the capital response is 45.7 percent higher with $F = 0$ when the price shock is 10 percent, but it is 32.7 percent higher when the price shock is 30 percent. Only in Year 5 are the responses similar (21.7 and 20.1 percent higher, respectively). Conversely, in steady state, the capital response to a 10 percent price increase is 1.8 percent higher in the absence of capital adjustment costs, but it is 5.4 percent higher if the price shock is of 30 percent.

This result is also driven by the incentives to investment inaction generated by the fixed costs. Given the value of F in the baseline, a larger price shock induces a larger proportion of firms to respond in the short-run. To put it differently, if the price shock is small when adjustment costs are high, fewer firms will find it optimal to adjust investment immediately after the shock. In the absence of those costs, thus, the same small price change will induce a much larger response of many of those firms that choose inaction in the baseline. As the price shock grows larger, these differential responses become smaller. In the long-run (in steady state, but also after about 5 years in our simulations) most firms have already adjusted and thus the differential responses narrow. Eventually, when capital adjustment is full (to its steady state), a larger price shock elicits larger, but only marginally so, responses.

4.3 Heterogeneous Firm Responses

In this section we exploit the fact that our simulations track individual firm behavior to explore heterogeneous firm-level investment responses. We classify firms into two groups, High-Technology and Low-Technology firms, based on their productivity A. We interpret this classification as a simple measure of firm heterogeneity. Using the simulation results described above, we compare now the equilibrium capital for each of the two types of firms. We do this for the baselines scenario (with investment inaction) and the counterfactual scenario (without inaction). Results are reported in Table **??** (changes in capital levels) and Table 11 (proportional changes).

In the baseline scenario, for a given price shock, both firm types react, but high-tech firms respond more than low-tech firms. In the new steady state, for instance, high-tech firms expand capital by 23.7 percent (for a 10 percent price shock) but low-tech firms do so by 21 percent. We also find that high-tech firms respond proportionately more when the price shock is larger. The steady state elasticity of capital to price for high-tech firms increases from 2.37 (10 percent price shock) to 2.48 (30 percent price shock); it is 2.11 and 2.10, respectively, for low-tech firms. These observations also hold during the transition. The reason behind these results is that high-tech firms are less likely to choose investment inaction, because they can better cover the capital adjustment costs. It is interesting to note that this heterogeneity dissipates in the absence of investment "inaction" costs (i.e., $F = 0$). In this case, low-tech firms actually react more than high-type firms and, in fact, the proportional response is about the same for both types (see Table 11). The reason is that, absent fixed costs, low-tech firms find it optimal to catch up, choosing investment action as their capital stock tends to be low in the face of the low-state technology shock (which implies lower optimal capital).

5 Conclusions

This paper develops a structural dynamic equilibrium model of the labor market with workers' mobility costs, firm heterogeneity and firms' capital adjustment costs. The model features firm investment decisions at the firm level, articulating both the product and labor market. This characteristic of the model allows us to analyze the role played by capital mobility and its mobility frictions on labor market after trade liberalization. We fit our model to household survey data and plant-level panel data from Argentina in order to recover a measure of the frictions faced both by workers and firms.

To be continued...

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A Appendix

A.1 Short-run profit maximization

The short-run profit maximization problem is:

$$\pi_{ft}^{j}(K_{ft}^{j}, A_{ft}^{j}; w_t^{j}; \tau^{j}) = \max_{L\geq 0}\{p^{j*}(1+\tau^{j})\widetilde{A}_{ft}^{j}K_{ft}^{\alpha_k}L_{ft}^{j\alpha_l} - w_t^{j}L_{ft}^{j}\}.$$

The first order condition leads to the following operating profits and labor demand functions:

$$\begin{aligned}
\pi_{ft}^{j}(K_{ft}^{j}, A_{ft}^{j}; w_t; \tau^{j}) &= (1+\tau^{j})^{\frac{1}{1-\alpha_l}}\varphi(w_t^{j})A_{ft}^{j}K_{ft}^{\theta}, \\
L^{d}(K_{ft}^{j}, A_{ft}^{j}; w_t^{j}; \tau^{j}) &= (1+\tau^{j})^{\frac{1}{1-\alpha_l}}\left(\frac{w_t^{j}}{\alpha_l}\right)^{\frac{1}{\alpha_l-1}}K_{ft}^{\theta}A_{ft}^{j},
\end{aligned}$$

where, $\theta = \frac{\alpha_k}{1-\alpha_l}$, $A_{ft}^{j} = (p^{j*}\widetilde{A}_{ft}^{j})^{\frac{1}{1-\alpha_l}}$, and $\varphi(w_t^{j}) = (1-\alpha_l)\left(\frac{w_t^{j}}{\alpha_l}\right)^{\frac{\alpha_l}{\alpha_l-1}}$.

A.2 Data Construction

We express all monetary variables in real terms. We deflated wages by the consumer price index and firm's variables using the wholesale price index. In particular, we deflated investment, capital and intermediate inputs by the general level of the index. Gross revenue, sales and profits were deflated using the four digit disaggregation of the index.

To construct the real investment series, we generate an initial measure of the real capital stock at the plant-level and then complete the series using the perpetual inventory method, $K_{f,t+1} = (1-\delta)K_{ft}+I_{ft}$, where I_{ft} is real investment, K_{ft} real capital stock, and δ is the capital depreciation rate. Real investment is defined as $I_{ft} = E_{ft} - S_{ft}$, where E_{ft} is real gross expenditures on capital equipment, and S_{ft} is real gross retirements of capital equipment.

Since our dataset does not contain information about the book value of capital, we approximate the initial capital stock of the firm as the average across years of the ratio between the amount of capital depreciation declared by the firm and the depreciation rate estimated for the industry. We deflate our measure of initial capital stock by the general level of the wholesale price index. We use sectoral depreciation rates estimated by the Bureau of Economic Analysis (BEA) of the United States (Fraumeni, 1997). Our depreciation rates include both in-use depreciation (which reflects declines in the efficiency of the asset because of aging or wear and tear) as well as retirements or discards (which reflects, for example, obsolescence).

A.3 Numerical Methods

This appendix describes some numerical techniques used to solve the firm's maximization problem and to estimate the firm's capital adjustment costs parameters through the simulated method of moments (SMM).

A.3.1 Value Function Iteration

To solve the value function for the estimation of the capital adjustment costs parameters with the simulated method of moments, we choose a grid of points in the variable space (K, I, A) and we discretize it. We discretize the state space of variables K and I with a grid of 400 points. Additionally, since we need to take expectations conditional on A, we follow Tauchen and Hussey (1991) to discretize the continuous AR(1) process with a 22-point grid. Therefore, the state space for variables (K, I, A) has dimensions $(400 \times 400 \times 22)$. For the solution, we start with a guess of the value function and we update these guesses by solving the Bellman equation. To ensure the convergence of the policy functions, we set as a termination condition a difference in the value function between two consecutive iterations smaller than the tolerance criterion 0.0001.[23]

A.3.2 The Simulated Annealing algorithm

We use an annealing algorithm for minimizing the distance function $\Gamma(\Theta_f)$. The search in the parameter space is as follows. First, for a given initial (arbitrary) set of parameters, we solve the value function and use the associated policy functions to generate a simulated dataset. Then, we calculate the selected set of moments from this dataset and we compute the loss/distance function $\Gamma(\Theta_f)$. In a second run, we conjecture a new guess of the initial set of parameters and we again compute the loss. Then, for the third iteration onwards, the guesses are updated based on the best prior guess. We perform this procedure over 6000 iterations. For the first 1500 iterations,

[23]Some regularity conditions ensure the existence of the value function: a) a continuous and time additively separable profit function; b) Markovian transition densities for the state variables; c) a bounded singled period profit function; and d) a discount factor $\beta_0 \in (0, 1)$. See Rust (1996) for a detailed discussion.

the updated set of parameters is based on a randomization from the best guesses. From iteration 1500 onwards, we add a directional component to the parameter search.[24] We also programme the algorithm so that the variance of the parameter declines with the number of iterations, allowing the SMM to refine the parameter estimates around the global best fit. We set up the estimation with different initial parameters and seeds to ensure convergence to the global minimum.

A.3.3 Standard Errors (SMM)

The formulas for the standard error for the SMM are straightforward. Given the efficient weighting matrix W, the SMM estimator is asymptotically normal for fixed H and T when $N \to \infty$:

$$\sqrt{N}(\widehat{\Theta} - \Theta^*) \to N(0, V)$$

where,

$$V = \left(1 + \frac{1}{H}\right) \left(J'WJ\right)^{-1}$$

with

$$J = \frac{\partial \Psi^S(\widehat{\Theta})}{\partial \Theta}$$

The Jacobian matrix J must be computed numerically. A practical issue is that the value of the numerical derivative, defined as $\frac{\partial \Psi^S(\widehat{\Theta})}{\partial \Theta} = \frac{\Psi^S(\widehat{\Theta}+\epsilon) - \Psi^S(\widehat{\Theta})}{\epsilon}$, is sensitive to the exact value of ϵ in which this derivative is evaluated. As stated by Bloom (2009), this is a common problem in numerical methods with simulated data which make use of functions with potential discontinuities (which may arise, for example, as a consequence of discretized state variables in the problem). To address this problem, we follow Bloom (2009) and we calculate four values of the numerical derivative for an ϵ of +1%, +2.5%, +5% and -1% of the estimated parameter. Then, we take the median value of these numerical derivatives. This procedure contributes to the robustness of numerical derivatives to outliers in the function under analysis (resulting from the potential discontinuities).

[24] We initially tried using the directional search component for all the 6000 iterations, but we often got trapped in local minima.

Table 1
National Industrial Survey (ENI)
Descriptive Statistics

Variables	All	Food and Beverages	Apparel, leather and textile products	Others	Nonmetallic mineral products	Primary metals and fabricated metal products
Gross Revenue	29131.4	33725.0	10032.8	30032.2	27850.6	35482.5
	(95944.2)	(79704.4)	(14761.0)	(105802.8)	(29373.3)	(137920.9)
Value Added	11052.6	12012.7	3603.5	11255.3	14750.1	13849.1
	(43687.5)	(49697.6)	(5539.1)	(43899.3)	(17417.7)	(58241.3)
Capital	15032.3	13099.1	3093.0	14304.2	15473.2	35304.0
	(69858.8)	(38669.1)	(4782.7)	(58524.3)	(17618.7)	(163685.4)
Investment	999.4	1043.7	350.5	1175.1	951.2	719.1
	(11899.9)	(5029.8)	(1965.0)	(16104.2)	(2418.0)	(3796.7)
Materials	18307.9	21875.9	6830.7	19208.5	12233.6	21397.4
	(61856.2)	(44795.4)	(12308.7)	(72365.3)	(12278.1)	(79665.1)
Labor	126.5	135.6	132.1	101.2	202.9	189.6
	(292.7)	(248.7)	(185.6)	(196.1)	(218.1)	(668.3)
Observations	4544	1008	488	2344	248	456
Plants	568	126	61	293	31	57

Source: ENI. Sample averages for selected variables (standard deviation within parenthesis below). All variables, except labor, are measured in thousands of 1993 pesos. Labor is measured in number of production workers.

Table 2
Production Function Parameters

	Manufacturing Firms	Non-Manufacturing firms
Labor (α_l)	0.5892***	0.3402
	(0.0131)	
Capital (α_k)	0.1420***	0.1153
	(0.0423)	
θ	0.3457	0.0844
Observations	4443	–
Plants	575	–
ρ_e	0.8853	0.8853
σ_e	0.6652	0.6652
δ	0.0991	0.0991

Source: ENI. Production function parameters for the manufacturing sector are estimated using Olley-Pakes (1996) procedure. The standard errors are computed via bootstrap. The bottom panel reports the parameters of the stochastic process for the profitability shocks (see text for details). The production function parameters for the non-manufacturing sector are calibrated.

Table 3
Investment Rate (i) Moments

Moments	All	Food and Beverages	Apparel, leather and textile products	Others	Nonmetallic mineral products	Primary metals and fabricated metal products
$mean(i)$	0.0971	0.0876	0.1218	0.1045	0.0793	0.0635
$sd(i)$	0.2289	0.1614	0.3528	0.2397	0.1600	0.1457
$skewness(i)$	5.2156	3.2596	3.3072	4.1096	2.0717	3.0668
$prop(\mid i \mid < 0.01)$	0.2917	0.2810	0.3187	0.2672	0.2863	0.4145
$corr(i, i_{-1})$	0.1870	0.2419	0.0947	0.2077	0.0312	0.1228
$spike^{+}$	0.1357	0.1110	0.1646	0.1509	0.1210	0.0899
$spike^{-}$	0.0271	0.0180	0.0146	0.0336	0.0323	0.0241
$prop(i < -0.01)$	0.0448	0.0260	0.0354	0.0552	0.0565	0.0373
$corr(i, a)$	0.1803	0.1989	0.1925	0.1792	0.2655	0.1291

Source: ENI. Notes: $mean(i)$: mean of investment rates; $sd(i)$: standard deviation of investment rates; $skewness(i)$: coefficient of skewness of the investment rate (mean by year); $prop(|i| < 0.01)$: inaction; $corr(i, i_{-1})$: serial correlation of investment rates; $spike^{+}$: positive spike rates; $spike^{-}$: negative spike rates; $prop(i < -0.01)$: fraction of observations with negative investment rate; $corr(i, a)$: correlation between investment rates and profitability shocks.

Table 4
Structural Parameters
Capital Adjustment Costs and Labor Mobility Costs

A) Capital Adjustment Costs					
Parameters	F		γ		p_s
	0.1451***		0.1132***		0.9143***
	(0.0403)		(0.0105)		(0.0727)
Moments	$corr(i, i_{-1})$	$corr(i, a)$	$spike^{+}$	$spike^{-}$	$\Gamma(\widehat{\theta})$
Observed	0.188	0.121	0.139	0.011	-
Simulated	0.149	0.306	0.135	0.013	47.38
B) Labor Mobility Costs					
Parameters	C^{m}		C^{nm}		ν
	2.07***		1.41***		0.78***
	(0.22)		(0.27)		(0.12)

Source: See text.

Table 5
Capital Response to Price Shocks

	Percentage price increase			
	5%	10%	20%	30%
Percentage Response				
Year 1	0	0	0	0
Year 2	2.7	5.6	12.3	19.6
Year 3	5.4	11.1	24.0	37.8
Year 4	7.4	15.1	32.0	50.1
Year 5	8.7	17.9	37.5	58.0
Year 10	11.2	22.6	46.3	71.1
Steady state	11.5	23.3	47.4	72.8
Elasticity				
Year 1	0	0	0	0
Year 2	0.54	0.56	0.62	0.65
Year 3	1.07	1.11	1.20	1.26
Year 4	1.47	1.51	1.60	1.67
Year 5	1.74	1.78	1.88	1.93
Year 10	2.24	2.26	2.31	2.37
Steady state	2.31	2.33	2.37	2.43
Convergence				
75%	5	5	5	5
90%	8	8	7	7
95%	9	9	9	9

xxxx

Table 6
Employment Response to Price Shocks

	Percentage price increase			
	5%	10%	20%	30%
Percentage Response				
Year 1	0	0	0	0
Year 2	3.7	7.4	14.5	21.4
Year 3	5.6	11.1	21.9	32.4
Year 4	6.5	13.0	25.8	38.2
Year 5	7.1	14.1	28.0	41.5
Year 10	7.8	15.6	31.0	45.9
Steady state	7.9	15.8	31.2	46.3
Elasticity				
Year 1	0	0	0	0
Year 2	0.74	0.74	0.73	0.71
Year 3	1.11	1.11	1.10	1.08
Year 4	1.31	1.30	1.29	1.27
Year 5	1.41	1.41	1.40	1.38
Year 10	1.57	1.56	1.55	1.53
Steady state	1.58	1.58	1.56	1.54
Convergence				
75%	4	4	4	4
90%	6	6	6	6
95%	7	7	7	7

xxxx

Table 7
Wage Response to Price Shocks

	Percentage price increase			
	5%	10%	20%	30%
Percentage Response				
Year 1	2.9	5.8	11.2	16.4
Year 2	1.8	3.5	6.8	10.0
Year 3	1.5	2.9	5.5	8.1
Year 4	1.3	2.7	5.0	7.4
Year 5	1.3	2.5	4.8	7.0
Year 10	1.3	2.5	4.8	7.1
Steady state	1.3	2.5	4.8	7.0
Elasticity				
Year 1	0.58	0.57	0.56	0.55
Year 2	0.35	0.35	0.34	0.33
Year 3	0.29	0.28	0.28	0.27
Year 4	0.27	0.27	0.25	0.25
Year 5	0.26	0.25	0.24	0.23
Year 10	0.25	0.25	0.24	0.24
Steady state	0.26	0.25	0.24	0.23
Convergence				
75%	3	3	3	3
90%	3	4	4	4
95%	4	5	4	4

xxxx

Table 8
Capital Response to Price Shocks. Counterfactual Adjustment Costs

	Percentage price increase			
	5%	10%	20%	30%
Percentage increase in response				
Year 1	--	--	--	--
Year 2	82.6	75.5	59.4	48.8
Year 3	49.1	45.7	37.4	32.7
Year 4	32.2	30.8	27.4	25.3
Year 5	22.0	21.7	20.0	20.1
Year 10	3.3	4.8	6.6	7.8
Steady state	0.4	1.8	4.4	5.4
Elasticity				
Year 1	0	0	0	0
Year 2	0.99	0.99	0.98	0.97
Year 3	1.60	1.62	1.65	1.67
Year 4	1.95	1.98	2.04	2.09
Year 5	2.12	2.17	2.25	2.32
Year 10	2.31	2.36	2.46	2.55
Steady state	2.32	2.37	2.47	2.56
Convergence				
75%	4	4	4	4
90%	5	5	5	5
95%	6	6	6	6

xxxx

Table 9
Employment Response to Price Shocks. Counterfactual Adjustment Costs

	Percentage price increase			
	5%	10%	20%	30%
Percentage increase in response				
Year 1	--	--	--	--
Year 2	6.8	6.6	5.9	5.4
Year 3	7.0	6.9	6.2	5.8
Year 4	6.5	6.4	6.0	5.7
Year 5	5.6	5.6	5.3	5.3
Year 10	1.8	2.1	2.5	2.6
Steady state	1.2	1.4	1.9	2.0
Elasticity				
Year 1	0	0	0	0
Year 2	0.79	0.79	0.77	0.75
Year 3	1.19	1.18	1.16	1.14
Year 4	1.39	1.39	1.37	1.35
Year 5	1.49	1.49	1.48	1.45
Year 10	1.60	1.60	1.59	1.57
Steady state	1.60	1.60	1.59	1.57
Convergence				
75%	4	4	4	4
90%	5	5	5	5
95%	6	6	6	6

xxxx

Table 10
Wage Response to Price Shocks. Counterfactual Adjustment Costs

	Percentage price increase			
	5%	10%	20%	30%
Percentage increase in response				
Year 1	0	0	0	0
Year 2	12.6	10.5	8.9	7.8
Year 3	9.2	9.9	9.8	9.3
Year 4	5.5	4.8	8.1	7.7
Year 5	2.1	4.4	6.1	7.0
Year 10	0.0	-0.9	-0.2	-0.1
Steady state	-5.8	-1.7	-0.1	0.0
Elasticity				
Year 1	0.58	0.57	0.56	0.55
Year 2	0.39	0.39	0.37	0.36
Year 3	0.32	0.31	0.30	0.29
Year 4	0.28	0.28	0.27	0.27
Year 5	0.27	0.26	0.26	0.25
Year 10	0.25	0.25	0.24	0.24
Steady state	0.25	0.24	0.24	0.23
Convergence				
75%	3	3	3	3
90%	5	5	5	4
95%	6	6	6	6

xxxx

Table 11
Capital Response to Price Shocks by Firm Type

	ESTIMATED COSTS				COUNTERFACTUAL COSTS			
	Percentage price increase				Percentage price increase			
	5%	10%	20%	30%	5%	10%	20%	30%
Elasticity Type High								
Year 1	0	0	0	0	0	0	0	0
Year 2	0.53	0.56	0.62	0.67	0.97	0.97	0.96	0.95
Year 3	1.06	1.11	1.22	1.29	1.58	1.60	1.63	1.65
Year 4	1.48	1.53	1.63	1.72	1.94	1.97	2.03	2.08
Year 5	1.75	1.81	1.92	2.00	2.12	2.17	2.24	2.31
Year 10	2.29	2.30	2.37	2.43	2.31	2.36	2.46	2.55
Steady state	2.34	2.37	2.43	2.48	2.32	2.37	2.47	2.56
Elasticity Type Low								
Year 1	0	0	0	0	0	0	0	0
Year 2	0.59	0.58	0.59	0.58	1.21	1.20	1.20	1.19
Year 3	1.10	1.09	1.08	1.06	1.79	1.81	1.86	1.89
Year 4	1.41	1.39	1.38	1.36	2.06	2.10	2.17	2.24
Year 5	1.65	1.63	1.61	1.59	2.19	2.23	2.33	2.41
Year 10	1.97	1.98	1.97	2.02	2.33	2.37	2.47	2.56
Elasticity (ss)	2.06	2.10	2.02	2.11	2.31	2.36	2.47	2.55
Gap High-Low								
Initial gap	444.5	444.5	444.5	444.5	934.6	934.6	934.6	934.6
Increase (ss)	6.9	12.1	31.8	37.0	0.6	0.6	0.4	1.1

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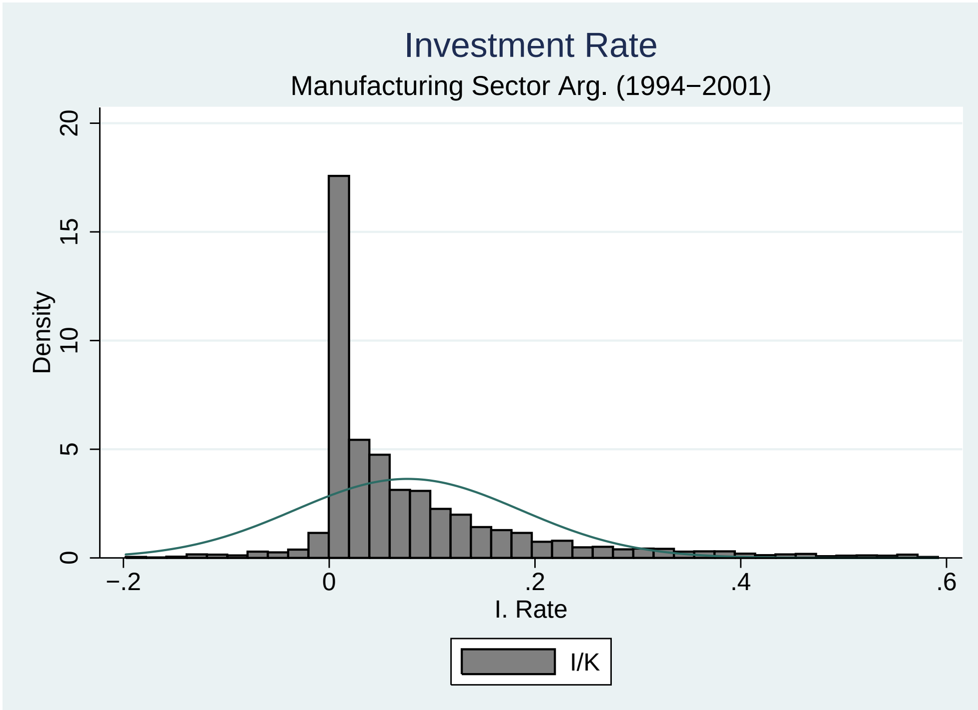
Figure 1
Investment Rate Distribution



Source: ENI, Encuenta Nacional Industrial (National Industrial Survey), Argentina 1994-2001.

Figure 2

Price Increase of 10 Percent

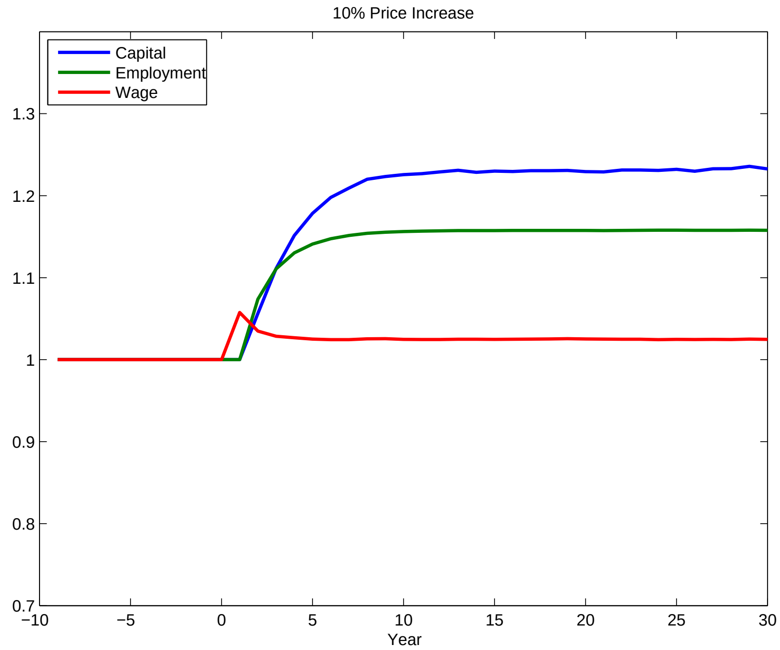


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Table B1
General Equilibrium Effects. Estimated Adjustment Costs

	OTHER TRADABLE GOODS				NON-TRADABLE GOODS			
	Percentage price increase				Percentage price decrease			
	5%	10%	20%	30%	5%	10%	20%	30%
Capital								
Year 1	0	0	0	0	0	0	0	0
Year 2	-0.22	-0.46	-0.93	-1.43	0.52	1.02	2.24	3.44
Year 3	-0.64	-1.24	-2.49	-3.74	0.84	1.68	3.64	5.63
Year 4	-0.97	-1.93	-3.94	-5.92	1.06	2.19	4.66	7.23
Year 5	-1.24	-2.46	-5.02	-7.53	1.17	2.48	5.28	8.26
Year 10	-1.86	-3.74	-7.59	-11.45	1.36	2.68	6.09	9.51
Steady state	-1.86	-3.76	-7.75	-11.88	1.38	2.83	5.98	9.74
Elasticity (ss)	-0.37	-0.38	-0.39	-0.40	0.28	0.28	0.30	0.32
Employment								
Year 1	0	0	0	0	0	0	0	0
Year 2	-1.34	-2.68	-5.37	-8.02	-0.03	-0.05	-0.08	-0.09
Year 3	-1.97	-3.95	-7.93	-11.86	-0.05	-0.09	-0.15	-0.19
Year 4	-2.29	-4.59	-9.24	-13.83	-0.06	-0.11	-0.20	-0.26
Year 5	-2.46	-4.95	-9.96	-14.90	-0.07	-0.13	-0.23	-0.30
Year 10	-2.71	-5.45	-10.93	-16.34	-0.08	-0.15	-0.27	-0.36
Steady state	-2.74	-5.50	-11.02	-16.50	-0.08	-0.15	-0.27	-0.37
Elasticity (ss)	-0.55	-0.55	-0.55	-0.55	-0.02	-0.02	-0.01	-0.01
Wage								
Year 1	-1.99	-3.87	-7.32	-10.44	-0.75	-1.43	-2.63	-3.63
Year 2	-1.46	-2.86	-5.41	-7.72	-0.67	-1.24	-2.15	-2.80
Year 3	-1.25	-2.42	-4.56	-6.48	-0.59	-1.09	-1.77	-2.20
Year 4	-1.16	-2.25	-4.24	-5.97	-0.56	-1.00	-1.55	-1.87
Year 5	-1.15	-2.19	-4.08	-5.71	-0.56	-0.97	-1.49	-1.73
Year 10	-1.12	-2.19	-4.05	-5.70	-0.51	-0.88	-1.39	-1.54
Steady state	-1.11	-2.13	-3.99	-5.64	-0.49	-0.85	-1.30	-1.45
Elasticity (ss)	-0.22	-0.21	-0.20	-0.19	-0.10	-0.08	-0.07	-0.05

xxxx

Table B2
General Equilibrium Effects. Counterfactual Adjustment Costs

	OTHER TRADABLE GOODS				NON-TRADABLE GOODS			
	Percentage price increase				Percentage price decrease			
	5%	10%	20%	30%	5%	10%	20%	30%
Capital								
Year 1	0	0	0	0	0	0	0	0
Year 2	-0.36	-0.71	-1.43	-2.16	0.93	1.88	3.78	5.72
Year 3	-0.96	-1.93	-3.90	-5.85	1.26	2.58	5.34	8.27
Year 4	-1.38	-2.79	-5.61	-8.47	1.39	2.84	5.99	9.40
Year 5	-1.61	-3.29	-6.62	-10.02	1.46	2.95	6.26	9.91
Year 10	-1.92	-3.85	-7.79	-11.76	1.49	3.01	6.43	10.28
Steady state	-1.91	-3.85	-7.83	-11.86	1.48	2.96	6.45	10.29
Elasticity (ss)	-0.38	-0.39	-0.39	-0.40	0.30	0.30	0.32	0.34
Employment								
Year 1	0	0	0	0	0	0	0	0
Year 2	-1.43	-2.86	-5.68	-8.45	-0.03	-0.05	-0.08	-0.09
Year 3	-2.10	-4.21	-8.40	-12.54	-0.05	-0.09	-0.16	-0.19
Year 4	-2.43	-4.87	-9.76	-14.58	-0.06	-0.12	-0.21	-0.27
Year 5	-2.59	-5.21	-10.45	-15.63	-0.07	-0.13	-0.24	-0.31
Year 10	-2.75	-5.54	-11.15	-16.70	-0.08	-0.15	-0.27	-0.36
Steady state	-2.76	-5.56	-11.19	-16.77	-0.08	-0.15	-0.27	-0.36
Elasticity (ss)	-0.55	-0.56	-0.56	-0.56	-0.02	-0.01	-0.01	-0.01
Wage								
Year 1	-1.99	-3.87	-7.32	-10.44	-0.75	-1.43	-2.63	-3.63
Year 2	-1.45	-2.82	-5.35	-7.62	-0.61	-1.13	-1.95	-2.50
Year 3	-1.26	-2.43	-4.57	-6.47	-0.55	-1.01	-1.63	-1.95
Year 4	-1.18	-2.27	-4.25	-5.96	-0.53	-0.95	-1.48	-1.68
Year 5	-1.15	-2.22	-4.11	-5.75	-0.51	-0.91	-1.39	-1.52
Year 10	-1.12	-2.15	-3.97	-5.52	-0.49	-0.87	-1.31	-1.38
Steady state	-1.11	-2.14	-3.96	-5.52	-0.50	-0.88	-1.31	-1.38
Elasticity (ss)	-0.22	-0.21	-0.20	-0.18	-0.10	-0.09	-0.07	-0.05

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