

**Industrial Evolution in Crisis-Prone Economies**

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## **Abstract**

Balance of payments crises and banking crises are commonplace in developing countries. Often they feed off one another, creating dramatic swings in the real exchange rate, real interest rates, and expectations about regime sustainability. We quantify the effects of these crises on industrial sector productivity distributions, size distributions and borrowing patterns. To do so, we first develop an industrial evolution model in which capital market imperfections link firms' ability to borrow and the wealth of their owners. Then we fit our model to firm-level panel data and macro data from Colombia that span the debt-crisis period of the 1980s. Finally, using the estimated parameters, we simulate industrial evolution patterns under alternative assumptions about the stochastic processes for exchange rates and interest rates.

Among other things, we find that increases in macroeconomic volatility reduce average productivity through selection effects. These effects are particularly dramatic in the immediate aftermath of a shift from a stable regime to a volatile regime because heightened uncertainty creates greater incentives for large, poorly-performing firms to delay exit in the hope that things will improve. We also find that improvements in the efficiency of loan contract enforcement lead to more borrowing, larger firms, more entrepreneurship among households with modest wealth, and a more egalitarian distribution of income.

## I. Overview

Balance of payments crises and banking crises are commonplace in developing countries.<sup>1</sup> Often they feed off one another, creating dramatic swings in the real exchange rate, real interest rates, and expectations about regime sustainability. The effects of these macro crises on productivity and wealth distributions can be severe, particularly in countries where credit markets function poorly and stock markets are thin. They can discourage investment overall, and favor firms with ample collateral.<sup>2</sup> Similarly, they can change patterns of job destruction and business failure, weakening the link between firms' real-side performance and their chances of survival.

Our objective is to model and quantify these relationships. We first develop an industrial evolution model in which capital market imperfections link firms' ability to borrow and the wealth of their owners. Then we fit our model to firm-level panel data and macro data from Colombia that span the debt-crisis period of the 1980s. Finally, using the estimated parameters, we simulate industrial evolution patterns under alternative assumptions about the stochastic processes for exchange rates and interest rates. In particular, we explore the effects of crisis-prone environments on entry and exit patterns, cross-firm investment patterns, industry-wide productivity, and wealth distributions.

The simulations yield a variety of results. Among other things, we find that

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<sup>1</sup> In a panel of 20 countries from Asia, Europe, Latin America and the Middle East, Kaminsky and Reinhart (1999) document 25 banking crises and 71 balance of payments crises during the period 1970-1995.

<sup>2</sup> Volatility may also change the types of capital goods that firms invest in. For example, uncertainty about the future can induce firms to avoid specialized technologies that are very efficient in some states of nature and very inefficient in others (Lambson, 1991). Also, by increasing the risk of a liquidity constraint in the future, volatility can discourage long-term investments in favor of shorter term, lower productivity alternatives (Aghion, et al, 2005). Our analysis does not deal with these phenomena.

heightened macro volatility reduces average productivity because of the selection effects it creates. Households with modest wealth are unable to bridge periods of temporary losses by borrowing, and are also discouraged from operating businesses because of their risk aversity. Also, in the immediate aftermath of a shift from a stable regime to a crisis regime, heightened uncertainty creates greater incentives for large, poorly-performing firms to delay exit in the hope that things will improve. The associated industry-wide productivity losses can range from 3 to 5 percent during the early years of a crisis.

In addition to exploring the effects of volatility, we quantify the effects of credit market imperfections. Our simulations suggest that improvements in the efficiency of loan contract enforcement would lead to more borrowing, larger firms, more entrepreneurship among households with modest wealth, and a more egalitarian distribution of income.

*Relation to the literature (to come)*

## **II. The Model**

Our industrial evolution model has several key features. First, it is partial equilibrium. More precisely, it describes a single industry operating in an exogenously determined macro environment. Second, to approximate financial market conditions in developing countries, we assume that securities markets are negligible, and that households hold their wealth as bank deposits and/or investments in proprietorships. Third, households can borrow to finance some of their business investments, but their loans must be sufficiently small that they pose no default risk to lenders. Fourth,

households are forward-looking, infinitely-lived, and risk-averse. They are also heterogeneous in terms of their ability to generate business income, which is subject to serially correlated, idiosyncratic shocks. Finally, all firms produce traded goods, so changes in the real exchange rate result in changes in output prices for firms.

Given this setting, households with different entrepreneurial abilities and wealth levels react differently to macro shocks. For example, owner-households with ample wealth may have no trouble weathering a period of exchange rate appreciation, while others may be induced to shut down their firms. Accordingly, macro crises affect firm ownership patterns, firm size distributions, productivity distributions, borrowing patterns, and cross-household wealth distributions. We now turn to model specifics.

#### **A. The Macro Environment**

Three macro variables appear in our model—the real exchange rate,  $e$ , the lending rate,  $r$ , and the deposit rate,  $r - \mu$ . The interest spread  $\mu > 0$  is parametrically fixed, so we can summarize the state of the macro economy at any point in time by the vector  $s = (e, r)$ . This vector evolves according to an exogenous Markov process,  $\psi(e_{t+1}, r_{t+1} | e_t, r_t) \equiv \psi(s_{t+1} | s_t)$ , which characterizes the extent to which the economy is crisis-prone.

#### **B. The Household Optimization Problem**

Households in our model fall into one of three categories: owner-households, which own incumbent firms, potential owner-households, which can start a firm if they incur the fixed entry cost, and non-entrepreneurial households. These households differ in their investment opportunities, and a particular household can move between types based on its entry–exit decisions. Non-entrepreneurial households have access only to

bank deposits as a return on their investment. Incumbent owner-households allocate their wealth between bank deposits and investments in the firm, with households being heterogeneous in that there are firm-specific productivity differences. An incumbent household that chooses to exit the industry will revert to being a non-entrepreneurial household that invests only in bank deposits. A potential entrant household that chooses to enter the industry will become an incumbent owner-household in the following period. The stock of potential entrant households is augmented each period by the arrival of an exogenously given number of new potential entrants.

All households are assumed to have a common CRRA utility function

$$U(c_{it}) = \frac{(c_{it})^{1-\sigma}}{1-\sigma}, \text{ where } c_{it} \text{ is consumption by household } i \text{ at time } t. \text{ Households are}$$

assumed to make decisions to maximize their discounted expected utility stream,

$$E_t \sum_{\tau=t}^{\infty} U(c_{i\tau}) \beta^{\tau-t}, \text{ where } E_t \text{ is an expectations operator conditioned on information}$$

available in period  $t$ , and  $\beta$  is a discount factor that reflects the rate of time preference.

We begin by considering the optimization problem for non-entrepreneurial households, who only have access to bank deposits as an investment opportunity.

Letting  $a_{it}$  denote household  $i$ 's wealth at the beginning of period  $t$  and  $y_{i0}$  its current (non-asset) income from other sources, the household's current consumption will be  $c_{it} = y_{i0} + (r_t - \mu) \cdot a_{it} - (a_{it+1} - a_{it})$ . We assume that non-entrepreneurial households are unable to borrow against outside income, which imposes the constraint that  $a_{it} \geq 0$ .

The optimization problem for a household with initial assets  $a_{it}$  in state  $s_t$  can be represented by the following dynamic programming problem:

$$V^E(a_{it}, y_{i0}, s_t) = \max_{a' \geq 0} \left[ U(y_{i0} + (r_t - \mu)a_{it} - (a' - a_{it})) + \beta \sum_{s'} \psi(s' | s_t) V^E(a', y_{i0}, s') \right] \quad (1)$$

The payoff to a non-entrepreneurial household will be important to the optimization problem for owner-households because it represents the exit payoff if an owner-household decides to leave the industry with wealth  $a_{it}$ .<sup>3</sup>

### B. The Decision problem for Incumbent Owner-Households

We next consider the decision problem for an incumbent owner-household, which is currently operating a firm. Incumbent households are heterogeneous in terms of their managerial skills, product market niche, local factor market conditions, and wealth. If an incumbent owner-household  $i$  chooses to operate a firm in period  $t$ , its earnings (before interest) from doing so are:

$$\pi(k_{it}, e_t, v_{it}) = \begin{cases} \exp(\eta_0 + \eta_1 e_t + v_{it}) \cdot R(k_{it}) - f - \delta k_{it} & \text{if } k_{it} > 0 \\ 0 & \text{if } k_{it} = 0 \end{cases} \quad (2)$$

Here  $f$  is fixed business expenses per period,  $\delta$  is the depreciation rate,

$\exp(\eta_0 + \eta_1 e_t + v_{it}) \cdot R(k_{it})$  is gross operating profits before interest and depreciation

( $R' > 0$ ,  $R'' < 0$ ,  $R(0) = 0$ ), and  $\exp(\eta_0 + \eta_1 e_t + v_{it})$  is an exogenous profitability

factor composed of firm-specific ( $v_{it}$ ) and exchange rate ( $e_t$ ) effects. The former reflects

managerial skills and investment opportunities, while the latter captures the effects of

exchange rate movements on input prices and demand. We assume that  $v_{it}$  evolves

according to the discrete Markov process  $\phi(v_{it+1} | v_{it})$  that it is independent of the

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<sup>3</sup> Assume for tractability that households that shut down their firms cannot start new businesses in the future.

macroeconomic state vector  $s_t$ .

The current state of an owner-household will be characterized by the vector  $(a_{it}, s_t, v_{it})$  representing its initial asset position, the macroeconomic state, and the household-specific firm productivity level. At the beginning of the period the owner-household must decide whether to continue the operation of the firm, given the current state, or to exit the industry and become a non-entrepreneurial household. If the owner chooses to exit the industry, the payoff is  $V^E(a_{it}, y_{i0}, s_{it})$ , derived in (1). In this section we will solve for the payoff the owner-household obtains if it continues to operate the firm, which we denote  $V^I(a_{it}, y_{i0}, s_{it}, v_{it})$ . The payoff to an owner household will then be the maximum of the payoff from exiting and the payoff from continuing in the industry,

$$V(a_{it}, y_{i0}, s_t, v_{it}) = \max[V^I(a_{it}, y_{i0}, s_t, v_{it}), V^E(a_{it}, y_{i0}, s_t)] \quad (3)$$

If the owner-household chooses to operate the firm in the current period, it must choose the allocation of its wealth between investments in the firm ( $k_{it}$ ) and bank deposits ( $a_{it} - k_{it}$ ). Negative bank deposits amount to bank loans, which are used to finance business investments. These bank loans will be subject to a quantitative restriction to be defined below that eliminates the default risk for lenders. Thus in period  $t$  the  $i^{\text{th}}$  household earns or pays  $(a_{it} - k_{it}) \cdot (r_t - \mu D_{it})$  in interest, where

$$D_{it} = \begin{cases} 1 & \text{if } a_{it} - k_{it} > 0 \\ 0 & \text{otherwise} \end{cases} \text{ is a dummy indicating whether the household holds bank}$$

deposits. Hence household consumption in period  $t$  is simply the sum of exogenous



income, business income, and interest income, net of wealth accumulation:

$$c_{it} = y_{i0} + \pi(k_{it}, z_{it}) + (r_t - \mu D_{it}) \cdot (a_{it} - k_{it}) - (a_{it+1} - a_{it}). \quad (4)$$

The borrowing decisions of households are assumed to be limited by the imperfect enforceability of debt contracts. More precisely, we assume that lenders are perfectly informed about the productivity of their borrowers' firms,  $\eta_0 + \eta_1 e_t + v_{it}$ , but they are unable to observe the uses to which these borrowers put their loans. If the  $i^{\text{th}}$  household borrows an amount  $(k_{it} - a_{it})$ , it can either invest that amount in the firm or sell the firm's capital stock and abscond with  $\theta k_{it}$ . The parameter  $\theta \in [0,1]$  captures all of the monetary and psychic costs of taking the money and running, including the possibility of future punishment.<sup>4</sup> Assuming that the defaulting borrower can be effectively excluded from future firm investment opportunities, the payoff to defaulting will be the valuation of a non-entrepreneurial household with assets  $\theta k_{it}$ . An owner household will not default on its loans as long as

$$V^I(a_{it}, y_{i0}, s_t, v_{it}) \geq V^E(\theta k_{it}, y_{i0}, s_t) \quad (5)$$

The borrowing of owner households will be subject to this no default constraint. The limiting cases of  $\theta = 0$  and  $\theta = 1$  correspond to perfectly enforceable debt contracts and costless default, respectively. The wealth of the household serves as collateral that relaxes the no default constraint.

If the incumbent owner household chooses to produce in the current period, it

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<sup>4</sup> No default constraints of this type have been used by Banerjee and Newman (1993, 2001) to examine the role of capital market imperfections. Cooley and Quadrini (2001) examine a model of capital market imperfections with costly state verification, where expected productivity of the firm is observable to lenders but the current period realization of the cash flow can only be observed with a positive cost.

chooses  $a_{it}$  and  $k_{it}$  to maximize discounted expected utility subject to the no default constraint on borrowing. Using (3) and (4), the value to an incumbent owner household of producing in the current period will be the solution to the following dynamic programming problem

$$V^I(a_{it}, y_{i0}, s_t, v_{it}) = \max_{a' \geq 0, k_{it} > 0} \left[ U(y_{i0} + \pi(k_{it}, e_t, v_{it}) + (r_t - \mu D_{it})(a_{it} - k_{it}) - (a' - a_{it})) + \beta \sum_{v'} \sum_{s'} V(a', y_{i0}, s', v') \cdot \psi(s' | s_t) \cdot \phi(v' | v_{it}) \right]. \quad (6)$$

subject to (5)

This problem captures two ways in which household assets serve as a basis for the self-financing of firms. The first is due to the wedge between the borrowing and lending rate for firms, which makes it more attractive for households to accumulate assets because of the higher return available when  $a_{it} < k_{it}$ . The second is due to the fact that increases in household wealth will relax the no default constraint in (5).

### C. Potential Entrant Households

We conclude our description of the model by characterizing the entry decision into the industry. Each period, an exogenously given number of households,  $N$ , become potential entrants to the industry. This can be thought of as reflecting the entry of new entrepreneurs into the population and/or the random arrival of new entrepreneurial idea in the population. If a potential entrant household chooses to enter, it must pay start-up costs,  $F$ , and draw an initial  $v_{it}$  from the distribution  $q_0(v)$ , which is common to all entrants. Given this  $v_{it}$ , the household then chooses initial  $k_{it}$  and  $a_{it+1} - a_{it}$  values. If

a potential entrant household chooses not to enter, it allocates its current income flow,  $y_{i0} + (r_t - \mu)a_{it}$ , between consumption and asset accumulation. A potential entrant that chooses not to enter in the current period has the option of entering in the future.

Let  $V^N(a_{it}, y_{i0}, s_t)$  denote the value to the potential entrant of entering in the current period and  $V^O(a_{it}, y_{i0}, s_t)$  the value of waiting until the next period to enter.

The potential entrant household will enter if

$$V^N(a_{it}, y_{i0}, s_t) > V^O(a_{it}, y_{i0}, s_t), \quad (7)$$

where:

$$\begin{aligned} V^N(a_{it}, y_{i0}, s_t) = & \sum_{\nu} \max_{a' \geq 0, k_{it} > 0} \left[ U(y_{i0} - F + \pi(k_{it}, e_t, \nu) + (r_t - \mu D_{it}) \cdot (a_{it} - k_{it}) - (a' - a_{it})) + \right. \\ & \left. \beta \cdot \sum_{\nu'} \sum_{s'} V(a', y_{i0}, s', \nu') \cdot \psi(s' | s_t) \phi(\nu' | \nu) \right] q_0(\nu) \end{aligned}$$

and

$$\begin{aligned} V^O(a_{it}, y_{i0}, s_t) = & \max_{a' \geq 0} \left[ U(y_{i0} + (r_t - \mu) \cdot a_{it} - (a' - a_{it})) + \right. \\ & \left. \beta \sum_{e'} \sum_{s'} \max[V^N(a', y_{i0}, s'), V^O(a', y_{i0}, s')] \psi(s' | s_t) \right]. \end{aligned}$$

Note that the value of entry is not conditioned on  $v_{it}$ , since the firm's productivity is only observed after the entry cost has been incurred.

Potential entrants might choose to postpone entry for two reasons. One

possibility is that the current macroeconomic state makes entry unattractive, so that the household waits until conditions improve to enter. A second possibility is that the potential entrant has a low level of initial wealth holdings. Such a household might choose to accumulate assets for one or more periods prior to entering in order to increase the probability of success by relaxing the borrowing constraint it will face upon entry.

#### **D. Industry Evolution**

The solutions to the optimization problems (6) and (7) can be used to characterize the evolution of the industry over time. The solution to the incumbent optimization problem (6) yields a policy function  $\tilde{a}(a_{it}, s_t, v_{it})$  describing an incumbent firm's asset choice for the next period and an indicator function  $\chi(a_{it}, s_t, v_{it})$  that is equal to one if the incumbent chooses to exit. Given an initial distribution of incumbent owner households,  $h^I(a_{it}, v_{it})$ , these policy functions will generate an expected frequency distribution over  $(a_{it+1}, v_{it+1})$ .

Similarly, the solution to the potential entrant optimization problem (7) yields a policy function  $\tilde{a}^N(a_{it}, s_t)$  for households that choose to enter, a policy function  $\tilde{a}^O(a_{it}, s_t)$  for households that choose to postpone entry, and an indicator function  $\chi^N(a_{it}, s_t)$  that is equal to 1 if the household enters. Given an initial distribution of potential entrant firms over asset levels  $h^N(a_{it})$ , these policy functions can be used to generate an expected frequency distribution over  $(a_{it+1}, v_{it+1})$  for entering firms and an updated distribution of asset levels among potential entrants.

### III. Fitting the model to data

To give our model empirical content, we exploit Colombian time series on interest rates and exchange rates for the period 1982-2004, and we exploit plant-level panel data on apparel producers for the period 1981-1991. Our choice of country and time period partly reflects data availability. But it also reflects the fact that Colombian data exhibit the kind of variation we wish to study. The country underwent a debt crisis in the early 1980s; then it emerged into a period of relative stability. We focus on apparel producers because their products are tradeable, and because the entry costs for this industry are low. Tradeability means that output prices are largely determined by the exchange rate and global market conditions, as our model presumes.<sup>5</sup> Low entry costs make our assumption of monopolistic competition reasonable, and they ensure that small, closely held firms are the dominant business type.

Fitting the model to the Colombian data involves three basic exercises. First, we use annual plant level panel data on apparel producers to estimate the business earnings function  $\exp(\eta_0 + \eta_1 e_t + \nu_{it}) \cdot R(k_{it})$ , the transition density  $\phi(\nu_{it+1} | \nu_{it})$ , and the depreciation rate,  $\delta$ . Second, we use monthly time series on exchange rates and interest rates for the period 1982-2004 to estimate the transition density  $\phi(e_{t+1}, r_{t+1} | e_t, r_t)$  and the interest rate spread,  $\mu$ . Finally, with these results in hand, we use the dynamic implications of our model and various industry-wide summary statistics to estimate entry costs ( $F$ ), fixed costs ( $f$ ), and the credit market imperfection index ( $\theta$ ). (Our data do not contain much information about taste parameters, so we follow convention and them to  $\sigma = 0.5$  and  $\beta = 0.9$ .) Each step in the estimation process is described below.

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<sup>5</sup> Import penetration rates averaged \_\_\_\_ and export rates averaged \_\_\_\_ during the sample period.

### A. Estimating the profit function

Using book values of annual depreciation and capital stocks from our plant-level survey data, we calculate that the mean depreciation rate in apparel industry is  $\delta = 0.104$ . To obtain estimates of the remaining parameters in the function  $R(k_{it})$  and the transition density  $\phi(v_{it+1} | v_{it})$ , we must impose additional structure on our model. Let the production function for firm  $i$  be  $Q_{it} = \exp(u_{it}) \cdot k_{it}^\alpha l_{it}^\gamma$ , where  $u_{it}$  is a productivity index,  $k_{it}$  is the capital stock and  $l_{it}$  is an index of variable input usage—labor, intermediates, and energy. Given an exogenous world price ( $P_{it}$ ) for the  $i^{th}$  firm's product and an exogenous price for a unit bundle of its variable inputs ( $w_{it}$ ), this production function implies that the profit-maximizing values for total revenue ( $G_{it}^*$ ) and total variable costs ( $C_{it}^*$ ) are:<sup>6</sup>

$$G_{it}^* = \gamma^{-1} \exp(u_{it} (1 - \gamma)^{-1}) w_{it} \left( \frac{\gamma P_{it}}{w_{it}} \right)^{(1-\gamma)^{-1}} (k_{it}^\alpha)^{(1-\gamma)^{-1}}, \quad (9a)$$

$$C_{it}^* = \exp(u_{it} (1 - \gamma)^{-1}) w_{it} \left( \frac{\gamma P_{it}}{w_{it}} \right)^{(1-\gamma)^{-1}} (k_{it}^\alpha)^{(1-\gamma)^{-1}} \quad (9b)$$

Prices for inputs and outputs are not observable at the firm level, so we express  $w_{it} (P_{it} / w_{it})^{1/(1-\gamma)}$  as a Cobb-Douglas function of a time trend, the real exchange rate, and firm-specific shocks. Similarly we express  $u_{it}$  as a time trend and plus firm-specific shocks. This allows us to write (9a) and (9b) as:

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<sup>6</sup> Alternatively, one can begin from a monopolistic competition model in which each firm faces a downward sloping demand function in global markets. So long as each firm views itself as too small to influence the demand conditions it faces—that is, too small to influence the behavior of competing firms—we can characterize firms' behavior using a single-agent optimization problem.

$$G_{it}^* = \gamma^{-1} \cdot \exp(\eta_0 + \eta_1 e_t + \eta_2 t + \mu_i + \varepsilon_{it}^E) \cdot (k_{it})^{\eta_3}, \quad (10a)$$

$$C_{it}^* = \exp(\eta_0 + \eta_1 e_t + \eta_2 t + \mu_i + \varepsilon_{it}^E) \cdot (k_{it})^{\eta_3} \quad (10b)$$

where  $\eta_3 = \alpha / (1 - \gamma)$ . Note that the identity  $\exp(\eta_0 + \eta_1 e_t + \nu_{it}) \cdot R(k_{it}) = G_{it}^* - C_{it}^*$  implies  $R(k_{it}) = (\gamma^{-1} - 1)(k_{it})^{\eta_3}$  and  $\nu_{it} = \mu_i + \varepsilon_{it}^E$ . That is, we have expressed the firm-specific shocks introduced in section II as the sum of a fixed effect,  $\mu_i$ , and a random variable that evolves through time,  $\varepsilon_{it}^E$ . We impose no particular distribution on the fixed effects, but we assume that  $\varepsilon_{it}^E$  is normally distributed and follows the same AR(1) process for all firms.

Our industrial survey data provide plant-specific information on the value of output and expenditures on labor, intermediates and materials. So equation (10) provides a basis for estimating the income function  $R(k_{it})$  and the transition density  $\phi(\nu_{it+1} | \nu_{it})$ . To allow for noise in the data—particularly due to discrepancies between “true” variable costs and measured expenditures—we assume that reported revenues and costs are measured with serially-correlated error:  $G_{it} = G_{it}^* e^{\varepsilon_{it}^G}$ ,  $C_{it} = C_{it}^* e^{\varepsilon_{it}^C}$ , where  $(\varepsilon_{it}^G, \varepsilon_{it}^C)$  is a vector of orthogonal, normal AR(1) processes that are uncorrelated with  $\varepsilon_{it}^E$ . Substituting (10a) and (10b) into these expressions, taking logs yields:

$$\ln(G_{it}) = \eta_0^G + \eta_1 \ln e_t + \eta_2 t + \eta_3 \ln K_{it} + \varepsilon_{it}^E + \varepsilon_{it}^G \quad (11a)$$

$$\ln(C_{it}) = \eta_0^C + \eta_1 \ln e_t + \eta_2 t + \eta_3 \ln K_{it} + \varepsilon_{it}^E + \varepsilon_{it}^C \quad (11b)$$

Equations (11a) and (11b) can be estimated as a system, either in level form or in first differences. (The latter is appropriate if the disturbance terms include a permanent source of heterogeneity.) Further, because the profit disturbance is common to both equations while measurement errors are not, it is possible to identify the parameters of the transition density  $\phi(v_{it+1} | v_{it})$ .

Table 1 reports preliminary results for the Colombian apparel producers. Here, both level-form and differenced-form estimates are fit to the population of producers appearing in the annual manufacturing survey for a least one year between 1981 and 1991.<sup>7</sup> Also, to allow for the possibility that new entrants draw their initial productivity shock from a different distribution, we include a dummy for plants in their first year of operation.

Increases in the capital stock increase revenues, costs, and profits, as expected. However, the coefficient on capital is smaller for the differenced-form estimator. Most likely this is because capital is measured with error, and differencing the data exacerbates the associated bias (Griliches and Hausman, 1986). None of the other coefficients is very sensitive to differencing the data. The exchange rate coefficient implies each percentage point of devaluation reduces earnings, costs and profits by about one-third of one percent. Clearly, plant-specific profitability shocks are serially correlated—the root of this process is around 0.94, and is highly significant. However, profitability shocks exhibit very little trend. Finally, serially-correlated measurement errors appear to be present in both revenues and total variable costs.

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<sup>7</sup> The survey covers all plants with at least 10 workers. For our differenced-form estimator, plants must be present in the data set at least two years. Hence the sample is smaller for this set of results.



## B. Estimating the Markov process for macro variables

Our methodology for estimating the transition density  $\psi(e_{t+1}, r_{t+1} | e_t, r_t)$  comes from the econometric literature on regime switching, which was developed to characterize macro processes that change dramatically during certain periods (e.g., Hamilton, 1994, chapter 22). The notion is that the observed time series actually reflect multiple regimes. Estimation amounts to recovering the parameters that describe the stochastic process behind each regime, and recovering the transition probabilities that characterize movements between regimes.

A variety of specifications have been used for switching models, and it is not obvious *ex ante* which one is appropriate for our purposes.<sup>8</sup> Accordingly, we fit several models with different degrees of generality and compare them. First, to provide a base case, we estimate a simple VAR in the real exchange rate and the real interest rate. Second, we estimate a switching model that allows for Markov-switching heteroskedasticity (MSH). That is, the covariance matrix for the innovations are regime-specific, but nothing else is. Finally, we estimate a more general model in which all parameters of the VAR—intercepts, roots and covariance matrix—are allowed to be regime dependent (MSIAH).

Let  $y_t = \begin{pmatrix} e_t \\ r_t \end{pmatrix}$  be the vector of macro variables, and assume that under macro

regime  $m \in \{1, 2\}$  this vector evolves according to  $y_t = \beta_0^m + \beta_1^m y_{t-1} + v_t^m$ , where

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<sup>8</sup> Applications to exchange rates include Engel and Hamilton (1990) and Bollen, et al (2000). Applications to interest rate processes include Gray (1996). Although we are unaware of papers that apply switching estimators to the joint evolution of exchange rates and interest rates, the methodology for estimating multivariate switching models is well developed (e.g., Clarida *et al*, 2003).

$E\left(v_t^m v_t^{m'}\right) = \Sigma^m$ . Then the switching models we estimate can be summarized as a

simple VAR, in which there is a single regime (and all superscripts could be dropped);

the MSH model, in which  $(\beta_0, \beta_1, \Sigma^1)$  and  $(\beta_0, \beta_1, \Sigma^2)$  are the possible regimes; and

the MSIAH model, in which  $(\beta_0^1, \beta_1^1, \Sigma^1)$  and  $(\beta_0^2, \beta_1^2, \Sigma^2)$  are possible regimes.

Switches between regimes are governed by the transition matrix  $\mathbf{p} = \{p_{mn}\}$ , where  $p_{mn}$  is the probability of moving to regime  $m$ , given that the economy is currently in regime  $n$ .

Figure 1 presents monthly series on the Colombian real exchange rate and real interest rate, respectively (IMF, 2004). Lower exchange rate values correspond to a cheaper Colombian peso. Both series suggest the Colombia was in one regime during the early 1980s, when the debt crisis was at its most severe, and another regime thereafter. The data also suggest that month-to-month volatility is much different from year-to-year volatility, and that when crises hit, the macro volatility that they create is often concentrated within relatively short periods. Therefore, it seems preferable to estimate the models with monthly data; in fact, for the MSH specification it proved infeasible to do otherwise.

Using a variant of the EM algorithm described in Clarida *et al* (2003) we obtain the maximum likelihood estimates reported in table 2.<sup>9</sup> Likelihood ratio tests indicate that the MSH model and the simple VAR model can be rejected in favor of the MSIAH model, so we focus our attention on this latter specification. The two regimes it describes differ in terms of both roots and volatility. Regime 1, which is very likely to continue from one month to the next ( $p_{11} = 0.966$ ), exhibits strong serial correlation in

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<sup>9</sup> We use the Ox Professional MSVAR software package developed by Hans-Martin Krolzig. Details are available at on-line at: <http://www.economics.ox.ac.uk/research/hendry/krolzig/>.

both exchange rates and interest rates. It also exhibits relatively small variance in the process innovations (refer to  $\Sigma^1$ ), and relatively little interdependence between interest rates and exchange rates (refer to the off-diagonal elements of  $\beta_1^1$ ).

Regime 2 is relatively unlikely to occur, and when it does occur, it is relatively unlikely to persist ( $p_{22} = 0.384$ ). It is characterized by much weaker serial correlation, substantially higher variance in the process innovations, and substantial, positive interdependence between the exchange rate and the interest rate. This latter regime thus appears to correspond to the debt crisis years that occur during the first part of the sample period, and we will think of an increase in the volatility of macro conditions as an increase in the probability that the economy spends time in regime 2.

It remains to discuss the spread between the lending rate and the deposit rate,  $\mu$ . This differential is a fixed parameter in our model, so we simply estimate it as the mean difference between these two series over the sample period, obtaining  $\mu=0.060$ .

### **C. Estimating the remaining parameters**

#### *Estimation strategy*

To approximate the remaining parameters—entry costs ( $F$ ), fixed costs ( $f$ ), and the credit market imperfection index ( $\theta$ )—we embed our behavioral model in a method of moments estimator.<sup>10</sup> That is, we choose the  $(F, f, \theta)$  combination that minimizes a measure of distance between moments implied by model simulations and their sample counterparts. For any given  $(F, f, \theta)$  combination, we construct the distance measure as

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<sup>10</sup> Our data are not very informative about the preference parameters, so for this exercise we follow convention and set them to  $\sigma = 0.5$  and  $\beta = 0.9$ .

follows. First, using the candidate  $(F, f, \theta)$  vector and the estimated values for all of the other model parameters, we numerically solve for the value functions characterized in section IIB.<sup>11</sup> Second, using these functions in combination with randomly drawn macro shocks  $(\nu)$  and firm-level profitability shocks  $(\varepsilon^E)$ , we repeatedly simulate patterns of industrial evolution. Third, we average over these simulations to construct the expected entry rates, exit rates, and other moments implied by the candidate  $(F, f, \theta)$  vector. Fourth, calling the vector of simulated moments  $m(F, f, \theta)$  and their sample counterparts  $\bar{m}$ , we calculate our measure of distance between the sample and simulated moments as  $X(F, f, \theta) = (\bar{m} - m(F, f, \theta))' W (\bar{m} - m(F, f, \theta))$ , where  $W$  is a conformable matrix of weights.

In addition to the mean entry rate and the mean exit rate, the moments we base our estimator upon include the mean rate of growth in capital stocks among incumbents, and the mean, variance and pair-wise covariance of each of the following variables: log capital stock among incumbents, log operating profit among incumbents, log indebtedness among indebted firm/households. We also include the covariance of current and lagged log capital stocks to better capture the persistence in firm sizes.

Given that these sample moments are based on observations that are correlated in complicated ways, it would be a difficult matter to construct their covariance matrix. Hence, rather than use the efficient weighting matrix, we simply use an identity matrix

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<sup>11</sup> Since the value function enters the constraint in the optimization problem for incumbent firms, the dynamic programming problem defined in (6) is not a contraction and will in general have multiple solutions. Our objective is to find the largest value of  $V^j$  that solves this problem. Note that the mapping  $T(V)$  defined by the right hand side of (6) is non-decreasing in  $V$ . Letting  $V^*$  denote the solution to the optimization problem in (6) without the financing constraint, it will also be true that  $V^j \leq V^*$ . If we use the solution to the unconstrained problem as our starting point, value function iteration will result in a non-decreasing sequence of functions that converges to the desired solution (see e.g. Rustichini (1998)).

for  $W$ . The distribution of  $X$  is therefore unknown, but  $\arg \min X(F, f, \theta)$  is nonetheless a consistent estimator for  $(\theta, F, f)$ .

Several issues arise in constructing our simulations. First, we must discretize our variables in order to use standard solution techniques for firms' dynamic optimization problem. We do this using Tauchen's (1991) method. Second, we must impute an annual transition density for lending rates and exchange rates from our monthly transition densities in table 2. We do this by simulating long sequences of realizations from our table 12 estimates and then forming averages within 12 month blocks. Frequency counts on transitions among these averages provide our annual transition probabilities. Third, we must invent an initial cross-household distribution for profitability shocks ( $v_{it}$ ), exogenous income ( $y_{i0}$ ), and assets ( $a_{it}$ ). We base the  $v_{it}$  distribution on the steady state distribution for the profitability shocks ( $\varepsilon_{it}^E$ 's) from our estimated of profit function, we set  $y_{i0}$  at the approximate mean per capita Colombian income for all households, and we base the initial  $a_{it}$  distribution on an invented log-normal distribution. Although this asset distribution is arbitrary, we throw out the first 150 years of our simulations before constructing the vector  $m(F, f, \theta)$  in order to minimize its influence. (Note that this 150 year "burn-in" period induces correlation between assets and the profitability shocks, even though none is present in the initial year.)

Finally, given that we cannot observe the number of households that might potentially start new apparel firms, we must make some arbitrary assumptions. In the initial period we assume that there are 60 owner-households and 20 additional are available to start new firms. Also, since our model presumes that households cannot re-

enter the apparel industry once they have left, we add 20 new households to the population each period in order to avoid running out of entrants. (The asset stocks and initial  $v_{it}$  realizations for new households are randomly drawn from the distributions described in the previous paragraph.) These figures essentially serve to fix the number of active firms.<sup>12</sup> Experiments show that, holding other parameters fixed, variations in the number of new potential entrants per period have very little effect on the simulated moments.

A final issue is what algorithm to use when searching  $(\theta, F, f)$  space.

Exploratory grid searches indicate that  $X$  is neither smooth nor concave, so gradient-based algorithms fail to find global minima. We have experimented with both Nelder-Meade and genetic search algorithms; the results discussed below are based on the former. Bootstrap standard errors have not yet been generated.

### *Estimates*

Table 3 reports our estimates for  $(\theta, F, f)$  in the upper panel; the simulated moments that they imply are juxtaposed with corresponding data-based moments in the lower panel. Note that, in addition to the parameters of interest, we estimate the nuisance parameter,  $\lambda$ . This parameter is necessary to reconcile the concept of productive assets that appears in our model ( $k$ ) with the fixed assets measure that

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<sup>12</sup> Let  $I_0$  be the number of owner-households in period 0, and let  $N$  be the number of new households we add to the population each period. Then if the fraction of new households that creates firms is  $e$  and the fraction of owner-households that shuts down its firms every period is  $x$ , the population of owner-

households in period  $t$  is  $I_t = I_0(1-x)^t + eN \left( \frac{1-(1-x)^t}{x} \right)$ . Thus, with stable rates of entry and exit,

the current population approaches  $eN/x$  as  $t \rightarrow \infty$ , and the size of the initial population becomes irrelevant. Similarly, the asymptotic entry rate and exit rate depend only on  $e$  and  $x$ .

appears in our data.<sup>13</sup> Although our data set does not provide information on establishments' debts, it does include total interest payments. We therefore impute total debt for each observation as interest payments divided by the market lending rate.

Turning to the parameters of interest, we estimate that sunk entry costs amount to 71,000 1977 pesos (\$US 3,960), or about 14 percent of the value of the fixed capital stock for a firm of average size.<sup>14</sup> Thus, entrepreneurs who shut down average-sized firms typically recoup about 86 percent of their investment. One can think of this magnitude as reflecting installation and removal costs, as well as any customizing of equipment and facilities that does not add to their market value. The relatively low magnitude of this figure is probably traceable to the fact that it is identified by entry and exit patterns, which are dominated by small firms.

We estimate fixed costs to be 1,997,000 1977 pesos (\$US 111,300). These expenditures are incurred every year, regardless of production levels. They reflect the opportunity costs of the owner's time and various overhead expenses like insurance, marketing, and legal representation. Also, to the extent that the intercept term in our profit function was overestimated because of selection bias, this figure partly reflects an offsetting adjustment.

Our estimate for the credit market imperfection parameter,  $\theta$ , is nearly unity, suggesting that banks view households as capable of absconding with nearly the entire value of their firms' productive assets. Thus, our model implies there are severe

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<sup>13</sup> Conceptually,  $k$  includes inventories, net financial working capital, and fixed capital. In a sample of Colombian manufacturers from the 1970s, the ratio of total productive assets to fixed capital is approximately 3, so our estimate of this parameter seems quite reasonable.

<sup>14</sup> In 1977, there were 46.11 pesos per dollar. Thus we estimate sunk entry costs to be about \$US 1,500 in 1977 dollars, or given that the U.S. GDP price deflator grew by a factor of 2.57 between 1977 and 2004, sunk entry costs amount to about \$4,000 2004 dollars.

enforcement problems in Colombian credit markets, and suggests that borrowing is consequently infeasible for many entrepreneurs.

The moments reported at the bottom of table 3 show how well the model does in fitting the sample. It does an excellent job of matching the sample entry and exit rates, partly because we have given these moments heavy weight by expressing them in terms of percentages. It also does well in terms of matching the typical firm size, although it under-predicts firm heterogeneity. All simulated moments except one match their sample counterparts in sign, and many are reasonably close. Overall, given the small number of free parameters, the amount of structure imposed by the model, and the large number of moments considered, we view the fit as reasonably good.

#### **IV. Quantifying the Effects of Volatility and Credit Market Imperfections**

Given all of the parameters estimates discussed above, we can now use simulations to characterize the effects of crisis-prone macro environments on industrial evolution patterns. Similarly, we can explore the consequences of imperfect credit markets.

##### **A. The Effects of Volatility**

###### *Long run effects*

Our first exercise is to quantify the effects of volatility on the performance of the Colombian apparel industry, holding other parameters constant across regimes. To do so, we first simulate industrial evolution patterns under the assumption that macro variables are governed by the MSH process reported in table 2 (the “base case”). Then we re-simulate evolution patterns after increasing the degree of macro volatility by



setting all elements of the transition probability matrix,  $p$ , to 0.5 (the “counterfactual”). For both cases, we simulate patterns of industrial evolution over a 250 year period, 50 times. Throwing out the initial 50 years, we average our results to obtain the figures presented in Table 4.

Because we are using the MSH switching model for this exercise, mean values of the log exchange rate and the interest rate are the same in both columns. However, these variables both exhibit higher variance under the counterfactual assumptions. This heightened volatility has little effect on the number of firms, but it leads to more *variation* in the number of firms through time. It also induces firms to rely more heavily on debt—0.28 percent do so in the counterfactual environment, while only 0.13 percent do so in the base case. This reflects households’ desire to smooth their business income over periods of exchange rate fluctuation.

Heightened volatility also reduces average profitability ( $\eta_0 + v_{it}$ ) among active firms by about 0.01, which translates into a one percent loss in productivity. One possible explanation is that wealthy households diversify risk by holding some relatively low productivity firms; another explanation is that some households with high quality firms and little collateral are unable to borrow during periods of exchange rate appreciation. Finally, because it slightly increases turnover, heightened volatility slightly reduces the average age of active firms.

#### *Transition paths*

In addition to looking at long run differences between industrial evolution patterns in these two environments, it is interesting to examine the transition dynamics induced by a *change* in environment. For this exercise we compare our base case

scenario with a scenario in which volatility suddenly increases. More precisely, after putting households in the base case environment for 50 years, we suddenly confront them with the more volatile environment and we examine the transition path over the following 50 years. (Although the switch is modeled as a surprise when it occurs, the new macro process is presumed to be understood by all agents thereafter.) Figure 2a shows the average time paths followed by interest rates and exchange rates over this transition period; period 0 corresponds to the first year of the high-volatility macro environment.<sup>15</sup>

When firms are suddenly confronted with heightened volatility, they become less inclined to exit (figure 2b). That is, with the future less predictable, producers who are doing poorly perceive an increased option value to sticking around. Consequently, the number of active firms is initially larger when volatility increases, and average productivity levels are initially lower (figure 2c).

Interestingly, this option value effect is stronger among the larger poor-performing firms because they sacrifice a more valuable option when they abandon the market. (For example, a given movement in the exchange rate translates into a relatively large absolute change in business income for a firm with a relatively large capital stock.) Hence the correlation between profitability and size falls during the early years (figure 2d), and *size-weighted* average profitability falls by 3 to 5 percent (figure 2e). The option value effect weakens over time because firms that continue to do poorly eventually exit.

Finally, patterns of borrowing depend upon regime volatility, but in a way that

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<sup>15</sup> Because each figure is an average across 50 trajectories, these average paths substantially understate the amount of volatility any one trajectory would exhibit.

varies with firm size. Among smaller firms, extra volatility induces extra borrowing to help them through lean periods. But among larger firms, whose owners have less absolute risk aversion and more ability to self-finance, there is no obvious tendency to increase debt (figure 2f).

## **B. The Effects of Recurrent Crises**

In the previous section we considered the effects of volatility on industrial evolution, holding intercepts and roots for the macro processes fixed. We next investigate the more general shifts in the stochastic processes that are described by our MSIAH switching model. . . . (results to come)

## **C. The Effects of Credit Market Imperfections**

As a final exercise, we investigate the effects of credit market imperfections by comparing our base case simulations with a counterfactual in which owner-households lose their entire capital stocks if they default on their loans. This case, which we shall refer to as “perfect credit markets,” amounts to setting  $\theta = 0$ .<sup>16</sup> Elimination of the option to abscond with borrowed funds induces banks to lend to some owner-households that would have otherwise defaulted. Thus it relaxes the borrowing constraint faced by households with little wealth and/or poor  $v_{it}$  realizations (refer to equation 7).

To characterize the macro environment, we use the estimates for our most general model (MSIAH). Once again we throw out a burn-in period of 50 years, and we base our analysis on the following 100 years. The results are summarized in Table 5.

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<sup>16</sup> One might also regard the spread between the lending rate and the deposit rate as an index of capital market imperfections. However, for this exercise, we keep  $\mu$  at its estimated value of 0.06.

Note first that switching to perfect credit markets increases debt finance, and more than doubles the average firm size. In logs, the mean capital stock increases from approximately 5.9 to 7.2. So credit market imperfections can have a dramatic effect on the size distribution. Interestingly, although firms get much larger with improvements in credit markets, the average wealth of owner-households *falls* nearly 15 percent (Table 5 and figure 3a). This is because better functioning credit markets allow households with modest wealth to create new firms by relying partly on debt finance.

Some of this extra entry allows owner-households to exploit fleeting profit opportunities, and so exit rates rise as well, and the average age of active firms falls. Thus, although one would expect well-functioning credit markets to improve firms' ability to survive lean periods, this effect on longevity appears to be dominated by the additional short-horizon investment that they facilitate (Table 5).

Surprisingly, the effects of improved credit markets do not dramatically affect mean profitability shocks among active firms. The unweighted average value of  $\eta_0 + \nu_{it}$  does increase by 0.02 when  $\theta$  drops to zero, presumably reflecting better access to finance among relatively poor households with high-return investment opportunities (Table 5 and figure 3b). However, these small firms account for a small fraction of total output, so the size-weighted average profitability fails to improve.

## **V. Directions for Further Work**

Although our model is already rather complex, there are a number of ways in which it might be made more realistic. First, capital stock adjustment costs could be added, making owner-households pay extra to rapidly adjust the size of their firm.

Preliminary experiments with quadratic costs suggest that this would improve the ability of the model to explain the persistence in capital stocks that we find in the data (refer to the moments in Table 3). It would also create incentives for firms to borrow during periods in which they otherwise would have scaled back their operations.

Second, we have assumed that firms can only borrow in one currency. But in a number of macro crises, the currency denomination of firms' debt has been an important determinant of their profitability and ability to survive. In principle, it would be possible to add this dimension to the model.

Third, we have not exploited any information on the characteristics of owner-households because such information was not available from Colombian manufacturing surveys. However, it may be possible to obtain information on the wealth, income and ownership patterns of Colombian households from other surveys. Among other things, this would allow us to introduce heterogeneity in  $y_{i0}$ , and to perhaps to better characterize the population of potential entrants.

Finally, and most ambitiously, it might be possible to adopt a more realistic characterization of market structure. By assuming that all products are tradeable, and by relying on a "span of control" assumption to induce diminishing returns to capital investments, we have made it possible to ignore the number of competing firms as a profit determinant, and to analyze each household's behavior in isolation. For apparel, these assumptions may not be too unreasonable. But for other, less tradeable goods it would be better to adopt the assumption of monopolistic competition in domestic markets and move to a multi-agent optimization problem.

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**Table 1: Operating Profit Function Parameters, Colombian Apparel Producers**

	<b>Coefficient</b>	<b>Std. Error</b>	<b>Z-ratio</b>
<i>Level-form estimator</i>			
exchange rate	-0.329	0.038	-8.722
capital stock	0.201	0.007	29.400
trend term	0.007	0.003	2.038
initial year dummy	-0.015	0.013	-1.196
intercept, revenue equation	8.570	0.207	41.428
intercept, cost equation	8.319	0.207	40.221
Variance of innovations in $\varepsilon^E$ process	0.130	0.004	31.287
Root of $\varepsilon^E$ process	0.937	0.007	143.980
Variance of innovations in $\varepsilon^C$ process	0.027	0.003	8.072
Root of $\varepsilon^C$ process	0.260	0.022	11.987
Variance of innovations in $\varepsilon^R$ process	0.026	0.004	6.002
Root of $\varepsilon^R$ process	0.728	0.022	32.858
Number of observations	2,640		
<i>Difference-form estimator</i>			
exchange rate	-0.379	0.039	-9.788
capital stock	0.125	0.007	17.211
trend term	0.005	0.004	1.210
initial year dummy	0.010	0.014	0.721
Variance of innovations in $\varepsilon^E$ process	0.129	0.004	29.552
Root of $\varepsilon^E$ process	0.947	0.051	18.681
Variance of innovations in $\varepsilon^C$ process	0.032	0.002	18.245
Root of $\varepsilon^C$ process	0.686	0.036	19.211
Variance of innovations in $\varepsilon^R$ process	0.018	0.004	4.677
Root of $\varepsilon^R$ process	0.104	0.009	11.505
Number of observations	2,038		



**Table 2: Switching Model Parameters<sup>a</sup>**

	Simple VAR		MSH		MSIAH	
	<i>e</i>	<i>r</i>	<i>e</i>	<i>r</i>	<i>e</i>	<i>r</i>
$\beta_0^1$ (stable)	0.049 (0.072)	0.021 (0.41)	0.012 (0.03)	0.031 (0.01)	0.009 (0.03)	0.035 (0.014)
$\beta_0^2$ (volatile)	--	--	--	--	1.074 (0.75)	-1.011 (0.27)
$\beta_1^1$ (stable)	0.988 (0.009)	0.003 (0.035)	0.996 (0.006)	0.028 (0.02)	0.997 (0.006)	0.030 (0.02)
	-0.003 (0.004)	0.9547 (0.017)	-0.006 (0.002)	0.953 (0.011)	-0.006 (0.003)	0.952 (0.01)
$\beta_1^2$ (volatile)	--	--	--	--	0.754 (0.16)	0.310 (0.44)
	--	--	--	--	0.240 (0.06)	0.383 (0.16)
$\Sigma^1$ (stable)	9.03 e-4 -2.71 e-5	-2.71 e-5 2.20 e-4	3.94 e-4 -1.33 e-5	-1.34 e-5 7.01 e-5	3.94 e-4 -1.33 e-5	-1.16 e-5 7.12 e-5
$\Sigma^2$ (volatile)	--	--	9.25 e-3 -2.82 e-4	-2.82 e-4 2.69 e-3	8.01 e-3 1.28 e-3	1.28 e-3 9.16 e-4
$P$	--	--	0.965 0.598	0.035 0.410	0.966 0.616	0.034 0.384
Log likelihood	1291.03		1463.53		1472.83	
H <sub>0</sub> : same as base model	--		$\chi^2(8) = 344.99$		$\chi^2(12) = 363.59$	
H <sub>0</sub> : MSH and MSIAH are same	--		--		$\chi^2(4) = 18.80$	

<sup>a</sup>Based on monthly IFS data for Colombia, 1982 through 2004. Standard errors are in parentheses.

**Table 3: Estimated Fixed Costs, Entry Costs, and Credit Market Imperfection  
Colombian Apparel Producers**

	<b>Parameter</b>	<b>Standard Error</b>
Sunk entry costs ( $F$ )	71.306	n.a.
Fixed costs ( $f$ )	1997.2	n.a.
Credit market imperfection index ( $\theta$ )	0.994	n.a.
Ratio of total firm assets to fixed capital ( $\lambda$ )	2.958	n.a.
Objective function ( $X$ )	12.901	
	<b>Simulated Moment</b>	<b>Sample Moment</b>
Expected value of log capital stock	6.119	6.198
Variance of log capital stock	1.079	2.070
Expected value of log operating profits	7.907	6.757
Variance of log operating profits	0.884	2.064
Expected value of log debt (given debt is positive)	-1.617	-0.973
Variance of log debt (given debt is positive)	0.327	1.946
Expected growth in capital stock (net of deprec.)	-0.105	-0.062
Variance of growth in capital stock (net of deprec.)	0.245	0.215
Expected entry rate (expressed as a percentage)	15.813	17.390
Expected exit rate (expressed as a percentage)	16.192	15.170
Variance of entry rate	0.005	0.004
Variance of exit rate	0.005	0.001
Covariance of log capital and log operating profits	0.921	1.093
Covariance of log capital and lagged log capital	0.378	1.931
Covariance of log debt and log capital	0.000	-0.159
Covariance of log debt and log profits	0.000	0.379
Covariance of capital growth rate and log profits	0.201	0.007
Covariance of capital growth rate and log capital	0.261	0.200

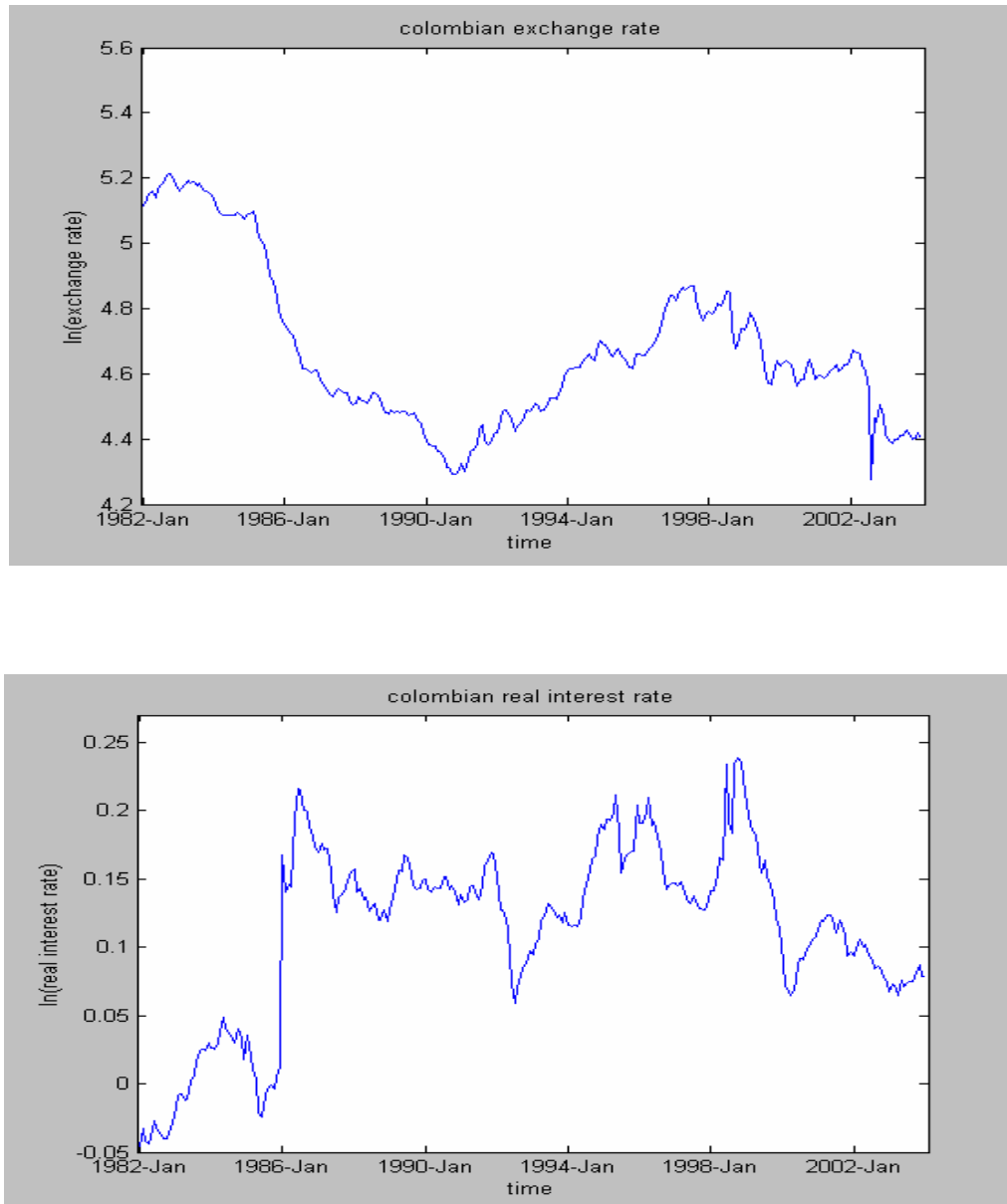
**Table 4: The Steady State Effects of Heightened Volatility**

	<b>Base Case</b>	<b>High Volatility</b>
<b>Aggregate shocks</b>		
Mean log exchange rate	4.406	4.412
Variance, log exchange rate	7.63E-05	3.37E-04
Mean lending rate	0.143	0.143
Variance, interest rate	1.78E-05	9.75E-05
<b>Industry characteristics</b>		
Mean number of firms	65.708	65.303
Variance, number of firms	17.333	19.142
Mean log capital among active firms	5.881	7.165
Mean rate of investment	-0.110	-0.104
Mean profit shock ( $\eta_0 + \nu_{it}$ ) among active firms	0.860	0.854
Size-weighted profit shock ( $\eta_0 + \nu_{it}$ ) among active firms	0.985	0.975
Mean entry rate	0.124	0.125
Mean exit rate	0.124	0.125
Mean age of active firms	2.917	2.881
Mean age of exiting firms	7.884	7.833
Mean debt to capital ratio among borrowers	0.234	0.228
Percent of firms with positive debt	0.134	0.280
<b>Owner-household characteristics</b>		
Mean log wealth of firm owners	8.974	9.033
Variance, log wealth of firm owners	0.621	0.654

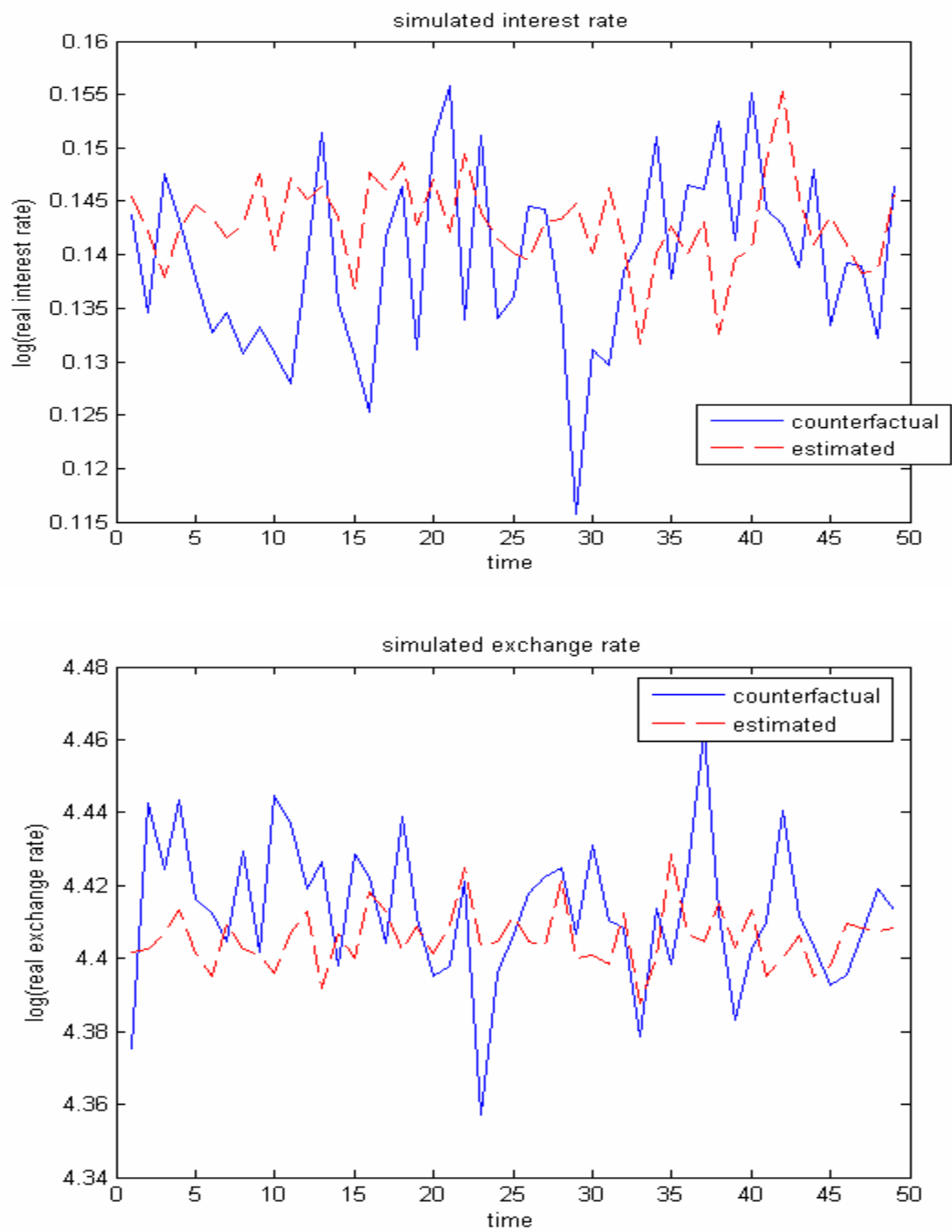
**Table 5: The Steady State Effects of Credit Market Imperfections**

	<b>Base Case (<math>\theta=.995</math>)</b>	<b>Perfect Credit Markets (<math>\theta=0</math>)</b>
<b>Aggregate shocks</b>		
Mean log exchange rate	4.459	4.459
Variance, log exchange rate	0.0105	0.0105
Mean lending rate	0.235	0.235
Variance, interest rate	1.23E-04	1.23E-04
<b>Industry characteristics</b>		
Mean number of firms	58.062	48.174
Variance, number of firms	3.995	3.129
Mean rate of investment	-0.091	-0.092
Mean profit shock ( $\eta_0 + \nu_{it}$ ) among active firms	0.868	0.888
Size-weighted profit shock ( $\eta_0 + \nu_{it}$ ) among active firms	0.661	0.656
Mean entry rate	0.129	0.151
Mean exit rate	0.129	0.151
Mean age of active firms	1.919	1.571
Mean debt to capital ratio among borrowers	0.232	0.386
Percent of firms with positive debt	0.027	1.577
<b>Owner-household characteristics</b>		
Mean log wealth of firm owners	9.957	9.894
Variance, log wealth of firm owners	1.103	0.965

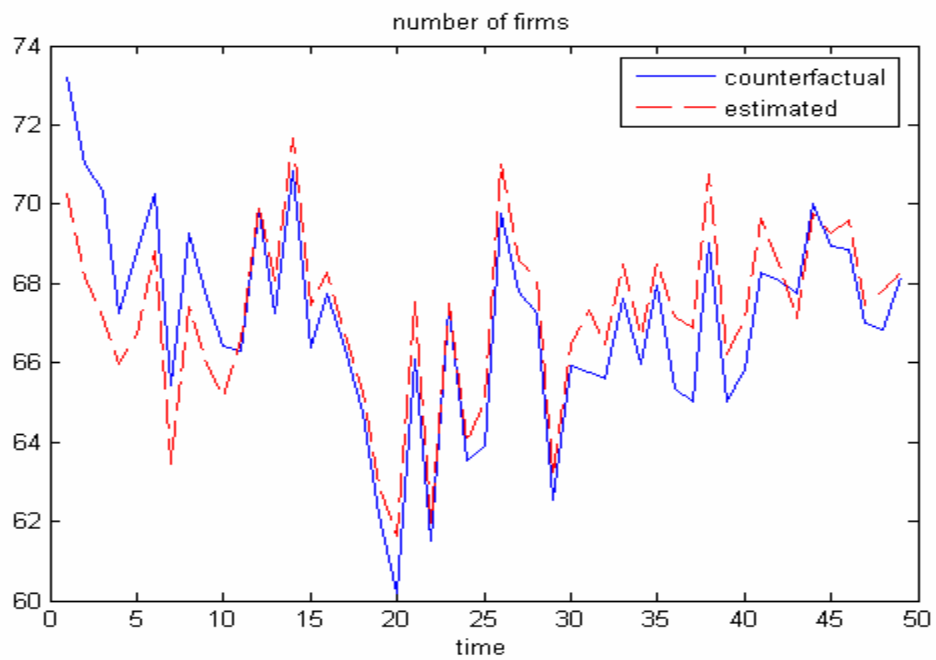
**Figure 1: Colombian Exchange Rates and Interest Rates**



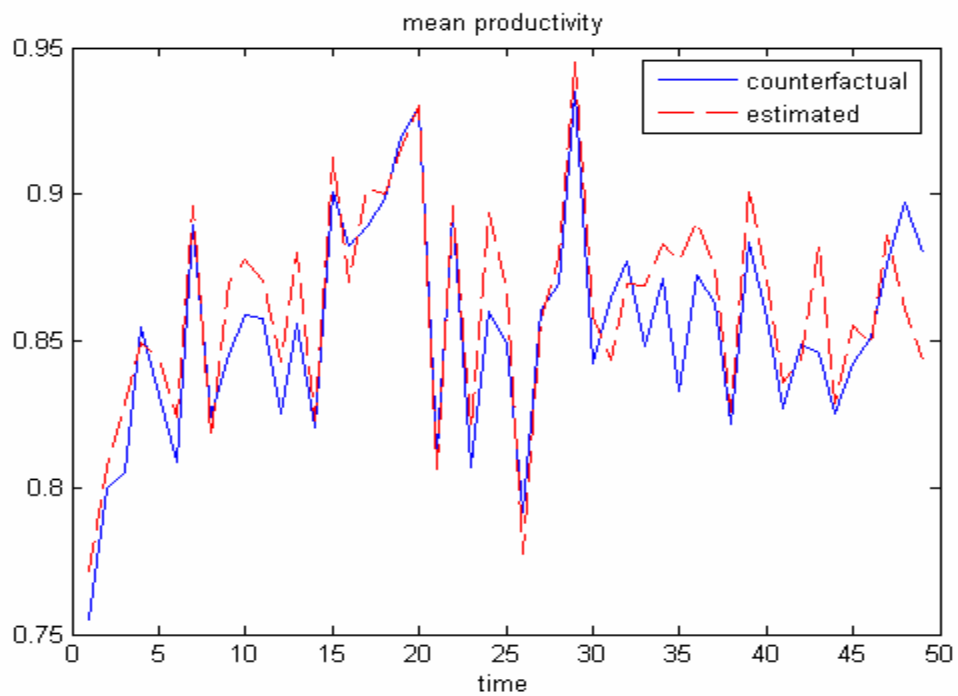
**Figure 2a: Exchange Rates and Interest Rates:**  
Base Case Versus Heightened Volatility



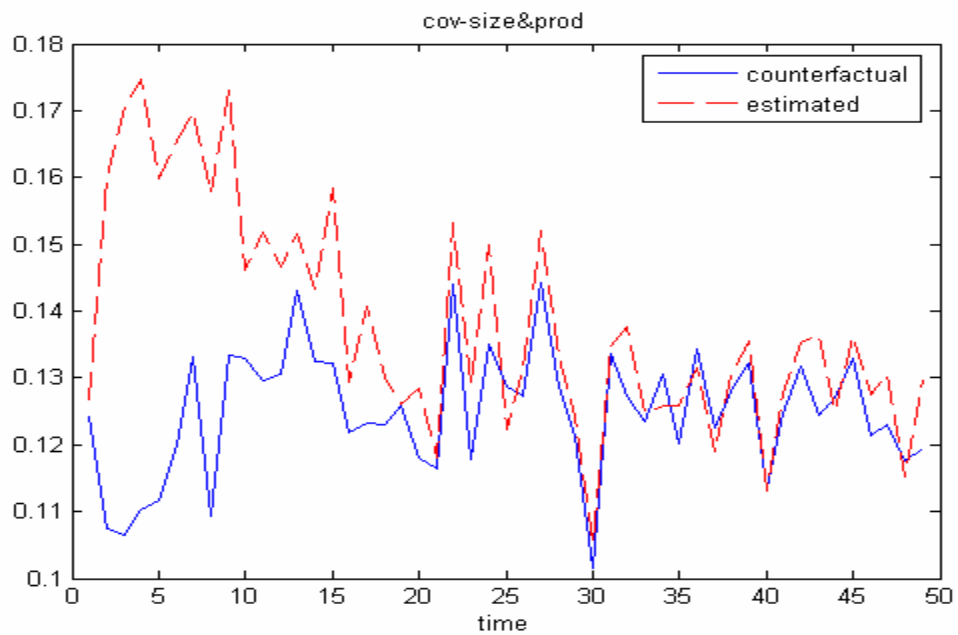
**Figure 2b: Number of Plants:**  
Base Case versus Heightened Volatility



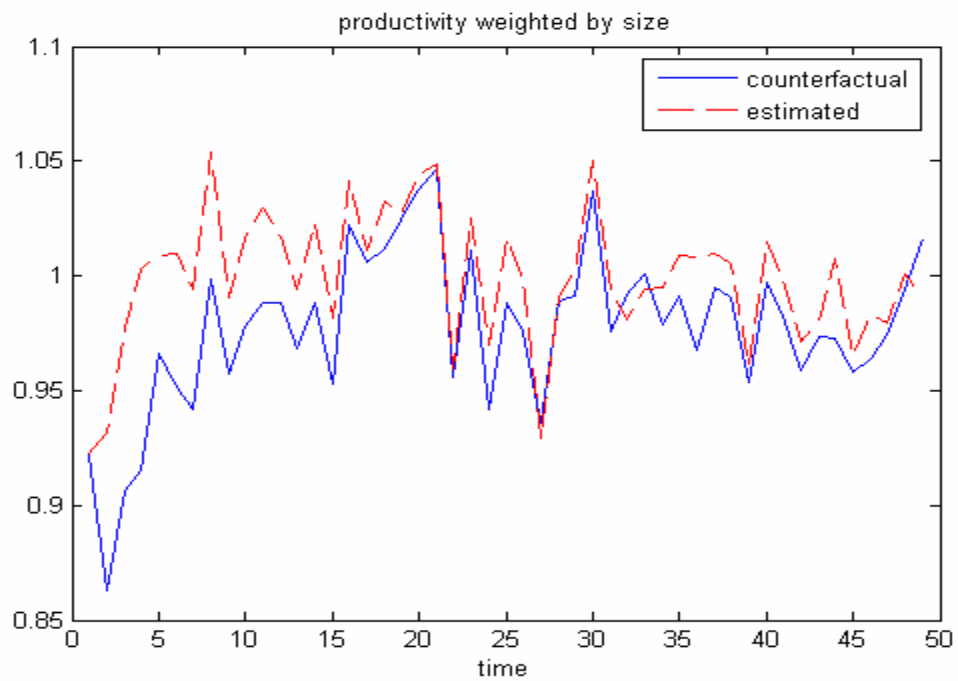
**Figure 2c: Mean Profitability Shock**  
Base Case versus Heightened Volatility



**Figure 2d: Covariance of Size and Profitability**  
Base Case versus Heightened Volatility

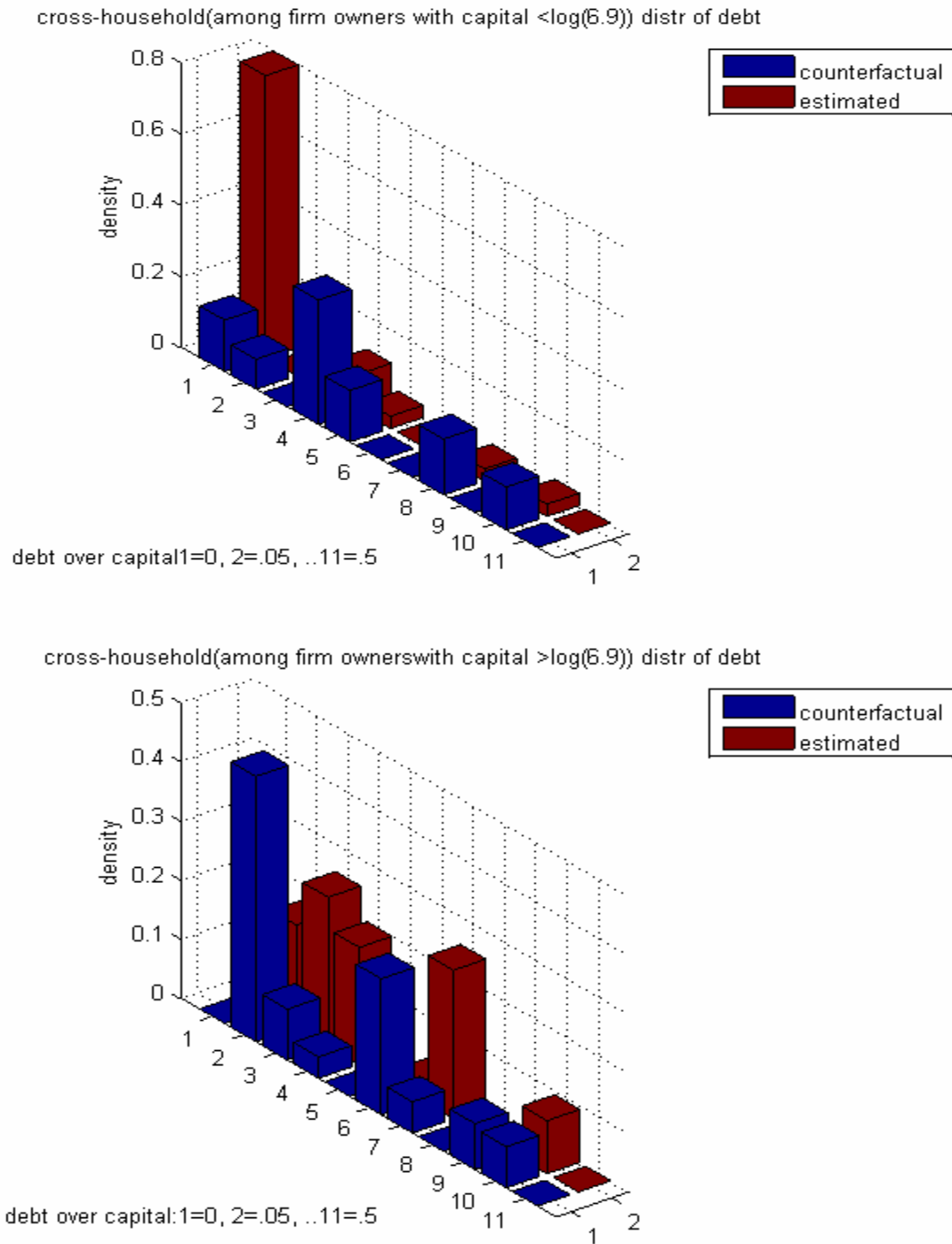


**Figure 2e: Size-weighted Average Productivity**  
Base Case versus Heightened Volatility

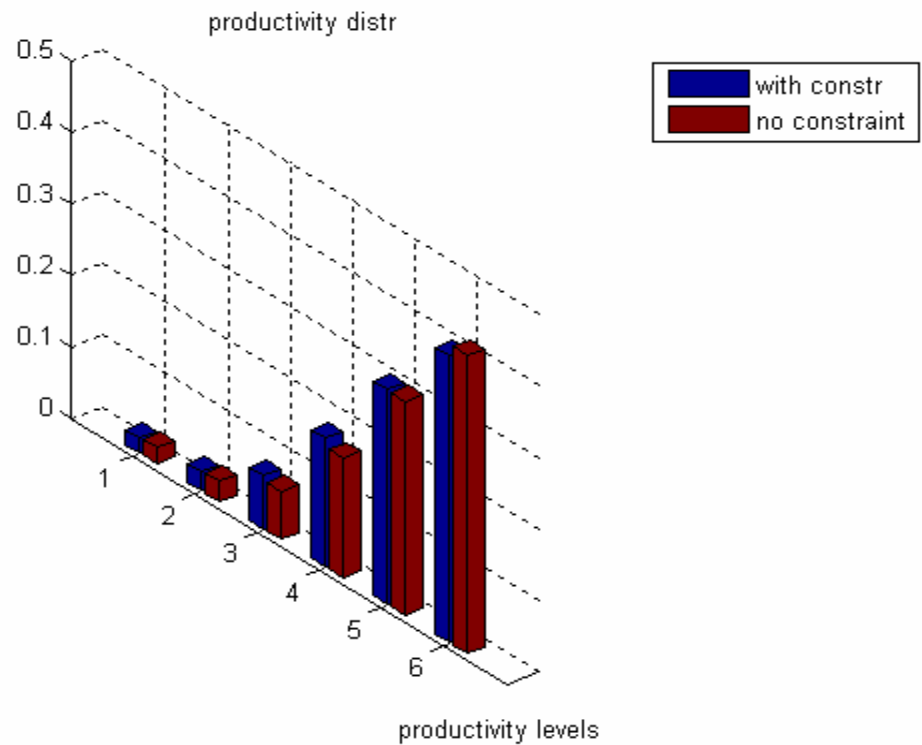




**Figure 2f: Debt-to-Capital Ratios Among Small and Large Firms**  
Base Case versus Heightened Volatility



**Figure 3a: Credit Market Imperfections and Productivity Distribution**



**Figure 3b: Credit Market Imperfections Wealth Distribution Among Owner-Households**

