

This work is distributed as a Discussion Paper by the  
**STANFORD INSTITUTE FOR ECONOMIC POLICY RESEARCH**

SIEPR Discussion Paper No. 07-13

**Firm Dynamics, Markup Variations, and the Business Cycle**

By  
Nir Jaimovich  
Stanford University

March 2007

Stanford Institute for Economic Policy Research  
Stanford University  
Stanford, CA 94305  
(650) 725-1874

The Stanford Institute for Economic Policy Research at Stanford University supports research bearing on economic and public policy issues. The SIEPR Discussion Paper Series reports on research and policy analysis conducted by researchers affiliated with the Institute. Working papers in this series reflect the views of the authors and not necessarily those of the Stanford Institute for Economic Policy Research or Stanford University.

---

# Firm Dynamics, Markup Variations, and the Business Cycle

Nir Jaimovich<sup>\*†</sup>

Stanford University

First Version: July 2004; Second Version: November, 2006; Current Version: March 2007

## Abstract

This paper suggests that the interaction between firms' entry and exit decisions and variation in the degree of competition gives rise to endogenous procyclical movements in measured total factor productivity (TFP). Based on this result, the paper suggests a simple structural method for the decomposition of variations in TFP into those that originate either endogenously from this interaction or from exogenous shocks. Moreover, the paper analyzes how such an interaction affects (i) the measurement of the volatility of exogenous shocks in the U.S. economy and (ii) the magnification of shocks over the business cycle. The analysis is based on a model in which net business formation is endogenously procyclical. The variations in the number of operating firms lead to endogenous countercyclical variations in markup levels along the cycle. The results in this paper support the view that a significant fraction of the movements in measured TFP results from the interaction between variations in the number of firms and the degree of competition. Accounting for this interaction implies that a substantially smaller proportion of the volatility of output is due directly to technology shocks.

**Keywords:** productivity, business cycle, firm dynamics, markup.

---

\*I am indebted to Gadi Barlevy, Larry Christiano, Martin Eichenbaum, and Sergio Rebelo for their guidance and support. I thank Martin Bodenstein, Ariel Burstein, Jeff Campbell, John Fernald, Jonas Fisher, Jim Hamilton, Nadav Levy, Rob Porter, Garey Ramey, Henry Siu, Valerie Ramey, Joseph Zeira, and seminar participants at Northwestern University, Columbia University, Harvard Business School, UCSD, University of British Columbia, University of Illinois at Urbana-Champaign, University of Maryland, GSIA at Carnegie Mellon, Yale University, University of Pennsylvania for their comments. Seth Pruitt has provided excellent research assistance.

<sup>†</sup>Department of Economics, Stanford University. njaimo@stanford.edu.

# 1 Introduction

This paper analyzes how the interaction between firms' entry and exit decisions and variation in competition gives rise to endogenous procyclical movements in measured total factor productivity (TFP). Three basic stylized facts motivate this paper: the existence of monopoly power in the U.S. economy; procyclical variations in the number of competitors; and markups being countercyclical and negatively correlated with the number of competitors.

In order to be able to account for these empirical observations, the paper formulates a dynamic general equilibrium model, where variations in the technology level lead to variations in the number of competitors. These in turn lead to endogenous countercyclical markup variations. To model the interaction between firms' entry/exit decisions and markup variations, I assume that the economy is characterized by the presence of many different sectors. Each sector is comprised of different, monopolistically competitive intermediate firms. Within a given sector, each firm takes into account the effect that the pricing and production of other firms have on the demand for its goods. This leads to the price elasticity of demand for the typical firm being positively related to the number of firms in its sector, and induces the setting of a lower markup in response to an increase in the number of competitors. The number of firms in a sector is determined by the equilibrium condition that all firms earn zero profits in every period. This condition is enforced by firms' decisions to either enter or exit an industry.

Based on the model, the paper suggests a simple structural method for decomposing variations in TFP into those originating endogenously from this interaction and those originating from exogenous shocks. Based on this decomposition the paper finds that a significant fraction of the movements in measured TFP can be attributed to the impact of firm entry and exit decisions on optimal markups. Further, the paper analyzes how the interaction between variation in the number of competitors and variations in the degree of competition provides a powerful internal magnification mechanism for shocks to agents' environments. Specifically, the paper shows that the strength of these magnification effects is evident in the estimated volatility of technology shocks and in statistics that summarize the quantitative properties of the magnification mechanism.

Before reviewing these results it is worth emphasizing that a virtue of the model here is that it represents a minimal perturbation of the prototype perfect competition real business cycle (RBC) model. This greatly simplifies comparisons with existing work and provides a simple structural

decomposition method of TFP. However, this simplicity is purchased at the cost of descriptive realism, and several empirical caveats should be highlighted (see Section 2 for a broader discussion of these issues). First, the model here is symmetric. This implies that the number of firms varies in all the sectors. However, is it the case that in the U.S. data the procyclicality in the number of firms is driven only by a few industries? To address this issue, I assemble a dataset that documents the number of failing firms in the U.S. economy in 46 industries over more than 40 years.<sup>1</sup> I find that all of these industries are characterized by countercyclical exit rates, where for 90% of these industries the negative point estimator is significant at the 10% level. Second, an additional concern is that smaller firms typically make up the majority of entrants and exits. This may imply that variations in their number are potentially less important and that entry rates should be weighted by the size of entrants. However, it is noteworthy that variations in the number of firms are only one of the channels that generate actual changes in the number of competitors, which from the model's perspective are the driving force. I thus analyze the time series of the number of franchises and establishments and show that they are both strongly procyclical. Moreover, using the Business Employment Dynamics (BED) data set I find that a third of the cyclical volatility in job gains (losses) is explained by opening (closing) establishments. This provides additional information as to the empirical significance of new potential competitors as it emphasizes the fact that entrants (exits) do account for significant fraction of employment volatility at the business cycle frequency. Finally, I show that these numbers characterize both the aggregate U.S. time series as well as for the different industries included in the BED.

I discuss now the main quantitative results of the model. With respect to the measurement of TFP the paper finds the following. First, any shock that induces net business formation leads to a fall in markups and a rise in measured TFP. Depending on the exact specification of the model, a 1% positive technology shock induces a rise in TFP ranging between 1.45% to 1.80%. Based on a variance-covariance decomposition, I estimate that in the post-war U.S. data, around half of the variation in measured TFP are due to the endogenous mechanism embedded in the firms' entry/exit dynamics model. In contrast, if the number of firms does not vary, and/or if the markup is held constant, then measured TFP moves one-to-one with technology shocks, and all of the variation in measured TFP is due to exogenous technology shocks. These results are related to the seminal

---

<sup>1</sup>Unfortunately, it has not been possible to construct a similar dataset for sectorial entry rates.

contributions of Hall (1986, 1988, and 1990), who finds evidence that variations in measured TFP co-vary with exogenous instruments. Hall (1986, 1988, and 1990) interprets these results as evidence in support of the existence of market power and increasing returns. The theoretical framework of this paper captures the "Hall effect." In the model, the cyclical variation of TFP is a result of variation in the number of operating firms and their effect on optimal markup pricing. Two key elements in the theoretical model that drive this effect are, indeed, imperfect competition and the presence of fixed cost, which gives rise to increasing returns to scale at the firm level.<sup>2</sup> However, the model suggests that the mere presence of monopoly power and a fixed cost does not impart a bias in the measurement of TFP. The presence of monopoly power and a fixed cost is a necessary condition in this model for the mismeasurement in TFP but not a sufficient one. The third necessary condition is that monopoly power is time variant.<sup>3</sup>

Consider now the magnification of fundamental shocks. As is well known, the RBC model does not embody a quantitatively important magnification mechanism.<sup>4</sup> As a result, in order to account for the observed fluctuations in aggregate economic activity, the RBC model must rely on highly variable, exogenous, aggregate technology shocks. The measurement of these type of shocks builds upon the interpretation of variations in the Solow residual as reflecting exogenous stochastic movements in the aggregate production technology. However, this interpretation is valid only under certain restrictive assumptions.<sup>5</sup> This paper suggests that the interaction between variation in the number of operating firms and variation in the degree of competition in the economy can help to overcome some of these deficiencies; further it investigates the qualitative and quantitative significance of this interaction. Specifically, in the model proposed here, any shock to agents' environments which generates new profit opportunities induces net business formation. The resulting rise in the number of firms reduces average markups. Other things equal, a fall in markups leads to an expansion in aggregate output. Thus, firms' entry and exit decisions provide a channel through

---

<sup>2</sup>In the theoretical model a key element is a zero profits equilibrium. Again, this formulation is consistent with Hall (1990), who writes "A second explanation for the failure of invariance (of the Solow residual) is that entry is free but technology has increasing returns. Then the equilibrium will involve just enough market power to pay for the inputs".

<sup>3</sup>This statement is formally proved in the Appendix.

<sup>4</sup>See e.g., Burnside, Eichenbaum, and Rebelo (1993), Cooper and Catterjee (1993), Cogley and Nason (1995), Burnside and Eichenbaum (1996), Devereux, Head, and Lapham (1996), Andolfatto (1996), Hall (1999), King and Rebelo (2000), Den Haan, Ramey, and Watson (2000).

<sup>5</sup>See e.g., Hall (1988), Burnside, Eichenbaum, and Rebelo (1993), Cochrane (1994), and Burnside and Eichenbaum (1996).

which the direct impact of a fundamental shock is magnified. Because conventional Solow residual accounting-based estimates of technology shocks do not allow for cyclical variations in the markup, I use the model to correct for this type of variation. Depending on the exact specification of the model, the estimated volatility of technology shocks falls between 40% and 55% relative to the technology shocks estimated in the RBC model. The magnification effects induced by the firms' entry/exit dynamics are sufficiently large that the model, driven solely by the corrected and less volatile technology shocks, performs as well as the RBC model in accounting for the volatility of output. Thus, one of the implications of firms' entry/exit dynamics is that a substantially smaller fraction of the standard deviation of output is due to the direct impact of technology shocks.

This paper belongs to a tradition in the macroeconomic literature stressing the role of imperfect competition in the business cycle. In a series of influential papers, Rotemberg and Woodford (1991, 1992, 1995 and 1996*a*) study the macroeconomic consequences of oligopolistic behavior. In their model, implicit collusion among a fixed number of firms leads to countercyclical movements in the markup. This in turn leads to increases in aggregate economic activity. Gali (1994) studies a model in which a fixed number of firms face demand from two sources. Variations in the composition of aggregate demand then lead to variations in the markup. Hornstein (1993) analyzes the implications of the presence of constant monopoly power for the measurement of technology shocks; he finds an implied reduction in the estimated volatility of technology shocks. He also shows that such a model cannot account for the volatility in the U.S. data because it lacks an internal magnification mechanism. Edmunds and Veldkamp (2006) analyze a model where the presence of asymmetric information and countercyclical income dispersion give rise to countercyclical markups. Cooper and Chatterjee (1993) and Devereux, Head, and Lapham (1996) focus on the productive efficiencies associated with cyclical variations in the variety of goods that are produced.<sup>6</sup> Bilbiie, Ghironi, and Melitz (2006b) study a similar model to these last two mentioned papers but in where firms face a sunk cost of entry and they interpret variations in the number of firms as variations in capital/production lines. Beaudry, Collard, and Portier (2006) study a model where the opening of new market opportunities causes an economic expansion by favoring competition for market shares and show that these can be an important driving force of the business cycle. The structural model presented in this paper is close to Portier's (1995) which documents the pro-cyclicality of

---

<sup>6</sup>See the working paper version of the paper for a discussion of this mechanism in the context of this paper.

business formation and the counter-cyclicality of markups in the French data. Portier studies the impulse response functions of his model economy to a technology shock and to government spending shocks; he concludes that the presence of variations in the number of firms, and their effect on the markup, serves as an internal magnification mechanism. Thus, this paper shares his conclusion and goes beyond it along the next several dimensions. First, I estimate the implications of this internal magnification mechanism for the actual measurement of technology shocks in the U.S. time series. Second, using this newly estimated series, the model here is then simulated and its time-series properties compared to those of the U.S. data. This allows me to both quantify the magnification mechanism embedded in the model, and show that using this "correct" estimated technology shocks that a substantially smaller fraction of the standard deviation of output is due to the direct impact of technology shocks. Rather it is the endogenous magnification embedded in the model that accounts for the volatility of output. Third, I show how the model gives rise to a structural decomposition of TFP fluctuations into those arising from exogenous shocks and those that are endogenous. The paper then estimates the fraction of the latter in the variations in TFP movements over the post-war period in the U.S.

Section 2 discusses the empirical caveats highlighted previously and provides some results that could potentially alleviate these concerns. Section 3 displays the benchmark model. Section 4 analyzes the implications of the model for (1) the structural decomposition of variations in measured TFP into pure exogenous technology shocks and those that arise endogenously from the model; and for (2) the measurement of technology shocks. In Section 5, I extend the benchmark model and introduce materials usage and capacity utilization into the analysis. This allows me to study the effects of the interactions between these two factors and the countercyclicality of the markups on the measurement of technology shocks and on the decomposition of TFP. Section 6 concludes.

## 2 Empirical Evidence

A survey of the literature estimating the level of markups in the U.S. is beyond the scope of this paper. Overall, the estimates of markups in value added data range from 1.2 to 1.4, while the estimated markups in gross output vary between 1.05 and 1.15.<sup>7</sup> Similarly, different studies have

---

<sup>7</sup>See, for example, Hall (1988), Morrison (1992), Norrbin (1993), Roeger (1995), Martins, Scapetta, and Pilat (1996), Basu and Fernald (1997), and Basu and Fernald (1999).

addressed the cyclical nature of the markup. Among the most prominent studies finding that markups are countercyclical in the U.S. are *Bils (1987)*, *Rotemberg and Woodford (1991)*, *Rotemberg and Woodford (1999)*, and *Chevalier, Kashyap, and Rossi (2003)*. *Martins, Scapetta, and Pilat (1996)* cover different industries in 14 OECD countries and find markups to be countercyclical in 53 of the 56 cases they consider, with statistically significant results in most of these. In addition, these authors conclude that entry rates have a negative and statistically significant correlation with markups.<sup>8</sup> *Bresnahan and Reiss (1991)* find that increases in the number of producers increases the competitiveness in the markets they analyze. Similarly, *Campbell and Hopenhayn (2005)* provide empirical evidence to support the argument that firms' pricing decisions are affected by the number of competitors they face; they show that markups react negatively to increases in the number of firms.

The procyclicality of the number of firms has been addressed in *Cooper and Chatterjee (1993)* and *Devereux, Head, and Lapham (1996)*; they show that both net business formation and new business incorporations are strongly procyclical.<sup>9</sup> Similarly, *Devereux, Head, and Lapham (1996)* report that the aggregate number of business failures is countercyclical. Moreover *Devereux, Head, and Lapham (1996)* analyze the dynamic (lead-lag) correlations between net business formation, new business incorporation and business failures with real GDP. They show that the strongest correlation of net entry takes place either contemporaneously or slightly prior to an increase in aggregate output.<sup>10</sup>

Direct measures of the number of operating firms in the U.S. economy exist for the years between 1988 and 2003, providing evidence for the procyclicality of the variations in the number of firms.<sup>11</sup> The contemporaneous correlation between the deviations from the HP trend of the number of firms and the deviations from the HP trend of real GDP equals 0.50 and is significant at the 5% level.<sup>12</sup>

As mentioned previously, one virtue of the model in this paper is that it represents a minimal perturbation of the prototype perfect-competition RBC model; this enables the paper to highlight

---

<sup>8</sup> *Donowitz, Hubbard, and Petersen (1986)* suggest that markups are procyclical. *Rotemberg and Woodford (1999)* highlight some biases in these results, as they use measures of average variable costs and not marginal costs.

<sup>9</sup> The quarterly data in *Devereux, Head, and Lapham (1996)* is between 1958 and 1995 and is based on *Dun & Bradstreet's* records. It was discontinued in 1995.

<sup>10</sup> This empirical fact is consistent with the model below where the number of firms rises at the same time as output.

<sup>11</sup> The data set that also contains the number of establishments (see below) can be found in <http://www.sba.gov/advo/research/>.

<sup>12</sup> All the correlations refer to the correlation between the deviations from the HP trend of two series. Similarly, whenever the paper reports the standard deviation, it is of an HP-filtered series.

the specific role of the interaction between variations in the number of firms and variations in degrees of competition for the measurement and decomposition of shocks over the business cycle. However, this simplicity comes at the cost of descriptive realism, and several empirical caveats should be highlighted.

First, while the results above suggest that the aggregate number of competitors varies procyclically in the U.S. data, this empirical observation might be driven by only certain industries, implying that a symmetric model is at odds with the data. To address this issue, I assemble a new dataset that documents the number of failing firms in the U.S. economy by industry at a yearly frequency between 1956 and 1996. Table 1 reports the point estimator and the significance level of the contemporaneous correlation between the number of failing firms for each of the industries included in the dataset and real GDP. While the point estimator differs across industries, all of the industries are characterized by countercyclical failure rates. This suggests that these are a characteristic of most U.S. industries at different aggregation levels. Of the 46 industries included in the dataset, 26 are characterized by countercyclical failure rates statistically significant at the 1% level. Twelve industries are characterized by countercyclical failure rates that are statistically significant at the 5% level, while three industries are characterized by countercyclical failure rates that are statistically significant at the 10% level. For the remaining five industries, the point estimator is negative but not significant at the 10% level.

Second, an additional concern is that smaller firms typically make up the majority of entrants and exits. This may imply that variations in their number are potentially less important and that entry rates should be weighted by the size of entrants.<sup>13</sup> However, it is noteworthy that variations in the number of firms are only one of the channels that generate actual changes in the number of competitors, which from the model's perspective are the driving force. Variations in the number of establishments are an additional channel affecting the number of competitors. The contemporaneous correlation between the number of establishments and real GDP is 0.44 and is significant at the 5% level. Furthermore, at the business cycle frequency, the number of establishments is significantly volatile. The ratio of the standard deviation of the number of establishments to real GDP is 1.3.

Additional information regarding this issue can be obtained from the BED, which documents job

---

<sup>13</sup>A time series of variations in the number of firms by size does not exist, to the best of my knowledge.

gains and losses at the establishment level, and at the quarterly frequency, for the period between the third quarter of 1992 and the second quarter of 2005. The job-gains series includes job-gains from either opening or expanding establishments. Similarly, the job-losses series is comprised of job losses from either closing or contracting establishments. This data allow me to analyze the fraction of job gains and losses explained by opening and closing establishments, respectively. This provides additional information as to the empirical significance of new potential competitors. The first row in Table 2 reports the results in the aggregate U.S. data. The first column in Table 2 shows that the average fraction of the quarterly gross job-gains in the U.S. economy explained by opening establishments is 21.86%. Similarly, the second column reports the fraction of the quarterly job-losses in the U.S. economy that is explained by closing establishments to be 21.17%. While the procyclicality in the number of establishments, which was reported earlier, together with the importance of variations in them for job creation and destruction, suggest that changes in establishment numbers are quite significant and play a potentially important role in affecting measures of competition, one might wonder how important they are at the business cycle frequency. In order to address this issue, I estimate the fraction of cyclical volatility in job gains and losses that is accounted for by cyclical volatility of employment in opening-and-closing establishments. I use two alternative methods. First, I extract the high-frequency component of the different series, removing the trend from each, using the HP filter. Column *III* reports how much of the cyclical volatility in job gains is explained by opening establishments: the estimate is 33.46%. Similarly, column *IV* indicates the extent to which cyclical fluctuations in job losses are explained by closing establishments: again, this fraction is estimated to be above 33%.

A potential bias of this method is that not all of the high-frequency fluctuations are directly attributable to the business cycle. In an attempt to address this issue, I project each of the detrended series on a constant, and on current and lagged detrended aggregate GDP.<sup>14</sup> The measure of cyclical volatility is the percent standard deviation of these estimated projections. Column *V* reports the fraction of the cyclical fluctuations in job gains that is accounted for by opening establishments; column *VI* reports the fraction of the cyclical fluctuations in job losses that is accounted for by closing establishments. Both of these are estimated to be around 20%. This dataset also provides additional evidence on whether fluctuations in the number of competitors is

---

<sup>14</sup>See Gomme, Rupert, Rogerson, and Wright (2004) for a similar approach when addressing the age difference in the cyclicity of hours worked in the U.S.

a characteristic of most U.S. industries, because it provides measures of job gains and losses for different industries. As can be seen from rows *II–XIII* of Table 2, figures similar to those obtained for the aggregate economy are obtained for all of the industries. This suggests that opening and closing establishments are of significant empirical relevance.<sup>15</sup>

Another channel that could generate possibly variations in the number of competitors is the variation in the number of franchises. As Lafontaine and Blair (2005) show, sales through franchising amounted to more than 13% of real GDP in the 1980s. Thus, this channel is important for the determination of aggregate output. The contemporaneous correlation between the number of franchises and real GDP is positive and equals 0.32, and the ratio of the standard deviation of the number of franchises to real GDP equals 2.8. These estimates suggest that franchises, as well as establishments, are potentially important sources of fluctuation in the number of competitors.

The changes described in these two examples will not be reflected in the data as changes in the number of firms. However, the model treats all three types of changes as equal forces, and should be seen as analyzing variations in the number of overall competitors, not just in the number of firms. While these results should be approached with caution given the level of aggregation, it is encouraging that these various pieces of evidence all point in the same direction: the existence of significant variations in the number of competitors at the business cycle frequency.

### 3 The Benchmark Model

#### 3.1 Population and Preferences

At each point in time the economy is inhabited by a continuum of identical households. The mass of households is normalized to one. It is assumed that the representative agent has preferences over random streams of consumption and leisure. The representative agent maximizes the following life-time utility:

$$\max_{C_t, H_t, K_{t+1}} E_o \sum_{t=0}^{\infty} \beta^t \left( \log(C_t) - \theta \frac{H_t^{1+\chi}}{1+\chi} \right)$$

---

<sup>15</sup>Obviously, these results should be approached carefully given that the time period covered in the sample is relatively short. Moreover, an additional concern is that new establishments by existing firms might have different effects on markups. Still, it is encouraging that these results suggest that entrants/exists are of important empirical significance.

subject to the law of motion of capital

$$K_{t+1} = ((1 - \delta) + R_t)K_t + W_t H_t + \Pi_t - C_t \quad (3.1)$$

where the initial capital stock is given and equals  $K_0$ .  $C_t$  and  $H_t$  denote consumption and hours worked by the household in period  $t$ , respectively.  $\beta \in (0, 1)$  and  $\delta \in (0, 1)$  denote the subjective time discount factor and the depreciation rate of capital, respectively.  $\chi \geq 0$  governs the Frisch labor supply elasticity, and  $\theta > 0$ . The households own the capital stock and take the equilibrium rental rate,  $R_t$ , and the equilibrium wage,  $W_t$ , as given. Finally, the households own the firms and receive their profits,  $\Pi_t$ .

### 3.2 Technology

The economy is characterized by a continuum of sectors of measure one. In each sector, there is a finite number of intermediate firms.<sup>16</sup> Each intermediate firm produces a differentiated good. These goods are imperfect substitutes in the production of a sectoral good.<sup>17</sup> In turn, the sectoral goods are imperfect substitutes for each other and are aggregated into a final good. It is assumed that the entry and exit of intermediate producers into the existing sectors take place such that a zero-profit condition is satisfied at each period in each sector.

**Final Good Production** The final good is produced with a constant-returns-to-scale production function

$$Y_t = \left[ \int_0^1 Q_t(j)^\omega dj \right]^{\frac{1}{\omega}}, \quad \omega \in (0, 1) \quad (3.2)$$

That is, the final good,  $Y_t$ , aggregates a continuum of measure one of sectoral goods, where  $Q_t(j)$  denotes sector  $j$ 's output. The elasticity of substitution between any two different sectoral goods is constant and equals  $\frac{1}{1-\omega}$ . The final good producers behave competitively, and the households buy the final good for both consumption and investment.

---

<sup>16</sup>A similar setup appears in Rotemberg and Woodford (1992).

<sup>17</sup>See the working paper version for an analysis of a model in which the monopolists produce a homogenous good.

**Sectoral Good Production** In each of the  $j$  sectors, there are  $N_t > 1$ , firms producing differentiated goods that are aggregated into a sectoral good by a *CES* aggregating function.<sup>18</sup> The output of the  $j^{th}$  sectoral good is given by

$$Q_t(j) = N_t^{1-\frac{1}{\tau}} \left[ \sum_{i=1}^{N_t} x_t(j, i)^\tau \right]^{\frac{1}{\tau}}, \quad \tau \in (0, 1) \quad (3.3)$$

where  $x_t(j, i)$  is the output of the  $i^{th}$  firm in the  $j^{th}$  sector.<sup>19</sup> The elasticity of substitution between any two goods in a sector is constant and equals  $\frac{1}{1-\tau}$ . The market structure of each sector exhibits monopolistic competition; each  $x_t(j, i)$  is produced by one firm that sets the price for its good in order to maximize its profit. Finally, it is assumed that  $\frac{1}{1-\omega} < \frac{1}{1-\tau}$ ; i.e., the elasticity of substitution between any two goods within a sector is higher than the elasticity of substitution across sectors.

**Intermediate Goods Production** Each intermediate good,  $x_t(j, i)$ , is produced using capital,  $k_t(j, i)$ , and labor,  $h_t(j, i)$ , with the following production function

$$x_t(j, i) = z_t k_t(j, i)^\alpha h_t(j, i)^{1-\alpha} - \phi \quad (3.4)$$

where  $\alpha \in [0, 1]$  and the log of technology shocks follow a stationary first order auto-regressive process,

$$\ln z_t = \zeta \ln z_{t-1} + \varepsilon_t. \quad (3.5)$$

It is assumed that  $|\zeta| < 1$ , and that  $\varepsilon_t$  is a normally distributed random variable, with a mean of zero and a standard deviation  $\sigma_\varepsilon$ . The parameter  $\phi > 0$  represents an "overhead cost" component. In each period, an amount  $\phi$  of the intermediate good is immediately used up, independent of how much output is produced. As in Rotemberg and Woodford (1996a), the role of this parameter is to allow the model to reproduce the apparent absence of pure profits in the U.S. industries despite the presence of market power. As Rotemberg and Woodford (1992) emphasize, one would assume that in a growing economy along a balanced growth path, the fixed cost also grows at the same rate. Then, as long as  $\phi$  growth at the same rate of the economy the markup level is constant along a

---

<sup>18</sup>Contrary to the measure of sectors, which is constant, the number of firms may vary across periods.

<sup>19</sup>The term  $N^{1-\frac{1}{\tau}}$  in (3.3) implies that there is no "variety effect" in the model. See the working paper version for an analysis of this effect which only magnifies the results presented here.

balanced growth path.

**Final Good Firms' Problem** The final good producer solves a static optimization problem that results in the following conditional demand for the  $j^{\text{th}}$  sectoral good

$$Q_t(j) = \left[ \frac{p_t(j)}{P_t} \right]^{\frac{1}{\omega-1}} Y_t \quad (3.6)$$

where  $p_t(j)$  is the price index of sector  $j$  at period  $t$  and  $P_t$  is the price of the final good at period  $t$ . As usual,  $P_t$  satisfies

$$P_t = \left[ \int_0^1 p_t(j)^{\frac{\omega}{\omega-1}} dj \right]^{\frac{\omega-1}{\omega}}. \quad (3.7)$$

**The Intermediate Good Producer's Problem** The conditional demand faced by the producer of each  $x_t(j, i)$  variant is

$$x_t(j, i) = \left[ \frac{p_t(j, i)}{p_t(j)} \right]^{\frac{1}{\tau-1}} \frac{Q_t(j)}{N_t} \quad (3.8)$$

where  $p_t(j, i)$  is the price of the  $i^{\text{th}}$  good in sector  $j$  at period  $t$ . Using (3.6) and (3.8), the conditional demand for good  $x_t(j, i)$  at period  $t$  expressed in terms of the final good is

$$x_t(j, i) = \left[ \frac{p_t(j, i)}{p_t(j)} \right]^{\frac{1}{\tau-1}} \left[ \frac{p_t(j)}{P_t} \right]^{\frac{1}{\omega-1}} \frac{Y_t}{N_t} \quad (3.9)$$

where the sectoral price at period  $t$ ,  $p_t(j)$  equals

$$p_t(j) = N_t^{\frac{1}{\tau}-1} \left[ \sum_{i=1}^{N_t} p_t(j, i)^{\frac{\tau}{\tau-1}} \right]^{\frac{\tau-1}{\tau}}. \quad (3.10)$$

Given the intermediate good producer's cost function

$$C^x(W_t, R_t, x_t) = \min_{h_t, k_t} W_t h_t + R_t k_t \text{ s.t. } k_t^\alpha h_t^{1-a} = \frac{x_t + \phi}{z_t} \quad (3.11)$$

and the demand function in (3.9), the intermediate producer solves its maximization problem.

### 3.2.1 The Elasticity of Demand

Dixit and Stiglitz (1977) assume that the single firm is small relative to the economy, and therefore it does not take into account its effect on the remaining firms. Following this assumption would imply that the  $x_t(j, i)$  producer has no effect on the sectoral price level,  $p_t(j)$ , and on the aggregate price level,  $P_t$ . It then follows from (3.9) that the  $x_t(j, i)$  producer faces a constant price elasticity of demand

$$\eta_{x(j,i)p(j,i)} = \frac{1}{\tau - 1} < 0 \quad (3.12)$$

implying a constant markup rule

$$\mu = \frac{p_t(j, i)}{MC_t(j, i)} = \frac{1}{\tau}. \quad (3.13)$$

However, as Yang and Heijdra (1993) emphasize, the assumption in Dixit and Stiglitz (1977) is merely an approximation when the "Dixit-Stiglitz aggregator" is defined over a finite number of goods as in (3.3). In this case, the price elasticity of demand that each firm faces is not constant, but rather is a function of the number of goods. This occurs because each monopolistic producer takes into account the effect it has on the price level.

In the model, there is a continuum of sectors, but within each sector there is a finite number of operating firms. This implies that while each  $x_t(j, i)$  producer does not affect the general price level,  $P_t$ , it does affect the sectoral price level,  $p_t(j)$ . The resulting price elasticity of demand faced by the single firm is therefore a function of the number of firms within a sector,  $N_t$ . In a symmetric equilibrium, it is

$$\eta_{x(j,i)p(j,i)}(N_t) = \frac{1}{\tau - 1} + \left[ \frac{1}{\omega - 1} - \frac{1}{\tau - 1} \right] \frac{1}{N_t} \quad (3.14)$$

implying that an increase in  $N_t$  in sector  $j$  induces the  $x_t(j, i)$  producer to face a more elastic demand curve.<sup>20</sup>

A solution to the monopolistic firm's problem has to satisfy the condition that marginal revenue equals marginal cost

$$\frac{p_t(j, i)}{MC_t(j, i)} = \mu(N_t) = \frac{(1 - \omega)N_t - (\tau - \omega)}{\tau(1 - \omega)N_t - (\tau - \omega)} > 1. \quad (3.15)$$

---

<sup>20</sup>Notice that in the case where  $N \rightarrow \infty$ , the resulting price elasticity of demand is the same as in (3.12). In this case, the approach in Dixit and Stiglitz (1977), and the approach suggested by Yang and Heijdra (1993), coincide. Clearly, this is due to the fact that, in this example, each firm has no actual effect on the sectorial price level because it is of a measure zero within a sector.

Note that the markup function is monotonically decreasing in the number of firms, i.e.

$$\frac{d\mu}{dN} < 0 \quad (3.16)$$

and that

$$\tau\mu(N) > 1.^{21} \quad (3.17)$$

The monopolistic firm's conditional demands for hours worked and capital are then given by

$$\frac{W_t}{p_t(j, i)} = \frac{z_t}{\mu(N_t)} \left[ (1 - \alpha) \frac{k_t^\alpha h_t^{1-\alpha}}{h_t} \right] \quad (3.18)$$

$$\frac{R_t}{p_t(j, i)} = \frac{z_t}{\mu(N_t)} \left[ \alpha \frac{k_t^\alpha h_t^{1-\alpha}}{k_t} \right]. \quad (3.19)$$

### 3.3 Symmetric Rational Expectations Equilibrium

As the economy's technology is symmetric with respect to all intermediate inputs, the paper focuses on symmetric equilibria

$$\forall (j, i) \in [0, 1] \times [1, N_t] : x_t(j, i) = x_t, \quad k_t(j, i) = k_t, \quad h_t(j, i) = h_t, \quad p_t(j, i) = p_t, \quad N_t(j) = N_t.$$

Aggregate capital and aggregate hours are then given by

$$K_t = N_t k_t ; \quad H_t = N_t h_t.$$

Finally, in the symmetric equilibrium, a zero-profit condition is imposed in every sector in every period, implying

$$p_t x_t = MC_t(x_t + \phi).$$

In a symmetric equilibrium, the intermediate producer's output, the number of intermediate

---

<sup>21</sup>From (3.15) it follows that  $\mu(1) = \frac{1}{\omega}$  ;  $\lim_{N \rightarrow \infty} \mu(N) = \frac{1}{\tau}$ . Since  $\tau > \omega$  and the markup function is monotonically decreasing in  $N$ , the result follows immediately.

producers per sector, and the aggregate final output are given by

$$x_t = \frac{\phi}{\mu(N_t) - 1} \quad (3.20)$$

$$N_t = z_t K_t^\alpha H_t^{1-\alpha} \left[ \frac{\mu(N_t) - 1}{\mu(N_t)\phi} \right] \quad (3.21)$$

$$Y_t = z_t \frac{1}{\mu(N_t)} K_t^\alpha H_t^{1-\alpha}. \quad (3.22)$$

Rewriting (3.21) as

$$N_t = \left[ \frac{\mu(N_t) - 1}{\phi} \right] Y_t$$

it immediately follows that  $N_t$  is procyclical, implying that  $\mu$  is countercyclical.

**The Markup Variation Effect** I let  $P_t$  be set as the numeraire and equal to 1. This implies that the price charged by an intermediate producer at a symmetric equilibrium is also 1. By (3.18)-(3.19) and (3.22) the equilibrium rental rate and wage in the economy are then given by

$$R_t = \frac{\alpha z_t}{\mu(N_t)} \frac{1}{K_t} [K_t^\alpha H_t^{1-\alpha}] = \alpha \frac{Y_t}{K_t} = \frac{1}{\mu(N_t)} [MPK_t] \quad (3.23)$$

$$W_t = \frac{(1-\alpha)z_t}{\mu(N_t)} \frac{1}{H_t} [K_t^\alpha H_t^{1-\alpha}] = (1-\alpha) \frac{Y_t}{H_t} = \frac{1}{\mu(N_t)} [MPL_t] \quad (3.24)$$

where  $MPK_t$  and  $MPL_t$  denote the marginal productivities of aggregate capital and labor respectively. Each  $x_t(j, i)$  firm is a monopolist in the production of its own differentiated product and faces a downward sloping demand curve. The economy's structure is such that an increase in  $N_t$  endogenously increases the price elasticity of demand that each producer faces, implying that the size of the price reduction required for selling an additional unit is lower. This increases the marginal revenue productivity of the factors of production.

## 4 The Measurement of TFP and Technology Shocks

To analyze the model's implications for the measurement of technology shocks, I begin by deriving the appropriate expression for the Solow residual and for TFP. This is followed by a quantitative analysis of the volatility of technology shocks and of the internal magnification mechanism. This section concludes by analyzing the model's time-series predictions.

Given the expression for aggregate output in (3.22), then letting TFP and the Solow residual (SR) be defined in the conventional way it turns out that

$$TFP_t = \frac{Y_t}{K_t^\alpha H_t^{1-\alpha}} = \frac{z_t}{\mu(N_t)} \quad (4.1)$$

$$SR_t = \widehat{Y}_t - s_k \widehat{K}_t - s_H \widehat{H}_t \quad (4.2)$$

where a hat over a variable denotes the percentage deviations from its trend, and where  $s_k = \alpha$  and  $s_H = 1 - \alpha$  denote the shares of capital income and labor income in final output respectively.<sup>22</sup> Then, using (3.22), (4.2) the SR can be written as.

$$SR_t = \widehat{TFP}_t = \widehat{z}_t - \widehat{\mu}_t \quad (4.3)$$

where  $\widehat{z}_t$ , and  $\widehat{\mu}_t$ , denote the technology and markup percentage deviations from their trend values respectively. As it has been established that the markup is countercyclical, this implies that the Solow residual is an upward biased estimator of the technology shock.

Equation (4.1) implies that measured TFP is comprised of two factors. A "true exogenous technology",  $z_t$ , and a "new", endogenous productivity measure,  $\frac{1}{\mu(N_t)}$ . This last element is a result of the interaction between net business formation and variation in the degree of competition. The channel through which this endogenous effect influences variations in measured TFP is as follows: in the model economy, a positive technology shock, through its effect on the marginal cost of production, generates new profit opportunities. These in turn lead to the entry of firms that takes place until the economy reaches a zero profit equilibrium. This process results in a fall in the markup. As the ratio of the fixed cost to the actual sales of the monopolistic producer is (see (3.20))

$$\frac{\phi}{x_t} = \mu(N_t) - 1 \quad (4.4)$$

then an expansion leads to a fall in the ratio of fixed cost to actual sales. The economic reasoning behind the fall in the share of the fixed cost is that following the entry of firms and the fall in the markup, all the firms need to "break even" and make, in equilibrium, zero profits. The fall in the markup implies that in order to recover the fixed cost of operation, the oligopolistic producer has

---

<sup>22</sup>Since there are zero profits in the model economy, the income shares of the factors of production are equal to the elasticity of output with respect to these.

to sell a higher quantity, which induces the ratio of fixed cost to actual sales to decrease. As capital and labor are used for the production of both actual sales and the fixed component, then this fall in the share of the fixed component implies that a lower share of resources is used for the production of non-actual sales. As TFP is measured only in terms of the actual sales, then this effect has the same observable implication of a true positive technology shock.<sup>23</sup>

**Solow Residual with Entry/Exit and Constant Markups** It is important to emphasize that the mere presence of monopoly power and a fixed cost does not impart a bias in the measurement of the Solow residual. That is, in a model with the same industrial structure as the one analyzed in this paper but in which the markup is not affected by variation in the number of firms and is rather a constant parameter, the Solow residual is

$$SR_t = \widehat{TFP}_t = \widehat{z}_t.$$

Thus, all of the variations in measured TFP in such a model would originate only from variations in the state of technology. The economic reasoning follows the same logic as in the previous discussion once one notices that the ratio of the fixed cost to actual sales is constant in such an economy. To see this formally, assume that equation (3.3) is replaced with

$$Q_t(j) = N_t^{1-\frac{1}{\tau}} \left[ \int_{i=0}^{N_t} x_t(j, i)^\tau di \right]^{\frac{1}{\tau}}$$

That is, monopolistic producers continue to enter and exit in and out of a sector until a zero-profits equilibrium is reached. However, each monopolistic producer is now of a measure zero within a specific sector. In this case, the price elasticity of demand the monopolistic producer faces is constant and given by  $\eta_{x(j,i)p(j,i)} = \frac{1}{\tau-1}$ , implying a constant markup rule  $\mu = \frac{p_t(j,i)}{MC_t(j,i)} = \frac{1}{\tau}$ . I derive the equilibrium of this version of the model in the Appendix and formally show that in this case, there are no movement in measured TFP that are not due to true technology shocks. Thus, to conclude this discussion, note that the level of the markup by itself has no effect in this model - rather it has an impact via its effect on the elasticity of the markup with respect to output (see

---

<sup>23</sup>Obviously the opposite process occurs in the case of a negative expectations shock.

the discussion of the calibration of this elasticity in the next sub-section). This is in contrast to the literature that followed Hall (1990) which has stressed that the presence of monopoly power by itself generates a bias in the measurement of the Solow residual. In the appendix it is shown that in this version of the model, the existence of entry/exit of firms in the presence of constant markups assures that at any point in time a constant ratio of the fixed cost of operation to sales occurs. This constant ratio implies that there are no movement in measured TFP that are not due to true technology shocks.

**Variance Decomposition** As is well known, a significant fraction of the movements in aggregate output over the business cycle is attributable to variations in measured TFP (for example, in the sample period analyzed in this paper, the ratio  $\frac{Var(\widehat{TFP}_t)}{Var(\widehat{Y}_t)}$  equals 0.3). Equation (4.3) implies that variations in measured TFP are given by

$$VAR(\widehat{TFP}_t) = VAR(\widehat{z}_t) + VAR(\widehat{\mu}_t) - 2COV(\widehat{z}_t, \widehat{\mu}_t). \quad (4.5)$$

That is, the variations in measured TFP can be decomposed into those originating from "true" technology shocks,  $VAR(\widehat{z}_t)$ , and those that arise because of the endogenous effect of the interaction between the number of operating firms and the markup. It is therefore of interest to quantify the variations in TFP that are due to each of these effects. In order to analyze the variance-covariance decomposition implied by equation (4.5), an "adjusted" time series of technology shocks must first be estimated. Since conventional Solow residual accounting-based estimates of technology shocks do not allow for cyclical variations in the markup, a new time series of technology shocks that is consistent with the model economy in this paper needs to be estimated. The paper proceeds with this estimation.

#### 4.1 Measurement and Magnification of Technology Shocks

In order to estimate an adjusted time series of technology residuals that is consistent with the model and allows for cyclical variations in the markup, I use the model's equilibrium conditions which imply that a time series of technology shocks can be estimated from

$$\widehat{z}_t = \left( \widehat{y}_t - s_k \widehat{k}_t - s_H \widehat{h}_t \right) + \widehat{\mu}_t$$

The expression in the parenthesis can be estimated directly from observable data,<sup>24</sup> but the time series of  $\hat{\mu}_t$  cannot be as easily estimated. However, the model's equilibrium conditions imply that  $\hat{\mu}_t = \frac{1-\tau\mu_{va}^*}{\tau\mu_{va}^*}\hat{y}_t$ .<sup>25</sup> Thus, given a calibration of the steady state value of the markup,  $\mu_{va}^*$ , then  $\tau$  needs to be calibrated. Note from the discussion in Section 2 that the steady state value of the markup over value added data in the U.S.,  $\mu^*$ , lies between 1.2 and 1.4.<sup>26</sup> Thus, for exposition purposes I describe the estimation of  $\tau$  for a value of  $\mu^* = 1.3$ . In the actual calibrations I adjust the estimation of  $\tau$  for different values of  $\mu^*$ .

I proceed with the two next alternative methods. Rotemberg and Woodford (1992) estimate the elasticity of the markup with respect to aggregate output to be equal to  $-0.19$ . Given this value and a value of  $\mu^* = 1.3$ , it turns that  $\tau$  equals 0.949. Alternatively, one can show that the model implies that  $\hat{n}_t = \left[ \frac{1-\tau}{\tau(\mu^*-1)} \right] \hat{y}_t$ . As discussed previously, the SBA assembled a data set on the total number of operating firms in the U.S. between 1988 and 2003. Using this data set and real GDP measures, I find  $\left[ \frac{1-\tau}{\tau(\mu^*-1)} \right]$  to equal 0.18. Given a value of  $\mu^* = 1.3$ ,  $\tau$  is then estimated to equal 0.948. Thus, two alternative methods yield a nearly identical value for  $\tau$ . As one might still be concerned about the robustness of these results I show in the working paper version that the log linearized markup in a Cournot setup can be expressed as  $\hat{\mu}_t = \left( \frac{1-\mu^*}{1+\mu^*} \right) \hat{y}_t$ , implying that the parameter  $\tau$  does not need to be estimated and that direct calibration of the steady-state markup level determined the movements in the markup. As I discuss in working paper version (and further below), the quantitative results in a Cournot setup are very similar to the results in the benchmark model suggesting that the results are robust to different values of  $\tau$ .

The first row in table 3 presents the the ratio of the unconditional variance of the implied technology shock process,  $\sigma_z^2$  between the entry/exit model and the perfect competition model. The second to fourth column present this ratio for three different steady-state values of the markup over value-added in the benchmark model. Similarly, the second row presents in the second to the fourth columns the ratio the innovation variance,  $\sigma_\varepsilon^2$ , between the entry/exit model and the perfect competition model. The seventh column presents the same two ratio for a Cournot model

---

<sup>24</sup>Notice that this expression is the time series of technology shocks in RBC model.

<sup>25</sup>Notice that  $\frac{1-\tau\mu_{va}^*}{\tau\mu_{va}^*} < 0$  as it has been shown in equation (3.17) that  $\tau\mu_{va}^* > 1$ .

<sup>26</sup>Recall that the only factors of production in the model presented in this section are capital and labor, and, therefore, the appropriate measure for the markup is one of value added. In Section 5, I analyze the case in which the firm uses materials as a factor of production as well. I then use measures of markup over gross output. Also, note that none of the dynamics depend on the value of  $\phi$  and  $\rho$ .

with homogenous goods.<sup>27</sup> First, the reported moments show that, relative to the RBC model, the incorporation of firm entry and exit decisions into the analysis leads to smaller estimates of the volatility of technology shocks. Relative to the RBC model, the variance of the innovation falls by between 30% and 48%. Similarly, relative to the RBC model, the unconditional variance of implied technology falls by between 32% and 47%. Similar magnitudes are estimated for the case of the Cournot model.

As is well known, the RBC model does not embody a quantitatively important magnification mechanism. Consequently, in order to account for the observed fluctuations in aggregate economic activity, the RBC model must rely on highly variable, exogenous, aggregate technology shocks. This raises the following question; can the interaction between the variation in the number of operating firms and the variation in the degree of competition help to overcome this deficiency? That is, is the internal magnification mechanism embedded in the entry/exit model powerful enough that, with a much less volatile time series of technology shocks, it can still account for the observed fluctuations in aggregate economic activity? In order to quantify the internal magnification mechanism, the model economy is simulated using the adjusted technology residuals time series.<sup>28</sup> Once the entry/exit model is simulated, it generates output, hours, investment and consumption volatilities that are nearly identical to those generated by the RBC model, which requires a much more volatile exogenous technology process.<sup>29</sup>

Thus, the key distinguishing feature of the entry/exit model relative to the RBC model is how it generates output volatility. Because the estimated volatility of technology shocks is smaller in the entry/exit model, it implies that the interaction between the variations in the number of firms and the markup endogenously magnifies these shocks. The third row in Table 3 quantifies the relative strength of the internal magnification mechanism by comparing the relative volatilities of the output and the technology process,  $(\frac{\sigma_y^2}{\sigma_z^2})$ . Relative to the RBC model, the estimated values of this ratio in the entry/exit model increase by 69% when the steady state markup value is 1.2; by 108% when  $\mu^* = 1.3$ ; and by 150% when  $\mu^* = 1.4$ . Thus, while the entry/exit model generates an

---

<sup>27</sup>The entry/exit model generates similar estimates of the  $AR(1)$  coefficient,  $\zeta$ , to those generated by the RBC model for all values of  $\mu^*$  that were considered.

<sup>28</sup>The calibration adopted is standard in the *RBC* literature:  $\beta = 0.99$ ,  $\delta = 0.025$ ,  $\alpha = 0.3$ ,  $\chi = 0.5$ .

<sup>29</sup>Similarly, the contemporaneous correlations between output growth and distinct variables of interest, the auto correlation function of these variables, and the persistence that the entry/exit model generates, are all identical to those generated by the RBC model.

output process at least as volatile as the one generated by the RBC model, the required technology volatility is substantially smaller in the entry/exit model. Again, for the case of the Cournot model similar results are obtained – relative to the RBC model, the estimated value of this ratio in the Cournot entry/exit model increases by 60%.

While the third row is informative with respect to the magnification mechanism embedded in the entry/exit model, one still wonders if the different variants of the entry/exit model can generate "sufficient" output volatility. That is, it might be possible that the resulting output volatility is very low because of the low variance of technology shocks that was estimated in the data under the entry/exit models. If this was the case, then it would be harder to argue that the entry/exit model could be a plausible data-generating-process in the U.S. economy. The last row in Table 3 shows that this is not true. This row reports the volatility of output in the different models relative to the output volatility in the RBC model. As can be seen, not only is the magnification mechanism stronger relative to the one in the RBC model, but also the resulting level of output volatility in the different variants of the entry/exit model is higher than the one in the RBC model. It is interesting to compare these results with those in Hornstein (1993), who analyzes a monopolistic model with a constant number of firms and a constant monopoly power. He shows that the model he analyzes induces a lower magnification mechanism than the one embedded in the benchmark RBC model. Moreover, he shows that this version of the monopolistic model implies that output fluctuates less than in the benchmark RBC model. Thus, the model I analyze here shows that firms' entry/exit and their effect on the markup has important ramifications for the magnification mechanism and for output fluctuations (note that the discussion in Section 4 implies that a version of the model with entry/exit and constant markups will have the same magnification mechanism and same output volatility as the benchmark perfect competition RBC model).

Interestingly, in order for the entry/exit model to generate such a powerful magnification mechanism, small movement in the markup are required. For example, in the simulations when the steady state value of the markup equals to 1.3, the highest value attained for the markup was 1.33 while the minimum value was 1.27. Figure 1 shows the time series of the markup that the model generates in each of the 132 periods of each of the 250 simulations. As it can be seen, more than 99% of the markup values are between 1.28 and 1.32. Thus, the model does not require huge and potentially unrealistic movements in the markup level. Rather, small fluctuations in it are sufficient

to generate the stated results.

An additional measure for magnification mechanism is as follows. Feeding the adjusted time series for technology shock into the model economy while holding the markup constant allows me to recover the output fluctuations that arise from the direct impact of the technology shocks. In this case, the output volatility generated accounts for 68% of the output volatility generated when the markup is also allowed to vary. Thus, the remaining 32% of the output variations are due to the markup variation effect. Once again this reflects the powerful internal magnification mechanism embedded in the entry/exit model.

Figure 2 addresses the internal magnification mechanism embedded in the entry/exit model by comparing the impulse response functions generated by this model and the RBC model in response to a 1% technology shock. Notice how, although the technology shock hitting the two models is identical in its magnitude, the entry/exit model magnifies the response of the economy to the shock in a quantitatively significant way. Similarly, Figure 3 depicts the dynamic response of the Solow residual and the technology process following a technology shock of a magnitude of one standard deviation of the innovation to technology. Notice that the model induces a persistent and quantitatively significant (45% at the impact period) deviation between the actual technology shock and the measured Solow residual. Since markups are countercyclical and the Solow residual follows (4.3), it rises by more than is implied by the mere technology shock. Clearly, this increase reflects the fact that, in this environment, Solow residual accounting, which attributes all TFP movements to technology shocks, overstates their true volatility.

I address the basic intuition behind the internal magnification mechanism by concentrating on the labor market. In the RBC model, the value of marginal productivity of labor (the labor demand schedule) is

$$L_{\text{RBC}}^d = (1 - \alpha)z_t K_t^\alpha L_t^{-\alpha}$$

The lack of magnification is evident in this equation. As capital almost does not fluctuate at the business cycle frequency (I address the issue of capacity utilization further below), than if the volatility of  $z_t$  is reduced, so is the volatility of labor and thus of output. However, in the entry/exit model, the marginal revenue productivity of labor is

$$L_{\text{Entry \& Exit}}^d = (1 - \alpha) \frac{z_t}{\mu(N_t)} K_t^\alpha L_t^{-\alpha}$$

In this case, the impact of variation in the number of firms on markup acts, as in a technology state itself, like a labor demand shifter. This same intuition lies behind the fact that a model with constant monopoly power does not have embodied in it an internal magnification mechanism that is stronger than the one embedded in the RBC model. In a model with constant monopoly power, the marginal revenue productivity of labor equals

$$L_{\text{Constant Monopoly}}^d = (1 - \alpha) \frac{z_t}{\mu} K_t^\alpha L_t^{-\alpha}$$

In this economy a reduction in volatility of  $z_t$  will imply that such a model cannot account for the volatility in the data. The markup is a constant parameter and thus does not serve as a labor demand shifter.

## 4.2 Decomposing and Measuring Variations in TFP

Once the adjusted time series of technology residuals is computed, the variance-covariance decomposition of the variations in measured TFP can be constructed from the simulated data. For the interim case of  $\mu^* = 1.3$ , the estimation results are that only 45% of the variations in measured TFP are due to the direct effect of true technology shocks. Thus, the endogenous interaction between net business formation and markup variations accounts for more than half of the variations in the model's measured TFP. The same analysis can be carried out with actual data. In this case  $\frac{\text{var}(\hat{z}_t)}{\text{var}(TFP_t)} = 0.59$ , and the endogenous interaction explains 41% of the variations in measured TFP. These results therefore suggest that the interaction between net business formation and variations in the degree of competition can provide an endogenous explanation for more than 40% of the variations in measured TFP.

Table 4 compares the statistical properties of TFP variations in the U.S. data with those generated by the RBC model and the entry/exit model. Even though the estimated volatility of technology shocks is smaller in the entry/exit model, the endogenous variations in the TFP process are such that the two models generate a TFP process that is almost identical. Thus, the fact that the entry/exit model is characterized by a less volatile technology process than the RBC model does not keep it from generating a similar TFP process to the one that the RBC model generates. In the U.S. data, the standard deviation of TFP is about half the standard deviation of

output. The entry/exit model, as well as the RBC model, generates a ratio that is nearly identical to the one observed in the data. Finally, the auto-correlation functions and the  $AR(1)$  coefficient of the TFP time series generated by the entry/exit model, as well as those generated by the RBC model, resemble their respective values in the U.S. data.

## 5 Materials Usage and Capacity Utilization

In recent years the business cycle literature has emphasized the important role of capacity utilization plays in the business cycle.<sup>30</sup> This literature finds that capacity utilization can account for endogenous variations in measured TFP and greatly amplify business cycle shocks. Therefore, I am motivated to incorporate an additional margin of capacity utilization into the model I presented in Section 3. This allows me to study the implications of the interaction between capacity utilization and firms' entry/exit for the measurement of TFP and technology shocks. Moreover, I extend the analysis by modifying the firms' production function to account for the presence of materials usage in the U.S. economy.<sup>31</sup> This modification allows me to address the effects of the presence of materials usage in an economy characterized by time-varying markups. It is important to emphasize that in the previous Section the markup was set by firms that were using only capital and labor for production. This implied that the relevant markup ratio was one over value added. In this Section, because firms use capital, labor, and materials as inputs into the production function, the relevant markup ratio is one over gross output.

The assumptions with respect to the population, preferences, final good producers, and sectoral output from Section 3 are retained. The production function of the intermediate firms is characterized by a constant elasticity of substitution between value added and materials and is given by

$$x_t(j, i) + \phi = \left( \sigma [z_t (u_t k_t(j, i))^\alpha h_t(j, i)^{1-\alpha}]^{-v} + (1 - \sigma) m_t(j, i)^{-v} \right)^{\frac{-1}{v}} \quad (5.1)$$

---

<sup>30</sup>See e.g. Kydland and Prescott (1988), Kydland and Prescott (1991), Greenwood and Huffman (1991), Shapiro (1993), Bils and Cho (1994), Burnside, Eichenbaum, and Rebelo (1995), Cooley, Hansen, and Prescott (1995), and King and Rebelo (2000).

<sup>31</sup>Estimating the share of labor and materials in gross output in the U.S. manufacturing sector, I find that the share of materials in gross output is almost always more than 50% and the sum of the shares of labor and materials is around 85%. I therefore calibrate the materials share to be 50% of gross output.

where

$$m_t(j, i) = \left[ \int_0^1 q_t(j)^\rho \right]^{\frac{1}{\rho}} \quad (5.2)$$

and where  $u_t \in (0, 1)$  is the rate of capacity utilization.<sup>32,33</sup> (5.1) and (5.2) imply that each firm uses an aggregate of the sectoral goods,  $m(j, i)$ , as an input in its production function, which I interpret as materials usage.<sup>34</sup> Note that the demand for each sectoral good,  $q_t(j)$ , and for each producer's good,  $x_t(j, i)$ , is composed of the demand from two sources: (i) other monopolistic firms that use these as inputs to their own production, and (ii) the demand of final good producers. The rest of the model remains the same.

It is easy to show that in this model, the higher the share of materials in gross output, the stronger is the internal magnification mechanism.<sup>35</sup> The economic intuition that I offer for the effect of the materials usage is as follows: the production of each firm depends on the output of other firms, which is reflected in each firm's production costs. While labor and capital are always on their respective supply curves, the output of other firms is priced with a markup. This implies that the entry of firms into the existing sectors leads to a reduction in the markup that each firm in each sector charges. This manifests itself in lower costs for all the remaining firms in the economy. Thus, the entry of firms into different sectors creates an added "spillover effect" between sectors that is absent in the value added analysis. This added "feedback effect" makes the magnification effects of a given technology shock stronger, relative to the benchmark case.<sup>36</sup>

The fifth column in Table 3 reports the ratio of the unconditional variance of the implied technology shock process,  $\sigma_z^2$  between the "extended" entry/exit model and the perfect competition model, as well as the ratio the innovation variance,  $\sigma_\varepsilon^2$ , between these two models.<sup>37</sup> As a comparison, the

---

<sup>32</sup>Note that I assume that the firms' elasticity of substitution between the different sectorial outputs is the same as the consumers' elasticity of substitution. This implies that none of the results depend on the composition of demand.

<sup>33</sup>I use the Greenwood, Hercowitz, and Huffman (1988) specification for the capacity utilization process. That is, I assume that the household decides on the optimal utilization of capital and that higher utilization implies higher depreciation rates. The specific functional form is given by  $\delta_t = \frac{1}{\theta} u_t^\theta$ ,  $\theta > 1$ .

<sup>34</sup>Basu (1995), among others, adopts the same interpretation of materials usage.

<sup>35</sup>The implication of capacity utilization for the internal magnification mechanism has been analyzed extensively in the literature.

<sup>36</sup>This last result relates to the idea emphasized by Basu (1995) who writes, "It is an old idea that an industrialized economy, with its greater interdependence and more roundabout production, is more subject to cyclical output fluctuations. The idea has been present at least since the work of Means (1935).....Means's suggestive evidence has led many to speculate on the relationship between output fluctuations and roundabout production. See for example Gordon (1990)."

<sup>37</sup>Since in this version of the model the targeted markup should be over gross output, a steady state markup of  $\mu_{GO}^* = 1.04$  is calibrated. From the discussion in the introduction, it follows that this value lies within the lower

sixth column reports these statistics for the case of the perfect competition model augmented with capacity utilization. The reported moments show that, relative to the RBC model, the variance of the innovation falls by 55%. Similarly, relative to the RBC model with capacity utilization, the variance of the innovation falls by 17%. Relative to the RBC model and to the RBC model with capacity utilization, the unconditional variance of the implied technology falls by 54% and 20% respectively. Note that Table 3 suggests that accounting separately for capacity utilization and markup variations will generate similar estimates for the volatility of technology shocks. However, accounting for these jointly reduces the estimated volatility of technology shocks by more than half relative to an estimation based on perfect competition.

Once this variant of the entry/exit model is simulated with a reduction of more than 50% in the volatility of technology shocks relative to the RBC model, the entry/exit model with materials usage and capacity utilization generates as much output volatility as the former model.<sup>38</sup> Again, the strength of the internal magnification mechanism embedded in the entry/exit model with materials usage and capacity utilization is evident in the value of the ratio  $(\frac{\sigma_y^2}{\sigma_z^2})$  which is reported in the third row. Relative to the RBC model and to the RBC model with capacity utilization, this ratio increases by 155% and 40% respectively.

Finally, once the adjusted time series of technology residuals is computed, the variance-covariance decomposition of the variations in measured TFP can be constructed. The simulated data generated by the entry/exit model with materials usage and capacity utilization implies that only 25% of the variations in measured TFP are due directly to the variance of technology, implying that around three quarters of the variations in TFP are due to the endogenous mechanism embedded in the model.

## 6 Conclusions

This paper formulates a simple structural IO model in a general equilibrium framework in which technology shocks induce the entry and exit of competitors. Endogenous variation in the number

---

estimates of the markup ratio in gross output. Targeting a higher value of the markup would strengthen the internal magnification mechanism even further.

<sup>38</sup>The two models generate similar volatilities in the other variables of interest. Moreover, similar results are obtained with respect to (i) the contemporaneous correlation with output growth, (ii) the auto-correlation function, and (iii) the persistence of these variables.

of operating firms in turn lead to endogenous variation in competition during the business cycle. As a result, the interaction between the number of firms and markup levels will lead to endogenous procyclical movements in TFP. The quantitative results of the paper suggest that about half of the variation in measured TFP in the U.S. are due to this interaction. Moreover, the impact of the number of operating firms on competition has additional implications for the measurement of technology shocks. When the measurement of U.S. technology shocks is adjusted for this interaction, the volatility of technology shocks falls by around half, relative to a benchmark competitive economy. Still, despite the significant reduction in the variance of technology, the model economy can account for the volatility seen in the U.S. data. This is because of the internal magnification mechanism that is embedded in the model economy. The reduction in the reliance on exogenous shocks as the sole force generating the cycle is evident in different statistics that summarize the quantitative properties of the magnification mechanism. Moreover, even though the estimated volatility of technology shocks is smaller in the entry/exit model, endogenous variations in the TFP process result in the model generating a TFP process that is almost identical to the one generated by the RBC.

## Appendix

As stated in the Section 4, assume that

$$Q_t(j) = N_t^{1-\frac{1}{\tau}} \left[ \int_{i=0}^{N_t} x_t(j, i)^\tau di \right]^{\frac{1}{\tau}}.$$

That is, monopolistic producers continue to enter and exit in and out of a sector until a zero-profits equilibrium is reached. However, each monopolistic producer is now of a measure zero within a specific sector. In this case the price elasticity of demand the monopolistic producer faces is constant and given by  $\eta_{x(j,i)p(j,i)} = \frac{1}{\tau-1}$ , implying a constant markup rule  $\mu = \frac{p_t(j,i)}{MC_t(j,i)} = \frac{1}{\tau}$ .

Since the zero-profits equilibrium is characterized by

$$p_t x_t = MC_t (x_t + \phi),$$

it follows that

$$x_t = \frac{\phi}{\mu - 1}. \quad (6.1)$$

Thus, first of all it follows that, since the markup is now a constant parameter, then the actual production per-firm does not vary during the cycle. Rather all the changes in aggregate output are due to the extensive margin, i.e., the entry/exit of firms.

Note that in a symmetric equilibrium, the production function of the monopolistic producer is given by

$$x_t = \frac{z_t K_t^\alpha H_t^{1-\alpha}}{N_t} - \phi.$$

These two last expressions for  $x_t$  imply that the equilibrium number of firms is given by

$$N_t = \frac{(\mu - 1)}{\mu \phi} z_t K_t^\alpha H_t^{1-\alpha}.$$

Aggregate output is given by

$$Y_t = N_t x_t = N_t \left( \frac{z_t K_t^\alpha H_t^{1-\alpha}}{N_t} - \phi \right) = z_t K_t^\alpha H_t^{1-\alpha} - N_t \phi, \quad (6.2)$$

and thus loglinearizing this last expression it follows that

$$\hat{Y}_t = \left( \frac{zK^\alpha H^{1-\alpha}}{Y} \right) \left( \hat{z}_t + \alpha \hat{k}_t + (1-\alpha)\hat{h}_t \right) - \frac{N\phi}{Y} \hat{N}_t.$$

From the equilibrium number of firms it follows

$$\hat{N}_t = \hat{z}_t + \alpha \hat{k}_t + (1-\alpha)\hat{h}_t,$$

and thus

$$\hat{Y}_t = \left( \frac{zK^\alpha H^{1-\alpha} - N\phi}{Y} \right) \left( \hat{z}_t + \alpha \hat{k}_t + (1-\alpha)\hat{h}_t \right).$$

But from equation (6.2) it follows that

$$\frac{zK^\alpha H^{1-\alpha} - N\phi}{Y} = 1.$$

Thus, the Solow residual measure,  $\hat{Y}_t - \alpha \hat{k}_t - (1-\alpha)\hat{h}_t$ , is in this case equal to  $\hat{z}_t$ . I.e., the mere presence of monopoly power and fixed costs of operation does not impart a bias in the measurement of the Solow residual. The existence of entry/exit of firms in the presence of constant markups assures that equation (6.1) holds at any point in time and implies a constant ratio of the fixed cost of operation to sales. This constant ratio implies that there are no movement in measured TFP that are not due to true technology shocks under constant markups with entry and exit.

## References

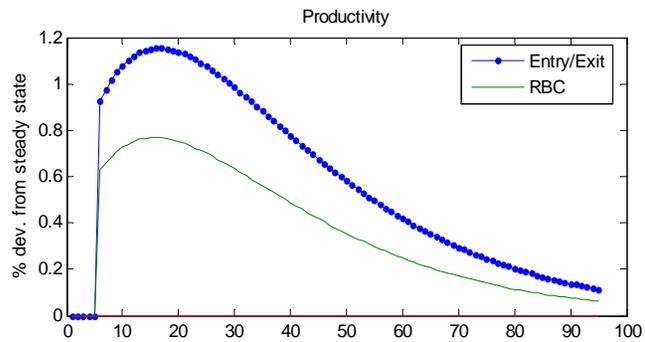
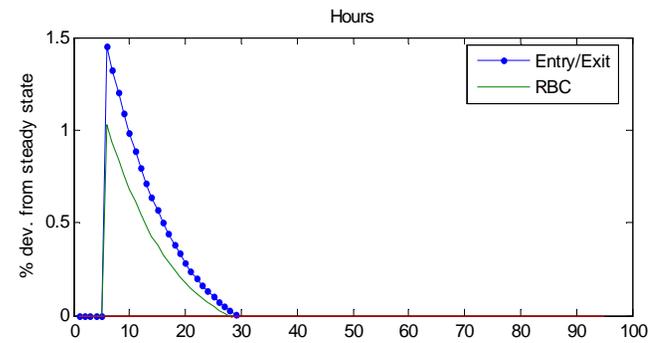
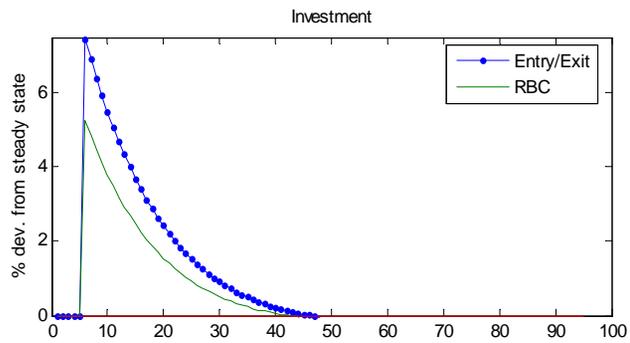
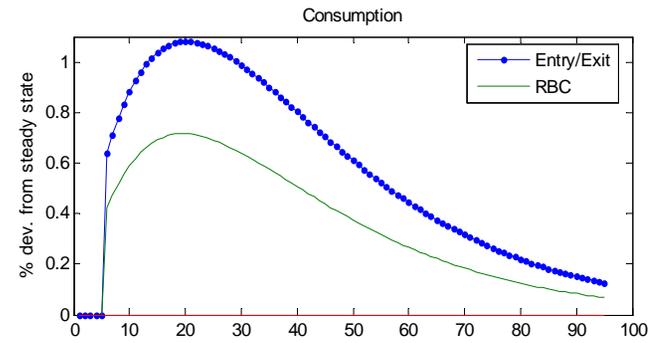
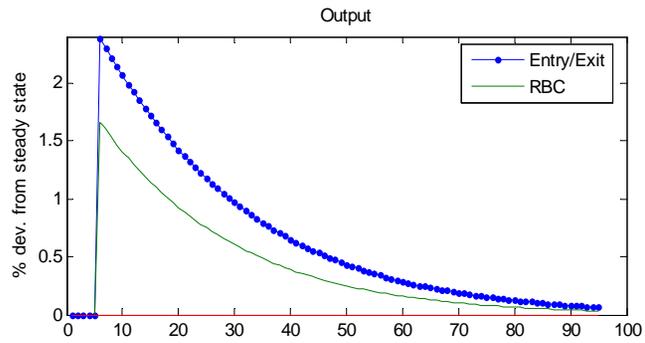
- ANDOLFATTO, D. (1996): “Business Cycles and Labor Market Search,” *American Economic Review*, 86(1), 112–132.
- BARSEGHYAN, L. (2006): “Entry Costs and Cross-Country Differences in Productivity and Output,” *Cornell University, Working Paper*.
- BASU, S. (1995): “Intermediate Goods and Business Cycles: Implication for Productivity and Welfare,” *American Economic Review*, 85(3), 512–531.
- BASU, S., AND J. FERNALD (1997): “Returns to Scale in U.S. Production: Estimates and Implications,” *Journal of Political Economy*, 105(2), 249–283.
- (1999): “Why Is Productivity Procyclical? Why Do We Care?,” *Board of Governors of the Federal Reserve System, International Finance Discussion Paper*, 638.
- BASU, S., J. FERNALD, AND M. KIMBALL (2004): “Are Technology Improvements Contractionary?,” *NBER Working Paper*, 10592.
- BEAUDRY, P., F. COLLARD, AND F. PORTIER (2006): “Gold Rush Fever in Business Cycles,” *NBER Working Paper*, 12710.
- BILBIIE, F., F. GHIRONI, AND M. MELITZ (2006a): “Endogenous Entry, Product Variety, and Business Cycles,” *Boston College, Working Paper*.
- (2006b): “Monopoly Power and Endogenous Variety in Dynamic Stochastic General Equilibrium: Distortions and Remedies,” *Boston College, Working Paper*.
- BILS, M. (1987): “The Cyclical Behavior of Marginal Cost and Price,” *American Economic Review*, 77(5), 647–666.
- BILS, M., AND J.-O. CHO (1994): “Cyclical Factor Utilization,” *Journal of Monetary Economics*, 33(2), 319–354.
- BRESNAHAN, T. F., AND P. C. REISS (1991): “Entry and Competition in Concentrated Markets,” *Journal of Political Economy*, 99(5), 977–1009.
- BURNSIDE, C., AND M. EICHENBAUM (1996): “Factor-Hoarding and the Propagation of Business Cycle Shocks,” *American Economic Review*, 86(5), 1154–1174.
- BURNSIDE, C., M. EICHENBAUM, AND S. REBELO (1993): “Labor Hoarding and the Business Cycle,” *Journal of Political Economy*, 101(2), 245–273.
- (1995): “Capital Utilization and Returns to Scale,” in *Ben S. Bernanke and Julio J. Rotemberg (eds.), NBER Macroeconomics Annual 1995, MIT press, Cambridge, MA.*, pp. 67–110.

- (1996): “Sectoral Solow Residuals,” *European Economic Review*, 40(3-5), 861–869.
- CAMPBELL, J. (1998): “Entry, Exit, Embodied Technology, and Business Cycles,” *Review of Economic Dynamics*, 1, 371–408.
- CAMPBELL, J., AND H. HOPENHAYN (2005): “Market Size Matters,” *Journal of Industrial Economics*, 53(1), 1–25.
- CHEVALIER, J., A. KASHYAP, AND P. ROSSI (2003): “Why Don’t Prices Rise During Periods of Peak Demand? Evidence from Scanner Data,” *American Economic Review*, 93(1), 15–37.
- COCHRANE, H. J. (1994): “Shocks,” *NBER Working Paper 4698*.
- COGLEY, T., AND J. NASON (1995): “Output Dynamics in Real Business Cycles Models,” *American Economic Review*, 85(3), 492–511.
- COOLEY, T., G. HANSEN, AND E. PRESCOTT (1995): “Equilibrium Business Cycles with Idle Resources and Variable Capacity Utilization,” *Economic Theory*, 6, 35–49.
- COOPER, R., AND S. CHATTERJEE (1993): “Entry and Exit, Product Variety and the Business Cycle,” *NBER Working Paper 4562*.
- DEN HAAN, W. J., G. RAMEY, AND J. WATSON (2000): “Job Destruction and Propagation of Shocks,” *American Economic Review*, 90(3), 482–98.
- DEVEREUX, M., A. HEAD, AND B. LAPHAM (1996): “Aggregate Fluctuations with Increasing Returns to Specialization and Scale,” *Journal of Economic Dynamics and Control*, 20(4), 627–657.
- DICECIO, R. (2005): “Comovement: It’s Not A Puzzle,” *Federal Reserve Bank of St. Louis Working Paper*.
- DIXIT, A., AND J. STIGLITZ (1977): “Monopolistic Competition and Optimum Product Diversity,” *American Economic Review*, 67(3), 297–308.
- DONOWITZ, I. R., G. HUBBARD, AND B. C. PETERSEN (1986): “Business Cycles and the Relationship Between Concentration and Price-Cost Margins,” *Rand Journal of Economics*, 17(1), 1–17.
- EDMUNDS, C., AND L. VELDKAMP (2006): “Income Dispersion, Asymmetric Information and Fluctuations in Market Efficiency,” *NYU Working Paper*.
- GALI, J. (1994): “Monopolistic Competition, Business Cycles, and the Composition of Aggregate Demand,” *Journal of Economic Theory*, 63(1), 73–96.
- GOMME, P., P. RUPERT, R. ROGERSON, AND R. WRIGHT (2004): “The Business Cycle and the Life Cycle,” *NBER Macro Annual*, pp. 415–461.
- GORDON, R. (1990): “What is New-Keynsian Economics?,” *Journal of Economic Literature*, 28(3), 1115–1171.

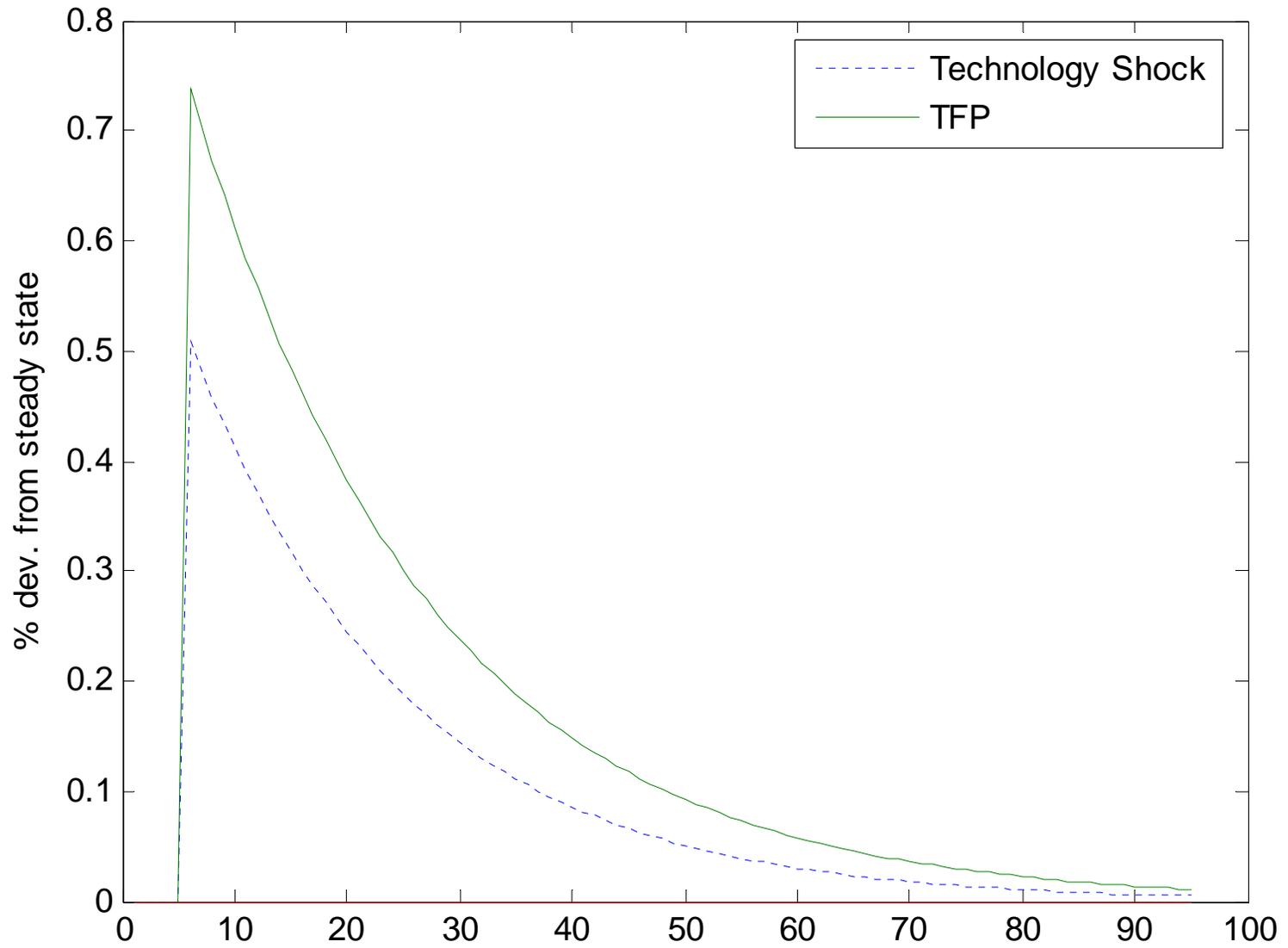
- GREENWOOD, J., Z. HERCOWITZ, AND G. HUFFMAN (1988): "Investment, Capacity Utilization, and the Real Business Cycle," *American Economic Review*, 78(3), 402–417.
- GREENWOOD, J., AND G. HUFFMAN (1991): "Tax Analysis in a Real-Business-Cycle Model," *Journal of Monetary Economics*, 27, 167–190.
- HALL, R. E. (1986): "Market Structure and Macroeconomic Fluctuations," *Brookings Papers on Economic Activity*, 2, 285–338.
- (1988): "The Relation Between Price and Marginal Cost in U.S. Industry," *Journal of Political Economy*, 96(5), 921–947.
- (1990): "The Invariance Properties of Solow's Productivity Residual," in P. Diamond (ed.), *Growth, Productivity, Unemployment*, MIT press, Cambridge MA.
- (1999): "Amplification and Persistence of Employment Fluctuations Through Labor Market Frictions," in John B. Taylor and Michael Woodford (eds.), *Handbook of macroeconomics*, Vol. 1B. New York: Elsevier Science., pp. 1137–70.
- HORNSTEIN, A. (1993): "Monopolistic Competition, Increasing Returns to Scale, and the Importance of Productivity Shocks," *Journal of Monetary Economics*, 31, 299–316.
- KING, R., AND S. REBELO (2000): "Resuscitating Real Business Cycles," in John Taylor and Michael Woodford (eds.) *Handbook of Macroeconomics*, North-Holland, pp. 927–1007.
- KYDLAND, F., AND E. PRESCOTT (1988): "The Workweek of Capital and its Cyclical Implications," *Journal of Monetary Economics*, 21(2-3), 343–360.
- (1991): "Hours and Employment Variation in Business Cycle Theory," *Economic Theory*, 1, 63–81.
- LAFONTAINE, F., AND R. BLAIR (2005): "The Economics of Franchising," *Cambridge University Press*.
- MARTINS, J., S. SCAPETTA, AND D. PILAT (1996): "Markup Pricing, Market Structure and the Business Cycle," *OECD Economic Studies*, 27, 71–105.
- MEANS, G. (1935): "Industrial Prices and Their Relative Inflexibility," *U.S. Senate Document 13, 74th Congress, 1st Session*. Washington, DC: U.S. Government Printing Office.
- MORRISON, C., J. (1992): "Markups in U.S. and Japanese Manufacturing: A Short-Run Econometric Analysis," *Journal of Business and Economic Statistics*, 10(1), 51–63.
- NORRBIN, S. (1993): "The Relation Between Price and Marginal Cost in U.S. Industry: A Contradiction," *Journal of Political Economy*, 101(6), 1149–1164.
- PANZAR, J. (1989): "Technological Determinants of Firm and Industry Structure," in R. Schmalensee and R.D. Willig (eds.) *Handbook of Industrial Organization*, Amsterdam: North-Holland, pp. 3–59.

- PORTIER, F. (1995): “Business Formation and Cyclical Markups in the French Business Cycle,” *Annales D’Economie et de Statistique*, 37/38, 411–440.
- ROEGER, W. (1995): “Can Imperfect Competition Explain the Difference Between Primal and Dual Measures? Estimates for US Manufacturing,” *Journal of Political Economy*, 103(2), 316–330.
- ROTEMBERG, J., J., AND M. WOODFORD (1991): “Markups and the Business Cycle,” in *O.J. Blanchard, and S. Fischer (eds.), NBER Macroeconomics Annual 1991 Cambridge, MIT Press.*
- (1992): “Oligopolistic Pricing and the Effects of Aggregate Demand on Economic Activity,” *Journal of Political Economy*, 100(6), 1153–1207.
- (1995): “Dynamic General Equilibrium Models with Imperfectly Competitive Product Markets,” In *Frontiers of Business Cycle Research, Edited by T.F. Cooley. Princeton, N.J: Princeton University Press.*
- (1996a): “Imperfect Competition and the Effects of Energy Price Increases on Economic Activity,” *Journal of Money Credit and Banking*, 28(4), 549–577.
- (1996b): “Real Business Cycle Models and the Forecastable Movements in Output, Hours and Consumption,” *American Economic Review*, 86(1), 71–89.
- (1999): “The Cyclical Behavior of Prices and Costs,” in *Taylor, J.B., and M. Woodford (eds.), Handbook of Macroeconomics, Vol.1B, Amsterdam: North-Holland.*
- SHAPIRO, D. M. (1993): “Cyclical Productivity and the Workweek of Capital,” *American Economic Review*, 83(2), 229–233.
- YANG, X., AND J. B. HEIJDRRA (1993): “Monopolistic Competition and Optimum Product Diversity: Comment,” *American Economic Review*, 83(1), 295–301.

# IRF: Response of Entry/Exit Model and RBC to a 1% Technology Shocks



# IRF: Technology Shock and TFP



## Time Series of the Markup: Steady State Value of 1.3

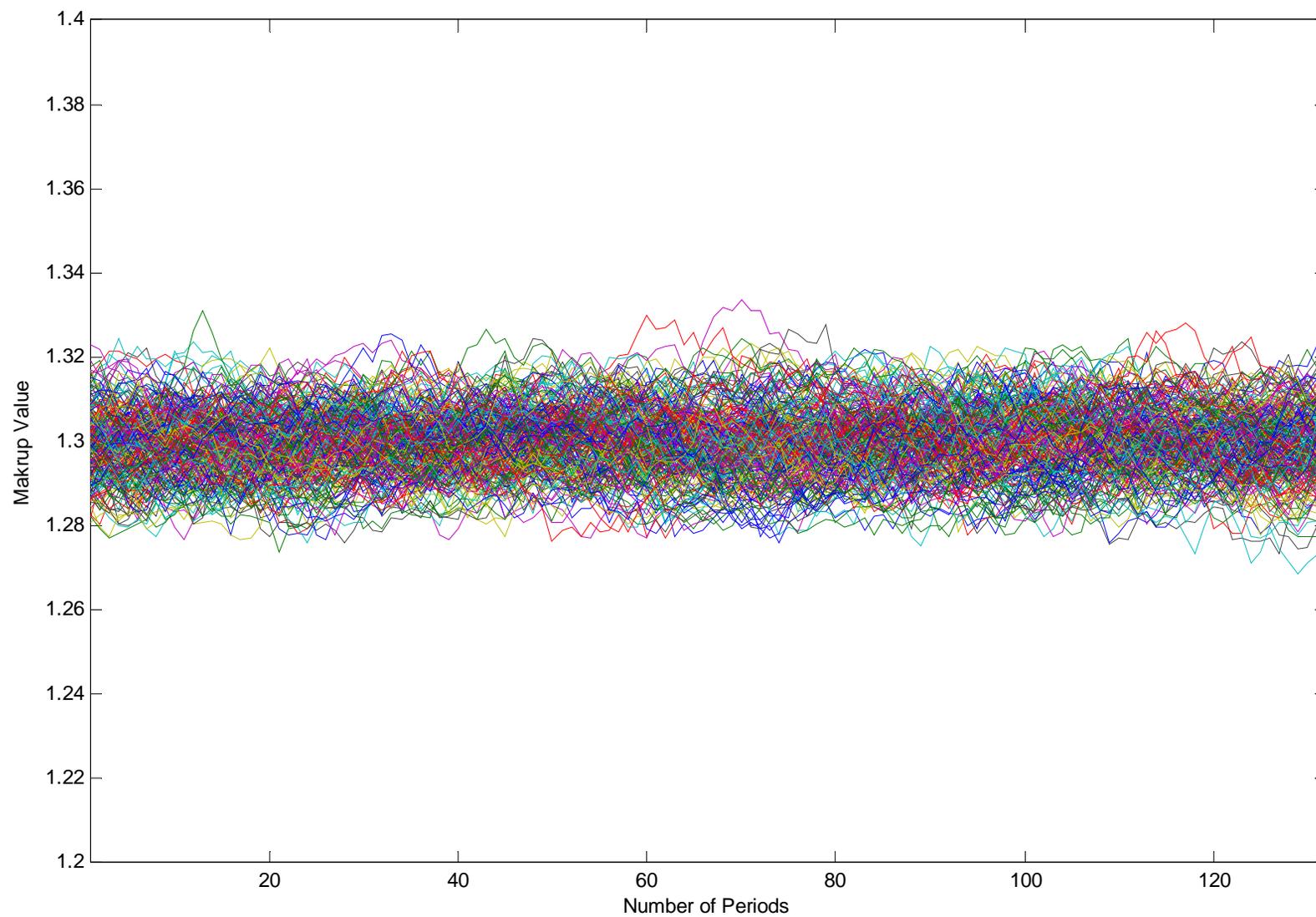


Table 1: Correlation between Output and Number of Failures by Industry

Industry	SIC Code	Contemporaneous Correlation with Aggregate Output
<i>MINING</i>		-0.2642*
<i>CONSTRUCTION</i>		-0.5224***
<i>MANUFACTURING</i>		
Durable Goods		
Lumber and wood products	(24)	-0.5045***
Furniture	(25)	-0.5427***
Stone, clay, & glass products	(32)	-0.4657***
Iron & Steel Products	(33-34)	-0.5660***
Electrical & electronic equipment	(36)	-0.4686***
Transportation Equipment	(37)	-0.4471***
Motor vehicle equipment	(371)	-0.3902**
Other machinery	(38)	-0.5757***
Misc. Industries	(39)	-0.5925***
Nondurable Goods		
Food & Kindred Products	(20)	-0.3331**
Textile mill products	(22)	-0.4891***
Apparel and other textile products	(23)	-0.5116***
Paper and allied products	(26)	-0.3731**
Printing and publishing	(27)	-0.5924***
Chemicals & allied products	(28)	-0.3217**
Petroleum, coal, & gas products	(29)	-0.2069
Rubber & misc. plastic products	(30)	-0.2950**
Leather & leather products	(31)	-0.4509**
<i>TRANSPORTATION AND PUBLIC SERVICES</i>		-0.4651***
<i>WHOLESALE TRADE</i>		
Durable		
Furniture and house furnishings	(502)	-0.5204***
Lumber and building materials	(503)	-0.5060***
Electrical goods	(506)	-0.3602**
Machinery equipment and supplies	(508)	-0.5220***
Nondurable		
Paper and paper products	(511)	-0.2191
Apparel and piece goods	(513)	-0.3565**
Groceries and related products	(514)	-0.3692**
Farm-product raw materials	(515)	-0.1212
Alcoholic Beverages	(518)	-0.2899*
<i>RETAIL</i>		
Building, farm, & garden stores	(52)	-0.6669***
Food Stores	(54)	-0.4394***
Automotive dealers and service stations	(55)	-0.4995***
Apparel and accessory stores	(56)	-0.4384***
Furniture and furnishings stores	(57)	-0.6606***
General and other stores	(59)	-0.2034
Liquor Stores	(592)	-0.3199**
Miscellaneous retail stores		
Book and stationery stores	(5942-5943)	-0.3636**
Jewelry stores	(5944)	-0.5503***
Fuel and ice dealers	(5982)	-0.4369***
<i>SERVICE INDUSTRIES</i>		
Hotels	(70)	-0.4496***
Personal Services	(72)	
Cleaning, laundry, repairing services	(721)	-0.4567***
Funeral services	(726)	-0.1647
Other personal services	(7299)	-0.3572**
Business services	(73)	-0.2940*
Repair services other than auto	(76)	-0.5502***

\*, \*\*, \*\*\* significant at 10%, 5%, and 1% level, respectively

**Table 2: Fractions of Job Gains and Job Losses  
Accounted for by Opening and Closing of Establishments**

	I	II	III	IV	V	VI
	Average Fraction of Job Gains Accounted for by Employment at Opening Establishments	Average Fraction of Job Losses Accounted for by Employment at Closing Establishments	Fraction of Cyclical Volatility in Job Gains Accounted for by Employment at Opening Establishments - Method I	Fraction of Cyclical Volatility in Job Losses Accounted for by Employment at Closing Establishments - Method I	Fraction of Cyclical Volatility in Job Gains Accounted for by Employment at Opening Establishments - Method II	Fraction of Cyclical Volatility in Job Losses Accounted for by Employment at Closing Establishments - Method II
Aggregate U.S. Data	0.2186	0.2117	0.3346	0.3375	0.1807	0.2627
Goods Producing	0.1834	0.1881	0.2893	0.2311	0.1285	0.1303
Natural Resources & Mining	0.1882	0.1843	0.2950	0.3240	0.2274	0.4288
Information	0.2354	0.2422	0.3279	0.3802	0.1998	0.2949
Financial Activities	0.2556	0.2688	0.4418	0.4808	0.2981	0.2828
Professional & Business Services	0.2185	0.2261	0.3134	0.2740	0.0837	0.1063
Leisure & hospitality	0.2659	0.2219	0.3167	0.4705	0.1785	0.4321
Construction	0.2133	0.2147	0.2585	0.2502	0.2033	0.2523
Manufacturing	0.1487	0.1647	0.2993	0.2180	0.0759	0.0657
Service-Providing	0.2294	0.2196	0.3632	0.3832	0.2007	0.3021
Wholesale Trade	0.2126	0.2370	0.3509	0.3817	0.1512	0.2910
Retail Trade	0.1926	0.1748	0.3680	0.3981	0.2434	0.3285
Transportation & Warehousing	0.1880	0.2066	0.2667	0.2316	0.1062	0.1872

Table 3 : Properties of the Technology Process and Magnification Ratios

	Perfect Competition	Entry & Exit $\mu=1.2$	Entry & Exit $\mu=1.3$	Entry & Exit $\mu=1.4$	Entry & Exit $\mu^{90}=1.04$	Perfect Competition (with Utilization)	Entry & Exit: Cournot $\mu=1.3$
$\sigma_z^2/\sigma_z^2, \text{Competition}$	1	0.685	0.595	0.532	0.46	0.576	0.697
$\sigma_\varepsilon^2/\sigma_\varepsilon^2, \text{Competition}$	1	0.698	0.600	0.524	0.45	0.539	0.700
$\sigma_y^2/\sigma_z^2$	0.457	0.775	0.951	1.15	1.165	0.832	0.740
$\sigma_y^2/\sigma_y^2, \text{Competition}$	1	1.162	1.238	1.339	1.173	1.049	1.129

The reported technology shocks are calculated using quarterly data 1955:I-2002:IV

Reported moments are means of statistics computed from 250 simulations, each of 132 periods in length.

Standard deviations are in parentheses. The U.S. data and the data generated by the models are HP filtered with a smoothing variable of 1600.

Table 4: Selective Moments of TFP

	Std. Dev. TFP	Ratio of Std. Dev of TFP to Std. Dev of Output	AC(1)	AC(2)	AC(3)	AR(1)
U.S. Data	0.85	0.54	0.71	0.48	0.20	0.71
RBC	0.81	0.57	0.70	0.46	0.25	0.70
Entry & Exit $\mu^{va}=1.3$	0.91	0.58	0.70	0.46	0.25	0.70

Reported moments are means of statistics computed from 250 simulations, each of 132 periods in length.

Standard deviations are in parentheses. The U.S. data and the data generated by the models are HP filtered with a smoothing variable of 1600.