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Firm dynamics, markup variations, and the business cycle ☆

Nir Jaimovich [a,*], Max Floetotto [b]

[a] Stanford University and NBER, USA
[b] Stanford University, USA

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ABSTRACT

We present a model in which net business formation is endogenously procyclical. Variations in the number of operating firms lead to countercyclical variations in markups that give rise to endogenous procyclical movements in measured total factor productivity (TFP). Based on this result, the paper suggests a simple structural decomposition of variations in TFP into those originating from exogenous shocks and those originating endogenously from the interaction between firms' entry and exit decisions and the degree of competition. The decomposition suggests that around 40% of the movements in measured TFP can be attributed to this interaction. Moreover, the paper analyzes the effects on (i) the measurement of the volatility of exogenous shocks in the U.S. economy and (ii) the magnification of shocks over the business cycle.

1. Introduction

The interaction between firms' entry and exit decisions and variation in the degree of competition can lead to endogenous procyclical movements in measured total factor productivity (TFP). Three basic stylized facts motivate this paper: (i) the existence of monopoly power in the U.S. economy, (ii) procyclical variations in the number of competitors and (iii) markups being countercyclical and negatively correlated with the number of competitors.

To account for these empirical observations, the paper formulates a dynamic general equilibrium model, where variations in the level of technology give rise to changes in the number of operating firms. These in turn lead to endogenous countercyclical markup variations. To model the interaction between firms' entry/exit decisions and markup variations, it is assumed that the economy contains a large number of sectors. Each sector is comprised of a finite number of differentiated, monopolistically competitive intermediate firms. Within a given sector, each firm takes into account the effect that the pricing and production decisions of other firms have on the demand for its goods. The price elasticity of demand faced by the typical firm is thus positively related to the number of firms in the sector. As a result, markups are set at a lower level in response to an increase in the number of competitors. The number of firms in a sector is determined by the equilibrium

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* Corresponding author. Department of Economics, Stanford University, Stanford, CA 94305, USA. Tel.: +1 650 7244902.
E-mail address: njaimo@stanford.edu (N. Jaimovich).

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condition that all firms earn zero profits in every period. This condition is enforced by firms' decisions to either enter or exit an industry.[1]

The setup of this model is used to show two quantitative results. First, one can derive a simple structural method for decomposing variations in TFP into those originating endogenously from the interaction of entry and exit decisions and markup variations and those originating from exogenous shocks. Based on this decomposition, the paper finds that around 40% of the movements in measured TFP can be attributed to the impact of firm entry and exit decisions on optimal markups. Second, the paper shows that the interaction between variation in the number of competitors and variation in the degree of competition provides a powerful internal magnification mechanism for shocks to agents' environments. Specifically, 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 presenting the results in more detail, it is worth emphasizing that the model represents a minimal perturbation of the prototype perfect competition real business cycle (RBC) model. This greatly simplifiescomparison with existing work and allows for a simple structural decomposition of TFP. However, this simplicity comes at the cost of descriptive realism, and several empirical caveats should be highlighted.[2] First, the model here is symmetric implying the same number of firms in all sectors. One might be worried that the procyclicality in the number of firms in the data is really driven by only a few industries. To address this issue, we assemble a data set that documents the number of failing firms in the U.S. economy in 46 industries over more than 40 years. All of these industries are characterized by countercyclical exit rates, which indicates that the aggregate result is not driven by just a few industries. Second, firms enter the model economy at the same size as existing firms. It is well known, however, that smaller firms constitute 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 is the key driving force in the model. For example, a new establishment or franchise by an existing firm increases the number of competitors without affecting the number of active firms. It turns out that the number of establishments and franchises are both strongly procyclical. Moreover, using the business employment dynamics (BED) data set one can show that a third of the cyclical volatility in job gains (losses) is explained by opening (closing) establishments. Additional evidence can be found in recent work by Broda and Weinstein (2007) who emphasize that most product turnover occurs within the boundaries of the firm. They find that net product creation is strongly procyclical. Hence, if one adopts a loose interpretation of entry and includes new establishments and franchises, as well as the introduction of new products by existing firms, this work provides evidence for a sizable variation in the number of competitors at the business cycle frequency.

The following paragraphs will discuss the main quantitative results of the model starting with the measurement of TFP. 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 positive 1% technology shock induces a rise in TFP between 1.45% and 1.80%. Based on a variance–covariance decomposition, it is estimated that in post-war U.S. data, around 40% of the variation in measured TFP is due to the endogenous mechanism embedded in the firms' entry/exit decisions. In contrast, if the number of firms does not vary, and/or if the markup is held constant, measured TFP moves one-to-one with the level of technology and all of the variation in measured TFP is due to exogenous technology shocks. These results are related to the seminal contributions of Hall (1986, 1988, 1990) who finds evidence that variations in measured TFP co-vary with exogenous instruments. He interprets these results as evidence in support of the existence of market power and increasing returns. The theoretical framework of this paper captures this effect. Here, the cyclicality of TFP is a result of variations in the number of operating firms and their effect on optimal markup pricing. Two key elements of the theoretical model that drive this effect are, indeed, imperfect competition and the presence of a fixed cost, which gives rise to increasing returns to scale at the firm level.[3] 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. Instead, those are only necessary conditions for the mismeasurement in TFP, but alone they are not sufficient. The third necessary condition is that monopoly power is time variant.

Consider now the magnification of fundamental shocks. As is well known, the standard RBC model does not embody a quantitatively important magnification mechanism.[4] In order to account for the observed fluctuations in aggregate economic activity, the RBC model must rely on exogenous aggregate technology shocks that are highly variable.[5] This paper suggests that the interaction between variation in the number of operating firms and variation in the degree of competition

[1] The entry decision in the baseline model is static. An extensive appendix studies the richer dynamic problem with sunk entry costs following Bilbiie et al. (2007). The results in the dynamic model are somewhat mitigated, but the key magnification mechanism remains quantitatively significant. The appendix can be found at www.stanford.edu/~njaimo/papers/entryexit_jme_appendix and as supplementary material to the article on Science Direct.

[2] See Section 2 for a more detailed discussion of these issues and a description of the data we use.

[3] In the theoretical model a key element is the 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."

[4] See, for example, Burnside et al. (1993), Cooper and Chatterjee (1993), Cogley and Nason (1995), Burnside and Eichenbaum (1996), Devereux et al. (1996), Andolfatto (1996), Hall (1999), King and Rebelo (2000), and Den Haan et al. (2000).

[5] The measurement of these types 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. See e.g., Hall (1988), Burnside et al. (1993), Cochrane (1994), and Burnside and Eichenbaum (1996).

in the economy can help to overcome some of these deficiencies. 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 which the direct impact of a fundamental shock is magnified. Because conventional Solow residual (SR) accounting-based estimates of technology shocks do not allow for cyclical variations in the markup, the model is used to correct for this type of variation. Depending on the exact specification, 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 builds on a large literature in macroeconomics that stresses the role of imperfect competition on the business cycle. In a series of influential papers, Rotemberg and Woodford (1991, 1992, 1995, 1996) study the macroeconomic consequences of oligopolistic behavior. In their model, implicit collusion among a fixed number of firms gives rise to countercyclical movements in the markup. 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 effect of constant monopoly power on the measurement of technology shocks and finds a 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 as it lacks an internal magnification mechanism. Edmunds and Veldkamp (2006) analyze a model where the presence of asymmetric information and countercyclical income dispersion leads to countercyclical markups. Cooper and Chatterjee (1993) and Devereux et al. (1996) focus on the productive efficiency associated with cyclical variations in the variety of goods that are produced. In the model of Bilbiie et al. (2006) firms face a sunk cost of entry and variations in the number of firms are interpreted broadly as variations in capital/production lines. Campbell (1998) studies firm entry and exit in a vintage capital model.

The structural model presented in this paper is close to Portier's (1995) who documents the pro-cyclicality of business formation and the countercyclicality of markups in 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 can serve as an internal magnification mechanism through the effect on the markups. This paper thus shares Portier's conclusion and goes beyond it along several dimensions. First, the implications of the internal magnification mechanism for the measurement of technology shocks is estimated in U.S. time series data. Second, using this newly estimated series, the model here is simulated and its time-series properties compared to those of U.S. data. This allows a quantification of the magnification mechanism embedded in the model, leading to the finding that a substantially smaller fraction of the standard deviation of output is due to the direct impact of technology shocks. It is the endogenous magnification embedded in the model that accounts for the volatility of output. Third, the model gives rise to a structural decomposition of TFP fluctuations into those arising from exogenous shocks and those that are endogenous.

Section 2 discusses the empirical caveats highlighted above and provides evidence that alleviates these concerns. Section 3 introduces the benchmark model. Section 4 analyzes the model's implications for the structural decomposition of variations in measured TFP into pure exogenous technology shocks and those that arise endogenously from the model. In Section 5, the benchmark model is extended and materials usage and capacity utilization are introduced into the analysis. This allows to study the effects of the interaction between these two factors and the countercyclicality of markups on the measurement of technology shocks and on the decomposition of TFP. Section 6 concludes.

2. Empirical evidence

A detailed survey of the literature that estimates 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 those in gross output vary between 1.05 and 1.15.[6] Many studies have addressed the cyclicality of the markup. Among the most prominent studies finding that markups are countercyclical in the U.S. are Bils (1987), Rotemberg and Woodford (1991, 1999), and Chevalier et al. (2003).[7] Martins et al. (1996) cover multiple 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. In addition, they conclude that entry rates have a negative and statistically significant correlation with markups. 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 showing 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) who show that both net business formation and new business incorporations are strongly procyclical. Similarly, Devereux et al. (1996) report that the aggregate number of business

[6] See, for example, Hall (1988), Morrison (1992), Norrbin (1993), Roeger (1995), Martins et al. (1996), and Basu and Fernald (1997, 1999).

[7] Donowitz et al. (1986) suggest that markups are procyclical. Rotemberg and Woodford (1999) highlight a bias in these results, as measures of average variable costs are used instead of marginal costs.

failures is countercyclical.[8] Direct measures of the number of operating firms in the U.S. economy exist for the years between 1988 and 2003.[9] The contemporaneous correlation between the number of firms and real GDP equals 0.50 and is significant at the 5% level.[10]

The remainder of this section addresses two empirical caveats that were mentioned in the Introduction. First, while the aggregate number of competitors varies procyclically in the U.S. data, one might be worried that this empirical observation is driven by just a few industries. Second, an additional concern might be that smaller firms typically make up the majority of entrants and exits, potentially implying that variations in their number are less important.

To address the first issue, a new data set is assembled that documents the number of failing firms in the U.S. economy by industry at a yearly frequency between 1956 and 1996.[11]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 data set 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 characteristic of most U.S. industries at different aggregation levels.

With respect to the second empirical concern, it is important to note that variations in the number of firms are only one of the channels that generate actual changes in the number of competitors, which is the driving force from the model's perspective. For example, variations in the number of establishments and franchises are additional channels. 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 very volatile. The ratio of the standard deviation of the number of establishments and real GDP is 1.3.[12] With respect to franchises, the contemporaneous correlation between the number of these 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.[13] These estimates suggest that franchises, as well as establishments, are potentially important sources of fluctuation in the number of competitors.

Additional information as to the empirical significance of new potential competitors can be obtained from the BED.[14] The BED documents job 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 job losses from either closing or contracting establishments. Table 2 reports the fraction of job gains and losses explained by opening and closing establishments, respectively, using three different methods. The first (second) column reports the average fraction of the quarterly gross job-gains (losses) in the U.S. economy explained by opening (closing) establishments. Columns three and four estimate the fraction of the volatility in job-gains (losses) that is accounted for by the cyclical volatility of employment in opening (closing) establishments.[15] The first row refers to aggregate U.S. data. The average fraction of quarterly gross job-gains (losses) that can be explained by the opening (closing) of establishments is about 20%. Similarly, around a third of the cyclical volatility of the job-gains (losses) comes from opening (closing) establishments. Hence, cyclical fluctuations in the number of establishments are of empirical significance and play a potentially important role in affecting measures of competition. The results in column three and four might be overstated if not all the high-frequency fluctuations are directly attributable to the business cycle. To address this issue, we project each of the detrended series on a constant, and on current and lagged detrended aggregate GDP. The measure of cyclical volatility is the percent standard deviation of these estimated projections.[16] Column five (six) reports the fraction of these cyclical fluctuations in job-gains (losses) that is accounted for by opening (closing) establishments. Both of these are estimated to be around 20% in aggregate data. We can compute the same statistics for different industries in the US. As rows 2–13 suggest, similar figures are obtained for all industries. This provides additional evidence with respect the empirical significance of fluctuations in the number of establishments.[17]

Changes in the number of establishments or franchises will not be reflected in the data as changes in the number of firms. However, the model interprets entry more broadly, and should be seen as analyzing variations in the number of

[8] Moreover Devereux et al. (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. This empirical fact is consistent with the model below where the number of firms rises at the same time as output.

[9] The data set that also contains the number of establishments (see below) comes from the United States Small Business Association (SBA) and can be found at www.sba.gov/advo/research.

[10] 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.

[11] The raw data on failing firms is taken from Dun and Bradstreet's records.

[12] The data are again taken from the SBA.

[13] Data on the number of franchises are at the annual frequency and taken from the book by Lafontaine and Blair (2005). They also show that sales through franchising amounted to more than 13% of real GDP in the 1980s. This suggests that this channel is important for the determination of aggregate output.

[14] The data can be found at www.bls.gov/bdm.

[15] We extract the high-frequency component of the different series, removing the trend from each, using the HP filter. We then analyze the second moment properties of the deviations from the HP trend.

[16] See Gomme et al. (2004) for a similar approach when addressing the age difference in the cyclicality of hours worked in the U.S.

[17] Obviously, these results should be approached carefully given that the time period covered is relatively short. Moreover, an additional concern is that new establishments by existing firms might have differential effects on markups. Still, it is encouraging that these results suggest that entrants/exists are of empirical significance.

Table 1
Correlation between failures by industry and real GDP

Industry (SIC)	Corr. with aggr. output
Manufacturing	
Durable goods	
Lumber and wood products (24)	−0.5045***
Furniture (25)	−0.5427***
Stone, clay, and glass products (32)	−0.4657***
Iron and steel products (33–34)	−0.5660***
Electrical and 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 and 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 and allied products (28)	−0.3217**
Petroleum, coal, and gas products (29)	−0.2069
Rubber and misc. plastic products (30)	−0.2950**
Leather and leather products (31)	−0.4509**
Service industries	
Hotels (70)	−0.4496***
Cleaning, laundry, repair 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***
Wholesale trade	
Durable goods	
Furniture and house furnishings (502)	−0.5204***
Lumber and building materials (503)	−0.5060***
Electrical goods (506)	−0.3602**
Machinery equipm. and supplies (508)	−0.5220***
Nondurable goods	
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*
Retail	
Building, farm, garden stores (52)	−0.6669***
Food stores (54)	−0.4394***
Autom. 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**
Book and stationery stores (5942–5943)	−0.3636**
Jewelry stores (5944)	−0.5503***
Fuel and ice dealers (5982)	−0.4369***
Mining	−0.2642*
Construction	−0.5224***
Transportation and public services	−0.4651***

Notes: The data are taken from Dun and Bradstreet's records with a sample lasting from 1958 to 1995. *, **, *** refer to significance at the 10%, 5%, and 1% level, respectively.

Table 2
Job gains (losses) accounted for by opening (closing) establishments

	Average fraction		Fraction of cyclical volatility (method 1)		Fraction of cyclical volatility (method 2)	
	Gains	Losses	Gains	Losses	Gains	Losses
Aggregate U.S. data	0.22	0.21	0.33	0.34	0.18	0.26
Goods producings	0.18	0.19	0.29	0.23	0.13	0.13
Natural resources and mining	0.19	0.18	0.30	0.32	0.23	0.43
Information	0.24	0.24	0.33	0.38	0.20	0.29
Financial activities	0.26	0.27	0.44	0.48	0.30	0.28
Professional and business services	0.22	0.23	0.31	0.27	0.08	0.11
Leisure and hospitality	0.27	0.22	0.32	0.47	0.18	0.43
Construction	0.21	0.21	0.26	0.25	0.20	0.25
Manufacturing	0.15	0.16	0.30	0.22	0.08	0.07
Service-providing	0.23	0.22	0.36	0.38	0.20	0.30
Wholesale trade	0.21	0.24	0.35	0.38	0.15	0.29
Retail trade	0.19	0.17	0.37	0.40	0.24	0.33
Transportation and warehousing	0.19	0.21	0.27	0.23	0.11	0.19

Notes: The data are taken from the BED and available at www.bls.gov/bdm. The first two columns refer to the average fraction of quarterly gross job-gains (losses) that are explained by opening (closing) establishments. Columns three and four list the fraction of the cyclical volatility in job-gains (losses) that is due to opening (closing) establishments. That fraction is calculated as the ratio of the percent standard deviation of job-gains (losses) in opening (closing) establishments to the percent standard deviation of total job-gains (losses). Lastly, we project the detrended series on a constant and on current and lagged detrended aggregate GDP. Columns five and six then list the ratio of the percent standard deviation of the estimated projection and the percent standard deviation of gross job-gains (losses).

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 the 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

This section contains a detailed description of the economic environment and a derivation of the model's equilibrium conditions.

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:

$$\max_{\{C_t,H_t,K_{t+1}\}} \mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\log(C_t) - \theta \frac{H_t^{1+\chi}}{1+\chi} \right) \tag{1}$$

subject to the law of motion for capital $\forall t$,

$$K_{t+1} = ((1-\delta) + R_t)K_t + W_t H_t + \Pi_t - C_t, \tag{2}$$

where the initial capital stock is given and equal to K_0. C_t and H_t denote consumption and hours worked by the household in period t. $\beta \in (0,1)$ and $\delta \in (0,1)$ denote the subjective time discount factor and the depreciation rate of capital, respectively. $\chi \geqslant 0$ governs the Frisch labor supply elasticity, and $\theta > 0$. Households own the capital stock and take the equilibrium rental rate, R_t, and the equilibrium wage, W_t, as given. Finally, households own the firms and receive their profits, Π_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 that each produce a differentiated good.[18] These goods are imperfect substitutes in the production of a sectoral good.[19] In turn, the sectoral goods are imperfect substitutes for each other when aggregated into a final good. Entry and exit of intermediate producers into the existing sectors occurs such that a zero-profit condition is satisfied in each period in every sector.

[18] A similar setup appears in Rotemberg and Woodford (1992).
[19] See the working paper version for an analysis of a model in which the monopolists produce a homogenous good.

The final good is produced with a constant-returns-to-scale production function, which aggregates a continuum of measure one of sectoral goods,

$$Y_t = \left[\int_0^1 Q_t(j)^{\omega}\,\mathrm{d}j\right]^{1/\omega}, \quad \omega \in (0,1). \tag{3}$$

$Q_t(j)$ denotes output of sector j. The elasticity of substitution between any two different sectoral goods is constant and equals $1/(1-\omega)$. The final good producers behave competitively, and the households use the final good for both consumption and investment.

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. Contrary to the constant measure of sectors, the number of firms may vary across periods. The output sectoral good j is given by

$$Q_t(j) = N_t^{1-1/\tau}\left[\sum_{i=1}^{N_t} x_t(j,i)^{\tau}\right]^{1/\tau}, \quad \tau \in (0,1), \tag{4}$$

where $x_t(j,i)$ is the output of firm i in sector j.[20] Within each sector there is monopolistic competition; each $x_t(j,i)$ is produced by one firm that sets the price for its good in order to maximize profits. The elasticity of substitution between any two goods in a sector is constant and equals $1/(1-\tau)$. It is assumed that the elasticity of substitution between any two goods within a sector is higher than the elasticity of substitution across sectors, $1/(1-\omega) < 1/(1-\tau)$.

Each intermediate good, $x_t(j,i)$, is produced using capital, $k_t(j,i)$, and labor, $h_t(j,i)$,

$$x_t(j,i) = z_t k_t(j,i)^{\alpha} h_t(j,i)^{1-\alpha} - \phi, \quad \alpha \in [0,1]. \tag{5}$$

The log of technology shocks follow a stationary first order auto-regressive process with persistence parameter $\zeta < 1$ and a normally distributed innovation, ε, with a mean of zero and a standard deviation σ_{ε}. The parameter $\phi > 0$ represents an *overhead cost*. In each period, an amount ϕ of the intermediate good is immediately used up, independent of how much output is produced. As in Rotemberg and Woodford (1996), the role of this parameter is to allow the model to reproduce the apparent absence of pure profits in the U.S. despite the presence of market power.[21]

The final good producer solves a static optimization problem that results in the usual conditional demand for each sectoral good,

$$Q_t(j) = \left[\frac{p_t(j)}{P_t}\right]^{1/(\omega-1)} Y_t, \tag{6}$$

where $p_t(j)$ is the price index of sector j in period t and P_t is the price of the final good in period t,

$$P_t = \left[\int_0^1 p_t(j)^{\omega/(\omega-1)}\,\mathrm{d}j\right]^{(\omega-1)/\omega}. \tag{7}$$

Denoting the price of good i in sector j in period t by $p_t(j,i)$, the conditional demand faced by the producer of each $x_t(j,i)$ variant is similarly defined,

$$x_t(j,i) = \left[\frac{p_t(j,i)}{p_t(j)}\right]^{1/(\tau-1)} \frac{Q_t(j)}{N_t}, \tag{8}$$

$$p_t(j) = N_t^{(1/\tau)-1}\left[\sum_{i=1}^{N_t} p_t(j,i)^{\tau/(\tau-1)}\right]^{(\tau-1)/\tau}. \tag{9}$$

Using (6) and (8), the conditional demand for good $x_t(j,i)$ at period t can then be expressed in terms of the final good as

$$x_t(j,i) = \left[\frac{p_t(j,i)}{p_t(j)}\right]^{1/(\tau-1)} \left[\frac{p_t(j)}{P_t}\right]^{1/(\omega-1)} \frac{Y_t}{N_t}. \tag{10}$$

3.3. The elasticity of demand

Dixit and Stiglitz (1977) assume that the single firm is small relative to the economy, and therefore does not take its effect on the remaining firms into account. Following this assumption would imply that the $x_t(j,i)$ producer has no effect on the sectoral price level, $p_t(j)$, or on the aggregate price level, P_t. It then follows from (10) that the $x_t(j,i)$ producer faces

[20] The term $N^{1-1/\tau}$ in (4) implies that there is no *variety effect* in the model.

[21] 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 ϕ grows at the same rate as the economy the markup level is constant along a balanced growth path.

a constant price elasticity of demand, $\eta_{x(j,i)p(j,i)} = 1/(\tau - 1)$, and hence uses a constant markup rule

$$\frac{p_t(j,i)}{MC_t(j,i)} = \mu = \frac{1}{\tau}. \tag{11}$$

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 (4). In this case, the price elasticity of demand faced by an individual firm is not constant, but rather a function of the number of competitors. This occurs because each monopolistic producer takes its effect on the price level into account.

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,

$$\eta_{x(j,i)p(j,i)}(N_t) = \frac{1}{\tau - 1} + \left[\frac{1}{\omega - 1} - \frac{1}{\tau - 1}\right]\frac{1}{N_t} \tag{12}$$

implying that an increase in N_t in sector j induces the $x_t(j,i)$ producer to face a more elastic demand curve.[22] A solution to the monopolistic firm's problem has to satisfy the condition that marginal revenue equals marginal cost,

$$\frac{p_t(j,i)}{MC_t(j,i)} = \mu(N_t) = \frac{(1-\omega)N_t - (\tau - \omega)}{\tau(1-\omega)N_t - (\tau - \omega)} > 1. \tag{13}$$

Note that the markup function is monotonically decreasing in the number of firms and that $\tau\mu(N) > 1$.[23] The monopolistic firm's conditional demands for hours worked and capital are given by

$$\frac{W_t}{p_t(j,i)} = \frac{z_t}{\mu(N_t)}\left[(1-\alpha)\frac{k_t^a h_t^{1-\alpha}}{h_t}\right], \tag{14}$$

$$\frac{R_t}{p_t(j,i)} = \frac{z_t}{\mu(N_t)}\left[\alpha\frac{k_t^a h_t^{1-\alpha}}{k_t}\right]. \tag{15}$$

3.4. Symmetric rational expectations equilibrium

As the economy's technology is symmetric with respect to all intermediate inputs, the paper focuses on symmetric equilibria, $\forall (j,i) \in [0,1] \times [1, N_t] : x_t(j,i) = x_t,\ k_t(j,i) = k_t,\ h_t(j,i) = h_t,\ p_t(j,i) = p_t,\ N_t(j) = N_t$. Aggregate capital and aggregate hours are then given by $K_t = N_t k_t$ and $H_t = N_t h_t$, respectively. Finally, in the symmetric equilibrium, a zero-profit condition is imposed in every sector in every period,

$$(\mu(N_t) - 1)x_t = \phi. \tag{16}$$

The number of firms per sector and aggregate final output can now be found by using (5) and the zero-profit condition (16),[24]

$$N_t = z_t K_t^\alpha H_t^{1-\alpha}\left[\frac{\mu(N_t) - 1}{\mu(N_t)\phi}\right], \tag{17}$$

$$Y_t = \frac{z_t}{\mu(N_t)} K_t^\alpha H_t^{1-\alpha}. \tag{18}$$

We can see that N_t is procyclical, implying that markups are countercyclical, by rewriting (17) and (18) as

$$N_t = \left[\frac{\mu(N_t) - 1}{\phi}\right] Y_t. \tag{19}$$

We use P_t as the numeraire and set it to 1. This implies that the price charged by an intermediate producer at a symmetric equilibrium is also 1. By (14), (15) and (18) the equilibrium wage and rental rates in the economy are given by

$$W_t = \frac{z_t}{\mu(N_t)}\left[(1-\alpha)\frac{K_t^\alpha H_t^{1-\alpha}}{H_t}\right] = (1-\alpha)\frac{Y_t}{H_t}, \tag{20}$$

[22] Notice that in the case where $N \longrightarrow \infty$, the resulting price elasticity of demand is again $1/(\tau - 1)$. 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 measure zero within a sector.

[23] From (13) it follows that $\mu(1) = 1/\omega$ and $\lim_{N\to\infty}\mu(N) = 1/\tau$. Since $\tau > \omega$ and since the markup function is monotonic in N, the result follows.

[24] To see this, multiply (5) with N_t and use the zero-profit condition to plug in for x_t. In order to find Y_t, multiply (17) by x_t and use the zero-profit condition again.

$$R_t = \frac{z_t}{\mu(N_t)}\left[\alpha \frac{K_t^{\alpha} H_t^{1-\alpha}}{K_t}\right] = \alpha \frac{Y_t}{K_t}. \tag{21}$$

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, the appropriate expression for the SR and for TFP are derived. This is followed by a quantitative analysis of the volatility of technology shocks and of the internal magnification mechanism. The section concludes by analyzing the model's time-series predictions.

4.1. The SR and TFP in the model

Starting from the expression for aggregate output in (18), a simple expression for TFP is given by

$$TFP_t = \frac{Y_t}{K_t^{\alpha} H_t^{1-\alpha}} = \frac{z_t}{\mu(N_t)}. \tag{22}$$

Let a hat over a variable denote percentage deviations from its trend, and $s_k = \alpha$ and $s_H = 1-\alpha$ denote the shares of capital income and labor income in final output, respectively.[25] Defining the SR in the conventional way and using (22), it turns out that it can be written as

$$SR_t = \widehat{Y}_t - s_k \widehat{K}_t - s_H \widehat{H}_t, \tag{23}$$

$$SR_t = \widehat{TFP}_t = \widehat{z}_t - \widehat{\mu}_t, \tag{24}$$

where $\widehat{z}_t$, and $\widehat{\mu}_t$, denote percentage deviations from the trend of technology and markups. It has been established that the markup is countercyclical, this implies that the SR is an upward biased estimator of the technology shock.

Eq. (22) implies that measured TFP is comprised two factors. A true *exogenous* technology, z_t, and a new *endogenous* productivity measure, $1/\mu(N_t)$. The latter 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 firm entry that takes place until the economy reaches a zero-profit equilibrium. The increase in the number of firms results in a fall of the markup. With a lower markup the oligopolistic producer now has to sell a higher quantity to recover the fixed cost of operation, which induces the ratio of fixed costs to actual sales to decrease. This can be seen by reformulating the zero-profit condition to find $\phi/x_t = \mu(N_t) - 1$. Capital and labor are used for the production of both actual sales and the fixed component. A fall in the ratio above thus implies that a smaller share of resources is used for the production of the fixed cost component. As TFP is measured only in terms of the actual sales, this has the same observable implication as a true positive technology shock.

It is important to emphasize that monopoly power and a fixed cost alone do not impart a bias in the measurement of the SR. That is, in a model with the same industrial structure as in this paper but with a constant markup that is not affected by variation in the number of firms, the SR is simply given by $\widehat{z}_t$. All of the variation in measured TFP would originate from variations in the state of technology. To see this, assume that each monopolistic producer is of a measure zero within its sector.[26] As before, firms enter and exit until a zero-profit equilibrium is reached. However, the price elasticity that the monopolistic producer faces is now constant and given by $1/(\tau - 1)$, implying a constant markup rule $\mu = 1/\tau$. The economic reasoning is identical to the discussion above once one notices that the ratio of fixed cost to actual sales is now constant.[27] This is in contrast to the literature following Hall (1990) which has stressed that the mere presence of monopoly power generates a bias in the measurement of the SR.

As is well known, a significant fraction of the movements in aggregate output over the business cycle is attributable to variations in measured TFP.[28] In the context of this model, Eq. (24) implies that variations in measured TFP are given by

$$Var(\widehat{TFP}_t) = Var(\widehat{z}_t) + Var(\widehat{\mu}_t) - 2\,Cov(\widehat{z}_t, \widehat{\mu}_t). \tag{25}$$

[25] Since there are zero profits in the model economy, the income shares are equal to the elasticity of output with respect to the factors of production.

[26] Formally, assume that Eq. (4) is replaced with $Q_t(j) = N_t^{1-1/\tau}[\int_{i=0}^{N_t} x_t(j,i)^{\tau}\, di]^{1/\tau}$.

[27] In the web appendix (see footnote 1), we derive the equilibrium for this version of the model and formally show that in this case, there are no movements in measured TFP that are not directly attributable to exogenous technology shocks.

[28] For example, in the sample period analyzed in this paper, the ratio $Var(\widehat{TFP}_t)/Var(\widehat{Y}_t)$ equals 0.3.

That is, variations in measured TFP can be decomposed into those originating from true *exogenous* technology shocks and those that arise because of the new *endogenous* effect of the interaction between the number of operating firms and the markup.

In order to analyze the variance–covariance decomposition implied by Eq. (25), one requires a time series of technology shocks. Since conventional SR accounting-based estimates do not allow for cyclical variations in the markup, a new *corrected* time series that is consistent with the model economy in this paper needs to be estimated. The following section proceeds with this estimation.

4.2. Estimating technology shocks

The model's equilibrium conditions can be used to estimate an adjusted time series of technology residuals that is consistent with the model and allows for cyclical variations in the markup. Using (23) and (24) exogenous technology shocks become

$$\widehat{z}_t = (\widehat{y}_t - s_k\widehat{k}_t - s_H\widehat{h}_t) + \widehat{\mu}_t. \tag{26}$$

The expression in parenthesis can be estimated directly from observable data, but $\widehat{\mu}_t$ is unobservable. However, the model implies that $\widehat{\mu}_t = ((1-\tau\mu^*)/\tau\mu^*)\widehat{y}_t$.[29] This allows to rewrite the expression above,

$$\widehat{z}_t = \frac{1}{\tau\mu^*}\widehat{y}_t - s_k\widehat{k}_t - s_H\widehat{h}_t \tag{27}$$

which implies that one can estimate the technology shocks once τ is known for a given calibration of the steady state markup.[30] To find τ, the equilibrium conditions implied by the model will be used. It is important to emphasize that the value of ω has no effect at all on the model's dynamics.

4.2.1. Calibration of structural parameters

One can show that $\widehat{n}_t = ((1-\tau)/\tau(\mu^*-1))\widehat{y}_t$.[31] This equation is used in two ways. First, $\hat{n}_t$ is regressed on $\hat{y}_t$ and a constant. Note that the condition above implies that given μ^* and the estimated coefficient one can back out τ.[32] As was argued in the Introduction, changes in the number of establishments might be a better measure of changes in the number of competitors in the economy. Therefore, data both on the number of firms and on the number of establishments are used.[33] The resulting estimates for τ range from 0.94 to 0.97.

Alternatively, one could calculate the ratio $std(\hat{n}_t)/std(\hat{y}_t)$ in the data and again use the equilibrium condition to back out τ. Using this approach, one finds estimates of τ that range from 0.87 to 0.94. Hence, both approaches give very similar results.[34] The benchmark calibration uses the median value of the estimates, $\tau = 0.94$.[35]

In order to show that the results are robust to this calibration procedure, we also derive a variant of the entry/exit model with Cournot competition.[36] In this setup, it can be shown that $\widehat{\mu}_t = ((1-\mu^*)/(1+\mu^*))\widehat{y}_t$, which implies that the estimation of technology shocks is independent of both τ and ω. Here, the elasticity of the markup with respect to output depends only on the steady state value of the markup which can be taken directly from the empirical evidence of Section 2. The quantitative implications of the Cournot model are very similar to those of the baseline entry/exit model as discussed below. This highlights that our results do not critically depend on the calibration of τ.

4.2.2. Estimation

Table 3 summarizes the estimates for the process of technology. The first column refers to the standard perfect competition RBC model. The second to fourth column present the results for three different steady-state values of the markup over value-added in the benchmark entry/exit model. The fifth column refers to a version of the model with

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[29] Note that (13) and (19) imply $Y_t(\mu_t\tau_t - 1)(1-\omega) = \phi(\tau-\omega)$. Log linearization then yields the expression above. Notice that $(1-\tau\mu^*)/\tau\mu^* < 0$ as it has been shown above that $\tau\mu^* > 1$.

[30] Note from the discussion in Section 2, that for value added data μ^* lies between 1.2 and 1.4. For expositional purposes we describe the estimation of τ for a value of $\mu^* = 1.3$. In the actual calibrations we adjust τ for different values of μ^*. Section 5 analyzes the case in which the firm uses materials as a factor of production as well. There, we use measures of markup over gross output.

[31] To see this, use (13) to find $N_t(\tau\mu_t - 1)(1-\omega) = (\mu_t - 1)(\tau - \omega)$ and log linearize.

[32] Obviously, the $\hat{n}_t$ and $\hat{y}_t$ variables are deviations from their respective trends. We hence use two detrending techniques, the HP filter and linear detrending. As the data are at annual frequency, we use a smoothing parameter of 6.25.

[33] The data are again taken from the SBA.

[34] An alternative approach would be to calibrate τ to match the elasticity of the markup with respect to the number of firms. While the IO literature (for example, Bresnahan and Reiss, 1991; Campbell and Hopenhayn, 2005) shows that an increase in the number of firms has an effect on competitiveness, these studies typically cover very specific industries. To the best of our knowledge, estimates of this elasticity across a wide range of industries or in aggregate data are limited.

[35] Additional evidence is provided by Rotemberg and Woodford (1991) who estimate the elasticity of the markup with respect to output to be -0.21 based on their structural model. Taking this estimate and the equilibrium condition, $\hat{\mu}_t = ((1-\tau\mu^*)/\tau\mu^*)\hat{y}_t$, one can find a value for τ of 0.97. The fact that this estimate is derived using a very different model is of course problematic. At the same time, it is encouraging to see that the implied τ does not vary significantly across different models.

[36] The derivation of this model can be found in an online appendix (see footnote 1).

Table 3
Properties of the technology process and magnification ratios

Statistic	Perfect competition	Entry/exit			Cournot	Extended entry/exit	RBC with cap. util.
		$\mu = 1.2$	$\mu = 1.3$	$\mu = 1.4$	$\mu = 1.3$		
$\sigma_z^2/\sigma_{z,\mathrm{RBC}}^2$	1.00	0.67	0.57	0.50	0.47	0.46	0.70
$\sigma_\varepsilon^2/\sigma_{\varepsilon,\mathrm{RBC}}^2$	1.00	0.71	0.62	0.56	0.72	0.45	0.70
σ_y^2/σ_z^2	0.45	0.74	0.95	1.16	0.71	1.16	0.74
$\sigma_y^2/\sigma_{y,\mathrm{RBC}}^2$	1.00	1.13	1.21	1.31	1.05	1.17	1.13

Notes: The reported technology shocks are estimated using quarterly data for the sample from 1955:I to 2002:IV. The U.S. data are HP filtered with a smoothing parameter of 1600. The data for real GDP are taken from the Bureau of Economic Analysis. For hours, we use series LPMHU from the DRI Basic Economics database. The annual data on the capitol stock, series KNIPQ, come from the same source. We construct a quarterly series by interpolation using the quarterly investment flows. The reported theoretical moments are derived from the model. The columns refer to (i) the benchmark RBC model; (ii)–(iv) the entry/exit model introduced in this paper; (v) the Cournot setup introduced in the web appendix; (vi) the entry/exit model with capacity utilization and materials usage from Section 5; and (vii) the RBC model with capacity utilization.

Table 4
Calibration

	Parameter	Calibrated to
$\mu^* - 1$	Markup in steady state	30%
τ	Elasticity within sector	0.949
ω	Elasticity across sectors	0.001
ϕ	Fixed production cost	0.127
α	Capital share	0.30
H^*	Time spent working	0.30
β	Time discount factor	0.99

Notes: The calibration of μ, τ and ω is explained in the main text. ϕ cannot be freely calibrated and is instead determined in steady state. In the benchmark case, the stochastic process is estimated as $\rho = 0.94$ and $\sigma_\varepsilon = 0.0056$. The remaining parameters are standard.

Cournot competition and homogenous goods. The first row presents the ratio of the unconditional variance of the estimated technology shock process, σ_z^2, between a given model and the perfect competition model. Similarly, the second row presents the ratio of the innovation variance, σ_ε^2, between the two models.[37] The reported moments show that the incorporation of firm entry and exit decisions into the analysis leads to significantly smaller estimates of the volatility of technology shocks. Relative to the RBC model, the unconditional variance of implied technology falls by between 33% and 50%. The variance of the innovation falls by between 29% and 46%. Similar magnitudes are estimated for the case of the Cournot model.

Given our estimates for the technology shocks, we can now decompose the variations in measured TFP. We find that $var(\widehat{z}_t)/var(\widehat{TFP}_t) = 0.57$, which implies that 43% of the variation in measured TFP can be attributed to the endogenous mechanism emphasized in this paper. These results suggest that the interaction between net business formation and variations in the degree of competition can provide an endogenous explanation for a significant share of the variation in measured TFP.

4.3. Magnification of technology shocks

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, it must rely on highly variable, exogenous technology shocks. 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 time series of technology residuals that was estimated in the previous section. In addition to the markup and the elasticities discussed above, a number of parameters have to be calibrated. This paper adopts the standard RBC calibration and the parameters are summarized in Table 4.

[37] The entry/exit model generates similar estimates of the $AR(1)$ coefficient, ζ, to those generated by the RBC model for all values of μ^* that were considered. The numbers we report use $\zeta = 0.94$. We estimate σ_ε to be 0.0056 in our favorite calibration of the entry/exit model and 0.0071 for the standard RBC model.

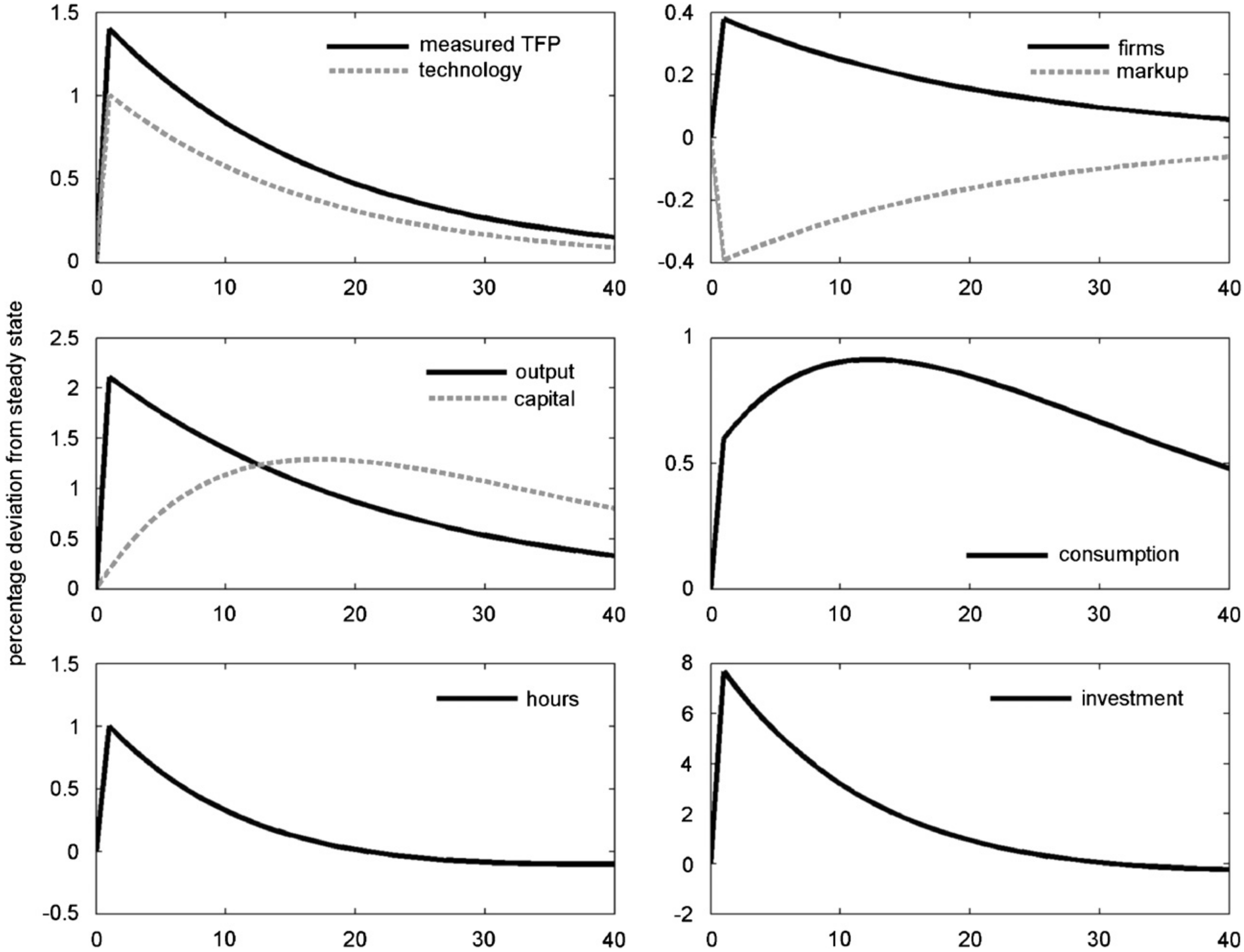

Fig. 1. Impulse response functions. Percentage deviations from the steady state for several key variables in the model following a one percent shock to the level of technology. Each period refers to one quarter.

The magnification effect is evident in the impulse response functions. The first panel in Fig. 1 depicts the dynamic responses of measured TFP and the level of technology following a technology shock of 1%. The model induces a persistent and quantitatively significant deviation (45% at the impact period). Clearly, in this environment, SR accounting, which attributes all TFP movements to technology shocks, overstates their true volatility. The second panel illustrates that, following a positive shock to technology, the number of firms shoots up before slowly converging back to the steady state. Markups are inversely related to the number of firms and thus below steady state during the boom. The remaining impulse responses in Fig. 1 are standard.

The simulated entry/exit model generates output, hours, investment and consumption volatilities that are nearly identical to those generated by the RBC model.[38] The key feature of the entry/exit model is that it generates significant output volatility from technology shocks that are far less volatile than those in the standard RBC model. 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 output and the technology process. Relative to the RBC model, the estimated values of this ratio in the entry/exit model increase by 64% when the steady state markup value is 1.2; by 111% when $\mu^* = 1.3$; and by 158% when $\mu^* = 1.4$. Again, for the case of the Cournot model similar results are obtained—relative to the RBC model, the estimated value of this ratio increases by 58%. While the third row is informative with respect to the magnification mechanism embedded in the entry/exit model, one might still wonder if the model can generate sufficient output volatility to be a plausible data-generating-process for the U.S. economy. The last row in Table 3 alleviates this concern. It reports the volatility of output

[38] 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.

Table 5
Selected moments of TFP

	$\sigma_{\mathrm{TFP}}/\sigma_Y$	$AC(1)$	$AC(2)$	$AC(3)$
Data	0.50	0.69	0.43	0.13
RBC	0.65	0.71	0.46	0.26
Entry/exit ($\mu^* = 1.3$)	0.66	0.70	0.46	0.25

Notes: The U.S. data and the data generated by the models are HP filtered with a smoothing parameter of 1600. See note of Table 3 for the underlying data sources.

relative to the RBC model. As can be seen, the resulting level of output volatility in the different variants of the entry/exit model is larger than the one in the RBC model.

Using the model, the variance–covariance decomposition of the variations in measured TFP can be constructed. For the interim case of $\mu^* = 1.3$, only 51% 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 almost half of the variation in measured TFP.[39] This magnitude is very similar to what can be found in the data as has been shown in Section 4.2.

Interestingly, only small movements in the markup are required for the entry/exit model to generate such a powerful magnification mechanism. For example, in the simulations when the steady state value of the markup equals 1.3, more than 99% of the observations fall between 1.28 and 1.32. The model does not require huge and potentially unrealistic movements in the markup level.

Table 5 compares the statistical properties of TFP variations in 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. 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 slightly higher than the one observed in the data.

It is interesting to compare these results with those in Hornstein (1993), who analyzes a monopolistic competition model with a fixed number of firms and constant monopoly power. He shows that this model induces a smaller magnification mechanism than the benchmark RBC model and less output fluctuation. The present paper shows that the interaction between firms' entry/exit decisions and the markup can have important ramifications for the magnification mechanism and output fluctuations. Recall the discussion in Section 4.1 which showed that a version of the model with entry/exit and constant markups will have the same magnification mechanism and output volatility as the benchmark perfect competition RBC model.

5. Materials usage and capacity utilization

In recent years the business cycle literature has emphasized the role of capacity utilization.[40] This literature finds that capacity utilization can account for endogenous variations in measured TFP and greatly amplify exogenous technology shocks. This Section will incorporate this additional margin into the entry/exit model. Moreover, the firms' production function is modified to account for the presence of materials usage.[41] The two modifications allow to study the interaction between capacity utilization and firms' entry/exit decisions as well as the effects of the presence of materials usage in an economy characterized by time-varying markups. Previously, firms were using only capital and labor for production. This implied that the relevant markup ratio was one over value added. Now, as firms use capital, labor, and materials, the relevant markup ratio is one over gross output.

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

$$x_t(j,i) + \phi = [\sigma[z_t(u_t k_t(j,i))^{\alpha} h_t(j,i)^{1-\alpha}]^{-\nu} + (1-\sigma)m_t(j,i)^{-\nu}]^{-1/\nu}, \quad \nu > -1, \tag{28}$$

$$m_t(j,i) = \left[\int_0^1 Q_t(j)^{\rho}\right]^{1/\rho}, \tag{29}$$

[39] We get even stronger results, if we assume a higher Frisch elasticity of labor supply (a lower value of χ), as hours then respond more strongly to a given shock. In that case, the share of variations in measured TFP that can be attributed to technology shocks is even lower. For the extreme case of $\chi = 0$ (indivisible labor), we find a share of only 35%.

[40] See e.g. Kydland and Prescott (1988), Kydland and Prescott (1991), Shapiro (1993), Bils and Cho (1994), Burnside et al. (1995), Cooley et al. (1995), and King and Rebelo (2000).

[41] Estimating the share of labor and materials in gross output in the U.S. manufacturing sector, it turns out that the share of materials in gross output is almost always above 50%. The sum of the shares of labor and materials is around 85%. The materials share is thus calibrated to be 50% of gross output.

where $u_t \in (0, 1)$ is the rate of capacity utilization.[42] Each firm uses materials, $m(j, i)$, an aggregate of the sectoral goods, as an input in its production function.[43] Note that the demand for each sectoral good 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, the model's internal magnification mechanism increases in the share of materials in gross output. The economic intuition is as follows: the production of each firm depends on output provided by other firms. While labor and capital are always on their respective supply curves, the output of other firms is priced with a markup. Firm entry in a specific sector leads to a reduction in the markup that firms in that sector charge. This manifests itself in lower costs for all the remaining firms in the economy. Thus, there is a *spillover effect* between sectors that is absent in the value added analysis. This increases the magnification effects of a given technology shock, relative to the benchmark case.

The fifth column in Table 3 refers to the extended entry/exit model presented in this section.[44] As a comparison, the sixth column reports the statistics for the case of the perfect competition model augmented with capacity utilization. The reported moments show that, in the current model the unconditional variance of the implied technology falls by 54% and the variance of the innovation falls by 55% relative to the benchmark RBC model. Table 3 suggests that accounting for capacity utilization and markup variations separately, generates similar estimates for the volatility of technology shocks. However, when employing both extensions jointly, the estimated volatility of technology shocks is reduced by more than half relative to the benchmark model.

Again, the strength of the magnification mechanism embedded in the entry/exit model with materials usage and capacity utilization is evident in the value of the ratio (σ_y^2/σ_z^2) which is reported in the third row. This ratio increases by 158% relative to the standard model and 57% relative to the model with capacity utilization. Moreover, the model with materials usage and capacity utilization generates as much output volatility as the standard model, despite using technology shocks that are only half as volatile.[45]

Finally, with the adjusted time series of technology residuals, the 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 movements 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 exogenous technology shocks induce the entry and exit of firms. Variation in the number of operating firms in turn leads to endogenous variation in the degree of competition over the business cycle. Hence, the interaction between the number of firms and markups charged gives rise to endogenous procyclical movements in TFP.

The quantitative results of the paper suggest that about 40% of the variation in measured TFP in the U.S. are due to this interaction. Moreover, when the measurement of technology shocks in the U.S. economy is adjusted for this interaction, the volatility of technology shocks is cut in half relative to a benchmark competitive economy. Despite this significant reduction in the variance of technology shocks, the model can still account for the volatility observed in U.S. data because of its strong internal magnification mechanism.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at 10.1016/j.jmoneco.2008.08.008.

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[42] This follows the Greenwood et al. (1988) specification of capacity utilization. That is, the household decides on the optimal utilization of capital and higher utilization implies higher depreciation rates. The specific functional form is given by $\delta_t = (1/\eta)u^\eta$, $\eta > 1$.

[43] Basu (1995), among others, adopts the same interpretation of materials usage.

[44] Since the targeted markup should be over gross output in this version of the model, 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 estimates of the markup ratio in gross output. Targeting a higher value of the markup would strengthen the internal magnification mechanism even further.

[45] 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.

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