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## Weird Ties? Growth, Cycles and Firm Dynamics in an Agent-Based Model with Financial-Market Imperfections

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# Weird Ties? Growth, Cycles and Firm Dynamics in an Agent-Based Model with Financial-Market Imperfections*

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**Abstract**

This paper studies how the interplay between technological shocks and financial variables shapes the properties of macroeconomic dynamics. Most of the existing literature has based the analysis of aggregate macroeconomic regularities on the representative agent hypothesis (RAH). However, recent empirical research on longitudinal micro data sets has revealed a picture of business cycles and growth dynamics that is very far from the homogeneous one postulated in models based on the RAH. In this work, we make a preliminary step in bridging this empirical evidence with theoretical explanations. We propose an agent-based model with heterogeneous firms, which interact in an economy characterized by financial-market imperfections and costly adoption of new technologies. Monte-Carlo simulations show that the model is able jointly to replicate a wide range of stylised facts characterizing both macroeconomic time-series (e.g. output and investment) and firms' microeconomic dynamics (e.g. size, growth, and productivity).

**Keywords**: Financial Market Imperfections, Business Fluctuations, Economic Growth, Firm Size, Firm Growth, Productivity Growth, Agent-Based Models.
**JEL Classification**: E32, G30, L11, O40

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# 1 Introduction

This paper investigates how the interaction between technological and financial variables shapes the dynamics of economies populated by heterogeneous agents.

The research on the roles played by finance and technology in determining the aggregate performance of a decentralized economy has a long history in economic analysis. Schumpeter (1934) was among the first to acknowledge that financial investments were as important as technical advances for long-run economic growth.

More recently, this argument has been employed to explain the spectacular performance of U.S. economy in the 90's on the basis of the widespread diffusion of information and communication technologies, and the huge financial investments that channelled it (see Levine, 2005; Aghion, Howitt, and Mayer-Foulkes, 2004; Carlin and Mayer, 2003). For example, Rossi et al. (2001), in line with the earliest work of Schumpeter, have shown that investment opportunities triggered by the introduction of new production possibilities are typically not sufficient to foster aggregate growth in the long-run. The efficiency of the system in conveying funds toward those opportunities is a crucial factor as well.

Furthermore, on a more short-run scale, diverse strands of research have identified either in technological shocks or in the dynamics of financial variables the main cause of business cycles. For instance, the "real business cycle" school (see Stadler, 1994, for a survey) has popularized the view that exogenous technological shocks to total factor productivity were responsible for fluctuations of main macroeconomic variables.

Conversely, the "financial accelerator" literature has attempted to account for business cycles on the grounds of firms' financial status (Bernanke, Gertler, and Gilchrist, 1996; Kiyotaki and Moore, 1997; Greenwald and Stiglitz, 1993). In this view, short-run movements in the main macroeconomic time-series are induced by shocks affecting balance sheets of firms and their ability to finance production and investment plans through internal and external resources.

Albeit providing important insights on how decentralized economies work both in the long-run and at business cycle frequencies, all contributions discussed so far aim at explaining statistical regularities at a very aggregate level. Any microfoundation of macroeconomic relations is usually carried over by sticking to the hypothesis of a representative agent facing an inter-temporal optimization problem. The analysis of cross-sectional properties of the agents (e.g., their persistent heterogeneity) is almost completely neglected.

Nevertheless, a good deal of resent research in industrial organization has been able to single out an impressive number of stylised facts concerning the cross-sectional evolution of firms and productivity. In particular, the micro-dynamics patterns displayed by "real-world" economies look quite different from the homogeneous one postulated in representative agent based models. Indeed, the presence of significant and persistent asymmetries among firms in terms of investment, output, employment, productivity levels, etc. – over the different phases of business cycles, as well as at a longer time spans – emerges as a distinctive feature of modern economies (Davis and Haltiwanger, 1992; Caballero, Engel, and Haltiwanger, 1995, 1993; Bartelsman and Doms, 2000).

This empirical evidence raises the question whether the foregoing asymmetries, robustly and persistently emerging at the micro-economic level, matter for the dynamics of the whole economy. As argued at more length in Dosi and Orsenigo (1994), a large part of existing macroeconomics literature, including both the "real business cycle" and the "financial accelerator" traditions, have made few attempts to investigate these micro-macro linkages (with the notable exception of Ricardo Caballero and his co-authors, see e.g. Caballero, Engel, and Haltiwanger (1995)).

In this paper, we make a preliminary step in filling this gap. More specifically, we explore the extent to which persistent heterogeneity in firms' technology and financial attributes is able robustly to affect the statistical properties of micro- and macro-dynamics. To this end, we propose an agent-based model where the source of business fluctuations and long-run growth is rooted in the behaviours of an evolving network of heterogenous firms. We follow a "bottom-up" approach to microfoundation and we analyze the ability of the model to jointly reproduce micro and macro empirical evidence. In particular, we are interested in two sets of stylised facts. First, on the macroeconomic side, we attempt to replicate some standard time-series properties concerning the coupled dynamics of aggregate output, investment and productivity. Second, on the microeconomic side, we are interested in the statistical properties of the cross-section distributions for some crucial firms' attributes (e.g., growth, productivity, etc.) and their dynamics.

In the model, a key role is played by financial and technological variables. Due to information asymmetries in capital markets, firms are prevented from raising equity externally. These informational imperfections have two major consequences. First, firms cannot completely diversify out the risks of bankruptcy inherent their actions. Second, they must resort to credit markets for external financing. The impossibility of washing away completely default risks leads firms to act in a risk-averse manner when setting their output investment and technological adoption plans. Firms' decisions on production levels and investment will thus be influenced by the level of firm's net worth, which acts as a buffer variable toward risk. Technology matters for the evolution of economic variables as well. Technical improvements are embodied in new machines. Their adoption allows productivity gains. The latter are affected by technological learning activities and occur both internally and externally to the single firm. In turn, the dynamics of individual variable costs depends on the gap between firm's productivity levels and the average variable cost prevailing in the market: firms with above-average productivity will have *coeteris paribus* lower costs, higher cash-flows, and will be able to bear in better way the risks of bankruptcy.

As mentioned, our model is well in the spirit of the "Agent-Based Computational Economics" approach (see e.g Testfatsion, 1997; Epstein and Axtell, 1996; Fagiolo and Dosi, 2003; Fagiolo, Dosi, and Gabriele, 2004), and heavily builds on Delli Gatti et al. (2005). Agent-based models have been developed to study the properties of systems characterized by a large number of heterogeneous interacting units. In these models, microfoundations are valued as reliable on the grounds of the empirical evidence they can account for, not necessarily on their coherence with optimizing principles. In line with ACE building blocks, the structure of our model allows for interactions among firms, both in the form of network externalities and through direct-price effects. While the former characterize learning activities performed on new technologies, the latter are embodied in labour and credit market variables. Together, they concur to determine competition and the ensuing selection of firms operating in the economy.

Simulation results show that the model is able to generate self-sustaining growth characterized by wide and persistent fluctuations in the time-series of aggregate output, investment, employment and productivity. Moreover, the statistical properties of the simulated output-investment dynamics match those empirically observed at business-cycles frequencies. Similarly, we are able to replicate the most important regularities characterizing technology and employment dynamics. The model is also consistent with the main stylised fact characterizing the cross-sectional dynamics of productivity, i.e. productivity levels of firms display a significant and persistent dispersion. Finally, our simulated data can replicate the most important productivity-growth and productivity-exit relations that we observe in reality.

The rest of the paper is organized as follows. Section 2 describes the model. Section 3 discusses qualitative and quantitative results of simulation exercises. Section 4 concludes and presents some future developments.

# 2 The Model

## 2.1 The Economy

Consider an economy with a homogenous good in which firms, labeled by the index $i = 1, 2, ..., N$, undertake decisions at discrete times $t = 1, 2, ..., T$. In each period production is carried out using capital and labour, under a Leontief technology:

$$Y_{it} = \min\left\{K_{it}, \alpha_{it} L_{it}\right\}, \tag{1}$$

where $K_{it}$ and $L_{it}$ are respectively capital and labour employed, and $\alpha_{it}$ is the productivity of labour.

The output produced by each firm is fully sold on the market at the price $P_{it}$. Therefore, we exclude the possibility of inventories accumulation. The relative price of firm's output is given by:

$$P_{it} = P_t u_{it}, \tag{2}$$

where $P_t$ is the general price level and $u_{it}$ is the relative price for the output of the single firm. We assume that $u_{it}$ is a random variable, uniformly distributed and independent on $P_t$ (see also below).

In any period each firm is endowed with a level of real net worth, $A_{it}$, which is defined as the stock of firm's assets in real terms that has been financed either through net profits or through equity issues. We assume that information asymmetries in capital markets are such that firms cannot gather funds through new equity issues. Accordingly, net worth can grow only through net profits and its dynamics reads:

$$A_{it} = A_{it-1} + \pi_{it-1}. \tag{3}$$

The equity-rationing hypothesis implies that the unique source of external financing is represented by debt supplied by financial intermediaries, $B_{it}$. In any period each firm pays a real interest rate equal to $r_{it}$ for the funds it borrows. For simplicity, we assume that the latter is also the return on real net worth. Accordingly, firm's financing costs are equal to:

$$r_{it}(A_{it} + B_{it}) = r_{it} K_{it}. \tag{4}$$

Variable costs are borne after production takes place. In addition, we assume that total variable costs of capital are proportional to financing costs. The equation of net profits in real terms thus reads:

$$\pi_{it} = \left(u_{it} - \frac{w_t}{\alpha_{it}} - r_{it}\mu_{it}\right) K_{it} \tag{5}$$

where $w_t$ is the real wage-rate and $\mu_{it}$ is a variable which takes value $\mu^n$ when replacement occurs and $\mu^o$ otherwise (with $\mu^n > \mu^o$ and $\mu^o > 1$).

We give now a brief account of the timing of events occurring in any period. Next, we describe in more detail each event separately.

## 2.2 Dynamics

At the beginning of each period $t$, the system is completely described by the vectors containing the state variables of our $N$ firms. Each vector includes time $t-1$ levels of net worth, production, net profits, capital stock, the stock of debt and the technological variables determining the productivity of the firm, i.e. the vintage of its capital stock and the skill with which it masters its embodied technology.

In each period firms must take two types of decisions: they must set the level of final output to be produced and sold, and they must decide whether to replace or not their capital stock with a new and more productive vintage. The sequence of events occurring in each period runs as follows:

1. Firms' net worth are updated: past net profits (positive or negative) are added to the past level of net worth.
2. The innovation process takes place. New vintages are introduced under an exogenous stochastic process.
3. The entry-exit process occurs.
4. Firms decide whether to switch or not to the new technology.
5. Labour and credit markets open: the wage-rate and the interest rates on loans are determined. Firms' unitary costs are determined.
6. The level of production is set. The corresponding labour and capital demand decisions are made.
7. Firms' production and replacement plans are realized.
8. The market for the final good opens. The relative prices for firms' output are drawn.
9. Firms' profits are determined.

## 2.3 Technological Progress

The introduction of new vintages in the economy follows a Poisson process with exogenous arrival rate $\lambda > 0$. Accordingly, the period of arrival of new capital-embodied technologies, $\tau$, is drawn from an exponential distribution with mean $1/\lambda$. Whenever an innovation occurs, the productivity $\theta$ increases at an exogenous rate $\xi > 0$. Therefore:

$$\theta(\tau) = \theta_0(1+\xi)^\tau, \quad \theta_0 > 0. \tag{6}$$

The actual productivity realized by a firm with a given vintage, $\alpha(\tau)$, is the product of the value given by (6) and the skill with which the firm masters the technology embodied in that vintage. The latter evolves, in turn, through learning activities, which are both internal and external to the firm. Let us denote with $s_{it} \in [0,1]$ the internal skill level achieved by firm $i$ on its operating vintage $v_{it}$. Internal learning on the technology embodied in the operating vintage evolves according to a *logistic* dynamics:

$$\Delta s_{it} = \beta(\frac{CU_{t-1}}{CCU_{t-1}})s_{it-1}(1 - s_{it-1}) \tag{7}$$

where $CU_{t-1}$ and $CCU_{t-1}$ are respectively *capacity utilization* (i.e. the ratio of production to capital stock) and *cumulative capacity utilization* realized with the operating vintage[1].

The skill reached by each single firm spills over and becomes available to the rest of the economy. Let us denote with $\bar{s}_t(\tau)$ the average skill achieved with vintage $v(\tau)$. We assume that in each period the technological externality on a given vintage is proportional to the average skill:

$$s_t^p(\tau) = \omega\bar{s}_t(\tau), \quad \text{with } \omega > 0 \text{ and } s_\tau^p(\tau) = \eta > 0. \tag{8}$$

Firms get the skill level $s_t^p(\tau)$ even if they do not currently own the vintage $v(\tau)$.

## 2.4 Entry-Exit

Firms exit the market whenever they go bankrupt, i.e. if their net worth becomes negative. From (2), (3) and (5), it follows that bankruptcy occurs if the relative price for firm's output is such to lead to losses greater than the present level of net worth. We can define this price level as the "reservation price" for firm $i$ in period $t$. Formally, it satisfies the following condition:

[1]In this fashion, internal skill dynamics acquires the features of the classic power law learning curves, whose presence has often been reported in the literature on technology diffusion (see Dosi, Silverberg, and Orsenigo, 1988).

$$\overline{u}_{it} : A_{it}(\overline{u}_{it}) \equiv 0. \tag{9}$$

Bankruptcy is costly for firms. Following Greenwald and Stiglitz (1993), we assume that bankruptcy costs are monotonically increasing and convex with respect to firm size:

$$CF_{it} = cY_{it}^2. \tag{10}$$

Each exiting firm is replaced by a new entrant firm. Therefore, the number of firms keeps constant through time. Furthermore, in order to avoid as much as possible biases to the overall dynamics, we assume that entrant firms are random copies of surviving ones with respect to levels of net worth, capital stock, production and initial debt. As far as technology is concerned, we suppose that the technology of any entrant firm is chosen at random between the most productive available and the one immediately following it.

## 2.5 Replacement Decisions

Replacement investment leads to an initial loss of production, equal to $\sigma_{it}K_{it}$, where $\sigma_{it} = \sigma < 1$ if replacement occurs and zero otherwise. These losses can be due, for example, to the deployment of part of labour force to tasks needed to bring the new vintage to operate at full productivity.

In deciding whether replacing or not the capital stock $K_{it-1}^s$ with a new vintage, each firm compares the expected rate of profits in the two alternatives[2]. However, since replacement is costly, it can also raise the risk of bankruptcy, i.e. the probability that the firm's output price falls below the threshold $\bar{u}_{it}$. We assume that, when comparing the outcomes of the two alternatives, firms take into consideration also the expected unitary bankruptcy costs involved. If we denote respectively with $\bar{u}_{it}(\sigma, \alpha(\tau), \mu^n, a_{it})$ and $\bar{u}_{it}(0, \alpha_{it}, \mu^o, a_{it})$ the reservation prices in case of replacement and no replacement, then from (5) and (10), it follows that the pay-off of the firm in case of replacement is:

$$1 - \sigma_{it} - \frac{w(t)}{\alpha(\tau)} - r\mu^n - pr\left\{u_{it} \leq \bar{u}_{it}\left(\sigma_{it}, \alpha(\tau), \mu^n, a_{it}\right)\right\} cK_{it-1}^s \tag{11}$$

whereas without replacement is:

$$1 - \frac{w(t)}{\alpha_{it}} - r\mu^o - pr\left\{u_{it} \leq \bar{u}_{it}\left(0, \alpha_{it}, \mu^o, a_{it}\right)\right\} cK_{it-1}^s \tag{12}$$

[2]Throughout the paper we assume that the replacement decision has a discrete form: either the firm replaces all its capital stock or it does not replace at all. In addition, new vintages are effective with one lag, i.e. once the capital stock has been replaced the new vintage becomes operative only after one period. Finally, there is no resale market for the scrapped capital stock.

where $pr\{\cdot\}$ stands for probability.

A firm will replace its capital stock with a new vintage if the pay-off in that case is higher, that is whenever:

$$\frac{w(t)}{\alpha_{it}} - \frac{w(t)}{\alpha(\tau)} \geq [\sigma + r\,(\mu^n - \mu^o)] + \Delta pr^f \cdot cK^s_{it-1}. \tag{13}$$

The product $\Delta pr^f \cdot cK^s_{it-1}$ measures the variation in expected bankruptcy risk induced by replacement, where $cK^s_{it-1}$ is the cost of bankruptcy and $\Delta pr^f$ is the variation in bankruptcy risk caused by the decision of adopting a new vintage. More formally:

$$\Delta pr^f = pr\left\{u_{it} \leq \bar{u}_{it}\left(\sigma, \alpha(\tau), \mu^n, a_{it}\right)\right\} - pr\left\{u_{it} \leq \bar{u}_{it}\left(0, \alpha_{it}, \mu^o, a_{it}\right)\right\}. \tag{14}$$

The rule in (13) simply states that a firm replaces its capital stock whenever savings on unitary real labour costs allowed by the new vintage (the L.H.S.) are greater or equal than the unitary costs of replacement (the R.H.S.), which include also a premium for the variation in bankruptcy risk caused by the replacement decision.

As far as uncertainty about technological parameters in (13) is concerned, we assume for simplicity that the subjective probability distribution of the relative price $u_{it}$ is the same for all firms, and equal to the objective probability distribution, with $E(u_{it}) = 1$. In addition, we suppose that relative prices are drawn from a uniform distribution with support $(\gamma, 2-\gamma)$. The foregoing assumptions imply that the expression for the risk premium term on the R.H.S. of (13), takes the form:

$$\Delta pr^f \cdot cK^s_{it-1} = \left[\left(\frac{w(t)}{\alpha(\tau)} + r\mu^n - a_{it}\right) - (1-\sigma)\left(\frac{w(t)}{\alpha_{it}} + r\mu^o - a_{it}\right)\right]\frac{cK^s_{it-1}}{2(1-\sigma)}. \tag{15}$$

## 2.6 Production Decisions

Each firm sets its desired level of production through the maximization of expected net profits minus expected bankruptcy costs. Formally, the problem of the firm can be stated in the following terms:

$$\max_{Y_{it}} \; E(\pi^e_{it}) - pr\left\{u_{it} \leq \bar{u}_{it}\left(\sigma_{it}, \alpha_{it}, \mu_{it}, a_{it}\right)\right\} \cdot CF_{it}. \tag{16}$$

The definitions of reservation price and net profits (Eqs. (9) and (5)), combined with the assumptions on the probability distribution of the relative price $u_{it}$ and on the bankruptcy costs (Eq. (10)), imply that:

$$pr\left\{u_{it} \leq \bar{u}_{it}\right\} \cdot CF_{it} = \frac{c}{2(1-\sigma_{it})(1-\gamma)}\left[\left(\frac{w(t)}{\alpha_{it}} + r_{it}\mu_{it}\right)Y_{it}^2 - A_{it}Y_{it}\right]. \quad (17)$$

Accordingly, the objective function to be maximized takes the form:

$$\left[(1-\sigma_{it}) - \frac{w_t}{\alpha_{it}} - r_{it}\mu_{it}\right]Y_{it} - \frac{c}{2(1-\sigma_{it})(1-\gamma)}\left[\left(\frac{w(t)}{\alpha_{it}} + r_{it}\mu_{it}\right)Y_{it}^2 - A_{it}Y_{it}\right]. \quad (18)$$

¿From first order conditions, the optimal level of production, $Y_{it}^*$, is given by:

$$Y_{it}^* = \frac{(1-\sigma_{it})(1-\gamma)}{c}\left[\frac{1-\sigma_{it}}{\left(\frac{w(t)}{\alpha_{it}} + r_{it}\mu_{it}\right)} - 1\right] + \frac{A_{it}}{2\left(\frac{w(t)}{\alpha_{it}} + r_{it}\mu_{it}\right)}. \quad (19)$$

Equation (19) simply states that the optimal level of production of firm $i$ in period $t$ is an increasing function of its expected net profitability (as captured by the mark-up expression in square brackets), and an increasing function of its financial robustness (as measured by the net worth $A_{it}$).

The assumptions on the technology of the firms (see Eq. (1)), imply that the optimal level of production $Y_{it}^*$ maps into a desired level for the capital stock in period $t$, $K_{it}^s$. More precisely, we assume that net investment, i.e. additions to firm's capital stock, occurs whenever the optimal level of production is greater than the total capacity of the firm, the latter being measured by firm's capital stock at the end of the previous period ($K_{it-1}^s$). Conversely, when optimal production is less than firm's capital stock, net investment is zero and total capacity is reduced by a constant fraction $\delta \in (0,1)$. It follows that the law of motion for the capital stock of firm $i$ is given by:

$$K_{it}^s = \begin{cases} K_{it-1}^s + \left(Y_{it}^* - K_{it-1}^s\right) & if \quad Y_{it}^* \geq K_{it-1}^s \\ (1-\delta)\,K_{it-1}^s & if \quad Y_{it}^* < K_{it-1}^s \end{cases} \quad (20)$$

## 2.7 The Labour Market

We study an economy characterized by an infinite supply of labour. Accordingly, output dynamics is driven by capital accumulation. Labour demand in period $t$ is given by:

$$L_{it} = \frac{K_{it}}{\alpha_{it}}. \quad (21)$$

The wage-bargaining process is not modelled in detail. We simply assume that in any period the wage-rate is proportional to the average productivity in the economy:

$$w_t = \phi \overline{\alpha}_t, \qquad \phi > 0. \tag{22}$$

## 2.8 The Credit Market

To close the model, we suppose that the credit market is composed of financial intermediaries, which take into account the risks of default in setting the clauses of the debt contract they offer to firms. We assume away the possibility of credit rationing. Therefore, firms can borrow as many funds as they wish at the interest rate set by the banks. The interest rate on debt contracts is equal to an exogenous level, $r$, plus a risk premium, which has two components: the first accounts for the "financial fragility" of the system, the second captures the relative riskiness of the single borrowing firm:

$$r_{it} = r[1 + \rho g(\overline{a}(t)) + (1-\rho) f(a_{max}(t) - a_{it})], \qquad g'(.) < 0, f'(.) > 0, \rho > 0 \tag{23}$$

where $\overline{a}(t)$ is the economy's average equity ratio (i.e. the ratio of net worth to capital stock), $a_{it}$ is firm equity ratio, and $a_{max}(t)$ is the highest equity ratio in the economy at time $t$.

## 2.9 A Risk-Based Approach to Replacement and Production Decisions: A Discussion

The framework exposed in the foregoing paragraphs aims at describing micro and macro phenomena on the grounds of the interactions between financial and technological variables. The effects of these interactions on firms' exit, competition and growth drive the outcomes of our model. Here, we briefly discuss these mechanisms before presenting the results of our analysis.

The economy under study features an inverse relation between firm financial robustness and firm probability of bankruptcy. Firms care about the risk of bankruptcy in every decision they make. In addition, equity rationing hampers them from washing away completely that risk. Thus, measures of firm financial robustness (net worth and equity ratio) enter directly in firm decisions about replacement and production (see respectively (13) and (16)).

By assumption, production goes always sold out in the output market. Accordingly, firm growth dynamics is driven by the decisions about how much output to produce. The latter are in turn determined by the expected risk of bankruptcy and by the dynamics of firm costs (see (16)). As mentioned, bankruptcy risks are inversely related to the financial robustness of the firm. The same is true for the cost of capital. Indeed, the interest rate rule in (23) implies that firms are ranked by banks according to their relative financial conditions. As a consequence, firms financially more (less) robust will pay, *coeteris paribus*, lower (higher) interest rates for the funds they borrow. Moreover, an increase in the economy-wide "financial fragility", as reflected by a reduction of the average equity ratio in the economy, maps, other things being equal, into higher interest rates for all firms operating in the market[3].

As far as labour cost is concerned, equation (22) states that labour cost inside the firm depends on firm's relative productivity with respect to the average level in the economy. Firms with productivity above (below) average have unitary labour costs which are below (above) average. This implies unitary expected profits above (below) the mean. Nevertheless, such an advantage is temporary, because it vanishes as new technologies spread throughout the economy. In this fashion, learning is coupled in the model with other key features (appropriability of innovations, market interactions) characterizing empirical dynamics of productivity at the micro level.

As a result, technological variables influence competition among firms and growth by determining productivity levels in the economy. On the one hand, both the vintage that each firm owns and the skill with which it masters its embodied technology determine its productivity level and, consequently, the magnitude of the relative advantage in labour cost. On the other hand, the speed of learning and diffusion, and the magnitude of technological spill-overs influence the duration of the cost advantage. Financial variables, in turn, play a key role for the productivity dynamics of the single firm. The ability to afford more productive vintages through replacement (see (13)) and to grasp the productivity gains allowed by them (see (7)) will depend on the degree of financial robustness of the firm.

Finally, the model features a mapping from the space of technological variables to the one of financial variables. Equation (22) implies that both the dynamics of unitary labour cost inside the firm, and the corresponding one for net profits, depend on the ratio between individual and average productivity. Firms more productive than the average will have *coeteris paribus* lower unitary variable costs. This will map into a better ability to absorb the impact of output price shocks. In other words, the effect of a negative (positive) demand shock will be dampened (reinforced) if real variable costs are lower. This will lead to an improvement (worsening) of the financial conditions of the firm, with a consequent

[3]There are many institutional settings for the credit market that lead to the rule stated in (23). For a survey on the working of credit markets under asymmetric information (and of its consequences for aggregate performance) see Greenwald and Stiglitz (2001). For an empirical investigation on the importance of firm financial conditions for credit contract clauses see Strahan (1999) and Hubbard, Kuttner, and Palia (1999).

higher (lower) probability of survival and future growth.

# 3 Simulation Results

In this Section, we report the results of Monte-Carlo simulation exercises carried out on the model presented in Section 2[4]. All simulations refer to a benchmark parameter setup (see Table 1) and homogeneous across-firm initial conditions (see Table 2)[5]. Homogeneity of initial conditions was assumed in order not to bias the subsequent micro- and macro-dynamics, and to better appreciate the emergence of heterogeneous across-firm micro-patterns.

For the sake of convenience, we employed in our simulations a linear form for the interest-rate rule introduced in (23):

$$r_{it} = r[1 + \rho\overline{a}(t) + (1-\rho)(a_{max}(t) - a_{it})] \tag{24}$$

Moreover, entrants' technologies were drawn from a discrete uniform distribution.

We analyze simulated data from both a time-series and a cross-section perspective. From a time-series (macro) point of view, we are interested in assessing whether our aggregate series (output, investment, etc.) match empirically-observed business-cycle regularities.

¿From a cross-section (micro) point of view, we want to understand if the model is able to replicate the most important stylised facts highlighted by the industrial dynamics literature (e.g., the properties of firm growth and productivity dynamics; see also below). To this end, we study the behaviour of the model after the system has relaxed to a sufficiently stable dynamical pattern, which typically happens – for our benchmark setup – around $T = 1000$[6].

In Section 3.1, we begin by presenting a qualitative and quantitative analysis of the macro-dynamics. Next, in Section 3.2, we turn to describe the features of the micro-dynamics of firm growth and productivity.

## 3.1 Macro-Dynamics

In this Section we study whether our simulated macroeconomic time series feature statistical properties similar to the empirically observed ones. We begin by assessing if the

[4]The simulation code (written in C++) is available from the authors upon request.

[5]All results presented below are reasonably robust to changes of the parameter setup and initial conditions in a fairly large neighborhood of our benchmarks. For a discussion, cf. Section 4.

[6]More precisely, this time-span allows for the convergence of recursive moments of all statistics of interest.

basic fact of modern capitalist economies, i.e. the emergence of self-sustaining growth, is displayed by our macro time series.

Next, we turn to an analysis of the properties of simulated aggregate variables at medium, business-cycle frequencies. In particular, we apply a band-pass filter (Baxter and King, 1999) to eliminate both low and high frequencies in the data. We then investigate the patterns of output volatility and output-investment relation. Recent empirical evidence has indeed documented the presence of significant changes in the volatility of aggregate output within countries (see e.g. McConnell and Perez-Quiros, 2000; Stock and Watson, 2002). Moreover, aggregate investment is more variable than output, and appears to be characterized by strong pro-cyclicality, with its movements being slightly coincident with the ones of output (Agresti and Mojon, 2001; Stock and Watson, 1999; Napoletano, Roventini, and Sapio, 2004).

Finally, we study whether technological shocks play any role in generating business cycles in our model. The relation between technological shocks and business cycles has been the object of a long debate over the last decades. Theoretical contributions have highlighted many different ways through which technical advances can impact on economic fluctuations at medium frequencies (Prescott, 1986; Kydland and Prescott, 1982; King and Rebelo, 1999). Nevertheless, empirical evidence accumulated so far has mostly rejected the hypothesis of technology-generated business cycles (see e.g. Galì, 1999; Forni and Reichlin, 1998; Jovanovic and Lach, 1997; Ramey and Francis, 2003). The impact of technology on main macroeconomic time series, if any, is too delayed in time to be relevant at business cycle frequencies[7].

### 3.1.1 Long-Run Properties

As Figure 1 shows, self-sustaining growth characterized by fluctuations robustly emerges in simulated aggregate output series. The same qualitative pattern is displayed by aggregate investment and employment series (not shown). Average productivity is characterized by long-run exponential growth as well (cf. Figure 2). Notice that technological improvements play a key role in productivity dynamics. Indeed, the trend of average productivity closely follows the one of the notional productivity of best vintages.

The qualitative results about the emergence of long-run growth are confirmed by a more quantitative analysis. The first two rows in Table 3 report Dickey-Fuller tests (with a drift in the null model) performed on the logarithms of our simulated macro series. Significance

[7]For example, Forni and Reichlin (1998) find that, although technological shocks account for half of the total variance of output, they cannot explain its dynamics at business cycle frequencies. Likewise, Jovanovic and Lach (1997) find that the diffusion of product innovations (i.e. technological shocks) has a huge impact on the *level* of output, but underpredicts output movements over the business cycle.

levels of the tests (in parentheses) clearly indicate that it is not possible to reject the null hypothesis of at least one unit root.

### 3.1.2 Business Cycle Dynamics

To analyze the properties of macroeconomic dynamics at business cycle frequencies, we applied a bandpass filter to our series[8]. Through this procedure, stochastic trends were removed (see the third and fourth rows in Table 3) and business cycle frequencies were isolated.

As Figure 3 displays, the behaviour of aggregate output at business cycle frequencies is qualitatively close to the empirically-observed one: wide fluctuations and volatility clusters emerge. In addition, the auto-correlation structure of output displays the typical decaying pattern observed in actual time series (cf. Table 4 and Figure 6).

As far as the output-investment relation is concerned, simulations indicate that the series of aggregate investment is much more volatile than the series of output (see Fig. 4, top-panel, and last row in Table 3). Moreover, aggregate investment is characterized by a pro-cyclical and leading behaviour with respect to output (see Figure 5, mid-left panel, and the investment column in Table 4).

Our analysis suggests that technological shocks play a secondary role in driving the business cycle. As a direct evidence of this proposition, Figure 7 reports cross-correlation coefficients between technological shocks at lead zero and aggregate output at positive leads[9]. The figure shows that the impact of technological shocks on output is very weak at business cycles frequencies, even at the farthest leads considered. The same result holds for the other variables. The unique notable exception is represented by average labour productivity (not shown), which is affected by technological shocks in a relevant way, especially at nearest leads.

Additional evidence about the weak effect of technological shocks on economic fluctuations at medium frequencies can be gathered by observing the coupled dynamics of output and average labour productivity. Indeed, since average labour productivity is driven by technological shocks (see discussion above), its behaviour with respect to output can be taken as an indirect indicator of the influence of technological shocks on business cycles.

[8] We employed a bandpass filter (6,32,50) in order to remove both highest and lowest frequencies in the data while preserving those at business cycle dates. The window for the filter (i.e. 6 to 32 periods) was calibrated on the one chosen by Stock and Watson (1999) for their analysis of the U.S. cycle. Our large simulated dataset allows us to adopt a higher level for the cut-off parameter (50 periods). Nonetheless, results at business cycle frequencies are robust to different specifications of the window and cut-off parameters. For an analysis of the pros and cons of the use of band-pass filtering in ACE models see Roventini, Fagiolo, and Dosi (2004).

[9] Technological shocks are defined as the change in the notional productivity of best vintages entailed by the introduction of a new vintage.

More precisely, if labour productivity had any effect on output, then its dynamics should have been – at the very least – coincident with (or leading) the output one. However, average labour productivity appears to be a pro-cyclical variable in our model, and its movements are lagging output ones. The bulk of its cross-correlations with output is indeed concentrated between lag 4 and 6 (Figure 5, bottom-left panel).

Finally, changes in average financial conditions in the economy sensibly affect the behaviour of aggregate output during business cycles. The volatility of aggregate net worth is indeed very close to the one of aggregate output (see Table 3). In addition, the dynamics of aggregate net worth over the cycle closely follows the dynamics of output (see the corresponding columns in Table 4 and Figure 5, bottom-right panel).

In summary, the coupled dynamics of financial and technological variables appears to be characterized by many qualitative and quantitative properties that are also displayed by empirical data, both in the long-run and at medium range, business-cycle frequencies. Changes in the average financial conditions in the economy emerge as the major cause of short-run fluctuations. In particular, movements in aggregate net worth appear to promote, first, changes in aggregate output and employment, and, subsequently, in aggregate investment and average productivity (Figure 5). Conversely, at business cycle frequencies the impact of technological shocks on the first moments of the distributions of financial and real variables is on average rather weak.

## 3.2 Micro-Dynamics

In recent years, a lot of effort has been devoted to the study of the statistical properties of firm growth and productivity dynamics. For example, the properties of firm growth dynamics have been tested against the benchmark hypothesis of randomness represented by the so-called "Gibrat's Law" (GL), which basically states the independence of firm growth from its size. A consistent amount of evidence has been produced against this law (Lee et al., 1998; Bottazzi and Secchi, 2003a). The statistical properties of firm size and growth distributions seem to significantly depart from the log-normal benchmark implied by the GL. On the other hand, a recent body of empirical research performed on longitudinal micro data sets has revealed that the process of productivity growth at the micro level is not as smooth as the one represented in more aggregate series (see Bartelsman and Doms, 2000, and references therein). In particular, the presence of significant and persistent differences in productivity levels among firms appears as the basic feature underlying the dynamics of productivity in most sectors and countries. Moreover, productivity seems to have non trivial effects on firm growth[10]. Indeed, firm productivity appears to be positively correlated with growth rates and exit probability.

In what follows, we will test whether firm size and growth rate distributions generated by our benchmark simulation are coherent with the implications of GL. Next, we will investigate the properties of the coupled productivity-growth dynamics.

### 3.2.1 Statistical Properties of Pooled Size and Growth Distribution

In one of its most widely accepted interpretations, the GL (also known as "Law of Proportionate Effects") states that firm growth is independent of firm size. Accordingly, the dynamics of firm size, $S_{it}$ can be formalized as follows:

$$S_{it} = S_{it-1}G_{it} \tag{25}$$

where $G_{it}$ is a random variable. If $g_{it} = log(G_{it})$ are i.i.d. random variables with finite mean and variance, then $S_{it}$ is well approximated, for large $t$, by a log-normal distribution. In addition, growth rates $g_{it} = \Delta log(S_{it})$ are normally distributed. A recent strand of empirical research has led to discard the implications arising from processes like the one formalized in (25). More precisely, tent-shaped growth rates densities appear as a robust feature both across sectors and at the aggregate level (Lee et al., 1998; Bottazzi and Secchi, 2003a). At the same time, the shape of log firm size densities is far from being well approximated by a log normal distribution and displays a strong cross-sector heterogeneity (Bottazzi and Secchi, 2003a).

Figure 8 shows the rank-size plot for the pooled simulated size distribution over the whole time span considered in our analysis[11]. Notice how the size distribution can hardly be approximated by a log-normal. In particular the mass of the distribution appears to be considerably shifted to the right. Furthermore, pooled growth rate distributions depart remarkably from the Gaussian benchmark. Indeed, as shown in Figure 9, growth rate distributions are characterized by fat tails and are well approximated by a symmetric Laplace density.

The foregoing evidence – departure from lognormality of firm size distributions and fat-tailed Laplace densities for firm growth rates – reveals that the simulated process of firm growth does not follow the Gibrat's dynamics formalized in (25), but closely matches the empirically-observed stylised facts.

[10]See Bottazzi, Cefis, and Dosi (2002) for a more skeptical view about the presence of the productivity-growth relation in Italian data.

[11]The size measure considered was the output level $Y_{it}$. Alternative measures of size (e.g., employment) produced the same results. The size measure considered was then depurated by years averages in order to remove time-trends in the moments of the distributions.

Notice that this result is due, in the model, to the interplay between two crucial factors. On the one hand, repeated interactions among heterogeneous firms generate, as mentioned above, an unequal distribution of growth opportunities in the market. On the other hand, the existence of dynamic increasing returns in credit and labour markets implies that growth opportunities in a given time span will mostly concentrate in a few firms, which will then display higher growth rates. This feature leads, in turn, to the emergence of leptokurtic densities of firm growth rates[12]. In the credit market, for example, firms who are more (less) financially robust will have higher (lower) unitary cost on capital. This implies a higher probability of having better (worse) financial conditions in next periods. Likewise, in the labour market firms who are more (less) productive (than the mean) have lower (higher) labour costs, and this maps in a higher chance of having better (worse) financial conditions in next periods. This may drive subsequent learning, a more effective technological adoption, and higher productivity.

### 3.2.2 Productivity Dynamics and the Evolution of the Productivity-Growth Relation

The presence of heterogeneity in firm productivity levels appears as a robust pattern characterizing the micro data in our benchmark simulations. Indeed, as Figure 10 shows, the standard deviation of productivity is positive and characterized by an exponential trend. Hence, asymmetries in the evolution of financial variables map in different abilities of catching the opportunities offered by new technologies. Indeed, firms which are more financially robust increasingly perform replacement investment and technological learning.

Productivity patterns are also characterized by a persistent heterogeneity among firms. Tables 5 and 6 show the average (forward and backward) productivity transition matrices over 20 periods[13]. More precisely, each row in Table 5 displays the average fractions of firms who were in a given quintile of the productivity distribution at the beginning of a twenty period interval and moved to each quintile of the distribution at the end of the interval. Each row in Table 6 shows instead the average fractions of firms in a given quintile of the productivity distribution at the end of a twenty period interval that come

[12]For a similar interpretation, cf. the "island-models" of firm growth (see e.g. Sutton, 1997; Ijiri and Simon, 1977; Bottazzi and Secchi, 2003b). In particular, Bottazzi and Secchi (2003b) show that, under very general conditions, Laplace densities emerge as long as the growth process features an asymmetric distribution of finite growth opportunities among firms and dynamic increasing returns in the technology of opportunities assignment.

[13]We split the whole time-span analyzed in equally longer intervals of twenty periods, and for each of them we computed the transition matrices of productivity of firms that were present both at the beginning and at the end of the interval considered. Tables 5 and 6 report the average transition values together with their standard deviations.

from each quintile of the distribution at the beginning of the interval[14]. The fact that the two matrices are very similar indicates a strong persistence of productivity differences in our sample.

Finally, we investigate the properties of productivity-growth and productivity-exit correlations. As mentioned, empirical evidence shows that more (less) productive firms are characterized by higher (lower) growth, and by a lower (higher) probability of exit. As Figure 11 indicates, both patterns emerge as quite robust properties in our model.

# 4 Conclusions

In this paper, we have presented an agent-based model which attempts to investigate how the coupled dynamics between financial variables and technological shocks shapes the aggregate dynamics of economies populated by heterogeneous agents. A key feature of the model is its bottom-up approach to the microfoundation of macroeconomic relations. We studied the extent to which the model was able to reproduce empirical properties characterizing aggregate time-series and cross-sectional dynamics.

Simulation results indicate that the adjustment to technology and demand shocks of heterogenous, myopic, firms that take into account the risk of bankruptcy in their decisions, allows for self-sustaining patterns of growth and business-cycle fluctuations in output, investment, productivity and employment. The statistical properties of the output-investment relation match, at business-cycle frequencies, those observed in reality. The same holds for other time-series, e.g. technological shocks. Changes to net worth distribution emerge as the major source of short-run fluctuations in the model. Conversely, the effect of technological shocks on the first moments of the distribution of the main macroeconomic time-series appears to be weak.

Our model is also able to reproduce the main stylised facts of firm growth and productivity dynamics. Indeed, the statistical features of firm size and growth rate distributions depart significantly from the "Gibrat's Law" benchmark. In particular, size distributions are more skewed to the right than log normal ones, whereas growth rate densities display excess kurtosis, with a shape well approximated by a symmetric Laplace density.

The productivity picture in our benchmark simulation is characterized by the presence of huge and persistent asymmetries in productivity levels among firms. Furthermore, a positive correlation between productivity and growth, and a negative one between produc-

[14]For example, cell (2,3) in Table 5 reports the average fraction of firms who were in the second quintile at the beginning of a twenty-period interval and moved to the third quintile at the end of the interval. Similarly, cell (2,3) in Table 6 reports the average fraction of firms who ended up in quintile 2 at the end of a twenty-period interval and were in quintile 3 at the beginning of the interval.

tivity and exit, emerge as distinctive attributes of our benchmark setup.

The foregoing findings should be tested against a deeper Monte-Carlo exploration of the parameter space. More precisely, one could study to what extent our results are modified when system parameters are varied across suitable intervals. For example, the consequences of changes in the interest rate for output, investment and employment dynamics could be investigated. Similarly, one could experiment the impact of alternative settings for labour and credit markets, as well as the effect of different entry-regimes (Geroski, 1995).

Furthermore, a more detailed investigation of the linkages between micro- and macro-dynamics is required. Two research questions seem to be particularly interesting. First, the time-evolution of cross-section distributions could be more carefully spelled out. In this way, one might address the issue whether micro-patterns change during the diffusion of a new technology. Second, the exploration of the impact of micro-dynamics on aggregate variables should not be confined – as we have done above – to averages only. For example, one could study whether technological shocks affect higher moments (e.g., variance) of output and investment series.

Finally, one might attempt to investigate the consequences of introducing more stringent bounds to agents' rationality (e.g., in the way firms form expectations about technology and prices and/or in the way they make choices under uncertainty). For instance, one could study the implications of injecting in the economy agents embedding the axioms of Prospect Theory (see e.g. Kahneman and Tversky, 1979; Camerer, Lowenstein, and Rabin, 2004) or, alternatively, agents behaving in more evolutionary, routinized ways (Fagiolo and Dosi, 2003).

# References


Aghion, P., P. Howitt and D. Mayer-Foulkes (2004), "The Effect of Financial Development on Convergence: Theory and Evidence", *NBER Working Paper*, 10358.

Agresti, A. M. and B. Mojon (2001), "Some Stylized Facts on the Euro Area Business Cycle", *European Central Bank Working Paper*, 95.

Bartelsman, E. and M. Doms (2000), "Understanding Productivity: Lessons from Longitudinal Microdata", *Journal of Economic Literature*, 38(3): 569–594.

Baxter, M. and R. King (1999), "Measuring Business Cycle: Approximate Band-pass Filter for Economic Time Series", *The Review of Economics and Statistics*, 81: 575–593.

Bernanke, B., M. Gertler and S. Gilchrist (1996), "Financial Accelerator and The Flight to Quality", *Review of Economics and Statistics*, 78(1): 1–15.

Bottazzi, G., E. Cefis and G. Dosi (2002), "Corporate Growth and Industrial Structures: Some Evidence from the Italian Manufacturing Industry", *Industrial and Corporate Change*, 11(4): 705–723.

Bottazzi, G. and A. Secchi (2003a), "Common Properties and Sectoral Specificities in the Dynamics of U.S. Manufacturing Companies", *Review of Industrial Organization.*, 23(3): 217–232.

Bottazzi, G. and A. Secchi (2003b), "Why are Distributions of Firm Growth Rates Tent-Shaped?", *Economic Letters*, 80(3): 415–420.

Caballero, R., E. Engel and J. Haltiwanger (1993), "Microeconomic Adjustment Hazards and Aggregate Dynamics", *Quarterly Journal of Economics*, 108(2): 359–383.

Caballero, R., E. Engel and J. Haltiwanger (1995), "Plant-Level Adjustment and Aggregate Investment Dynamics", *Brookings Papers on Economic Activity*, 2: 1–39.

Camerer, C., G. Lowenstein and M. Rabin (eds.) (2004), *Advances in Behavioural Economics*. Russell Sage Foundation - Princeton University Press, Princeton, New Jersey.

Carlin, W. and C. Mayer (2003), "Finance Investment and Growth", *Journal of Financial Economics*, 69(1): 191–226.

Davis, S. and J. Haltiwanger (1992), "Gross Job Creation, Gross Job Destruction, and Employment Reallocation", *Quarterly Journal of Economics*, 107(3): 819–63.

Delli Gatti, D., C. Di Guilmi, E. Gaffeo, G. Giulioni, M. Gallegati and A. Palestrini (2005), "A New Approach to Business Fluctuations: Heterogeneous Interacting Agents, Scaling Laws and Financial Fragility", *Journal of Economic Behaviour and Organization*, Forthcoming.

Dosi, G. and L. Orsenigo (1994), "Macrodynamics and microfoundations: an evolutionary perspective", in Granstrand, O. (ed.), *The economics of technology.* Amsterdam, North Holland.

Dosi, G., J. Silverberg and L. Orsenigo (1988), "Innovation, Diversity and Diffusion: A Self-Organization Model", *Economic Journal*, 98(393): 1032–1054.

Epstein, J. and R. Axtell (1996), *Growing Artificial Societies: Social Science from the Bottom-Up.* MIT Press.

Fagiolo, G. and G. Dosi (2003), "Exploitation, Exploration and Innovation in a Model of Endogenous Growth with Locally Interacting Agents", *Structural Change and Economic Dynamics*, 14(3): 237:273.

Fagiolo, G., G. Dosi and R. Gabriele (2004), "Matching, Bargaining, and Wage Setting in an Evolutionary Model of Labor Market and Output Dynamics", *Advances in Complex Systems*, 7(2): 237–273.

Forni, M. and L. Reichlin (1998), "Lets' Get Real: A Dynamic Factor Analytical Approach to Disaggregated Business Cycles", *The Review of Economic Studies*, 65(3): 453–473.

Galì, J. (1999), “Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations”, *American Economic Review*, 89(1): 249–271.

Geroski, P. (1995), “What Do We Know About Entry?”, *International Journal of Industrial Organization.*, 13(4): 421–440.

Greenwald, B. and J. Stiglitz (1993), “Financial Market Imperfections and Business Cycles”, *Quarterly Journal of Economics*, 108(1): 77–114.

Greenwald, B. and J. Stiglitz (2001), *Toward a New Paradigm in Monetary Economics.* Cambridge University Press, Cambridge.

Hubbard, G., K. Kuttner and D. Palia (1999), “Are There Bank Effects in Borrowers’ Cost of Funds?: Evidence from a Matched Sample of Borrowers and Banks“”, *Federal Reserve Bank of New York Staff Report*, 78.

Ijiri, Y. and H. A. Simon (1977), *Skew Distributions and The Sizes of Business Firms.* North-Holland.

Jovanovic, B. and S. Lach (1997), “Product Innovation and the Business Cycle”, *International Economic Review*, 38(1): 3–22.

Kahneman, D. and A. Tversky (1979), “Prospect Theory: An Analysis of Decision under Risk”, *Econometrica*, 47(2): 263–292.

King, R. and S. Rebelo (1999), “Resuscitating Real Business Cycles”, in Woodford, M. and J. Taylor (eds.), *Handbook of Macroeoconomics*, Vol. 1B, Amsterdam. North-Holland.

Kiyotaki, N. and J. Moore (1997), “Credit Cycles”, *Journal of Political Economy*, 105(2): 211–248.

Kydland, F. and R. Prescott (1982), “Time to Build and Aggregate Fluctuations”, *Econometrica*, 50(6): 1345–1370.

Lee, Y., L. N. Amaral, D. Canning, M. Meyer and H. Stanley (1998), “Universal Features in the Growth Dynamics of Complex Organizations”, *Physical review Letters*, 81(15): 3275–3278.

Levine, R. (2005), “Finance and Growth: Theory and Evidence”, in Aghion, P. and S. Durlauf (eds.), *Handbook of Economic Growth*, Vol. 3, Amsterdam. North-Holland, Forthcoming.

McConnell, M. M. and G. Perez-Quiros (2000), “Output Fluctuations in the United States: What Has Changed Since the early 1980’s”, *American Economic Review*, 90(5): 1464–1476.

Napoletano, M., A. Roventini and S. Sapio (2004), “Are Business Cycles All Alike? A Bandpass Filter Analysis of Italian and US Cycles”, *L.E.M. Working Paper*, 25.

Prescott, R. (1986), “Theory Ahead of Business Cycle Measurement”, *Federal Reserve Bank of Minneapolis Review*, 10(4): 9–22.

Ramey, V. and N. Francis (2003), "Is the Technology-Driven Real Business Cycle Hypothesis Dead? Shocks and Aggregate Fluctuations Revisited", *Unpublished Paper.*

Rossi, S., M. Bugamelli, F. Schivardi, F. Paternò and P. Pagano (2001), "Ingredients for the New Economy: how much does finance matter?", *Bank of Italy Discussion Paper*, 418.

Roventini, A., G. Fagiolo and G. Dosi (2004), "Animal Spirits, Lumpy Investment and Endogeneous Business Cycles", *Unpublished Paper.*

Schumpeter, J. A. (1934), *The Theory of Economic Development: An Inquiry into Profits Capital, Credit, Interest, and the Business Cycle.* Harvard University Press, Cambridge, Massachusetts.

Stadler, G. W. (1994), "Real Business Cycles", *Journal of Economic Literature*, 32(4): 1750–1783.

Stock, J. and M. Watson (1999), "Business Cycle Fluctuations in US Macroeconomic Time Series", in Woodford, M. and J. B. Taylor (eds.), *Handbook of Macroeconomics*, Vol. 1A, Amsterdam. North-Holland.

Stock, J. and M. Watson (2002), "Have Business Cycles Changed and Why?", *NBER Working Papers*, 9127.

Strahan, P. (1999), "Borrower Risk and the Price and Nonprice Terms of Bank Loans", *Federal Reserve Bank of New York Working Paper*, 90.

Sutton, J. (1997), "Gibrat's Legacy", *Journal of Economic Literature*, 35: 40–59.

Testfatsion, L. (1997), "How Economists Can Get Alife", in Arthur, B., S. Durlauf and D. Lane (eds.), *The Economy as a Complex Evolving System II.* Addison-Wesley.

| Description | Symbol | Value |
|---|---|---|
| Number of Firms | $N$ | 250 |
| Arrival Rate | $\lambda$ | 0.025 |
| Unitary Increment | $\xi$ | 0.200 |
| Speed of Learning | $\beta$ | 0.500 |
| Cost w/o Replacement | $\mu^o$ | 1.500 |
| Cost w/ Replacement | $\mu^n$ | 2.500 |
| Loss on Production due to Replacement | $\sigma$ | 0.050 |
| Learning Spill-Overs | $\omega$ | 0.330 |
| Initial Skill on New Technologies | $\eta$ | 0.200 |
| Wage/Productivity Ratio | $\phi$ | 0.700 |
| Exogenous Interest Rate | $r$ | 0.053 |
| Risk-Premium Coefficient | $\rho$ | 0.500 |
| Reduction of Capital Stock | $\delta$ | 0.025 |
| Support of Price Distribution | $\gamma$ | 0.250 |

Table 1: Benchmark Parametrization.

| Description | Symbol | Value |
|---|---|---|
| Initial Net Worth | $A(0)$ | 20 |
| Initial Capital Stock | $K(0)$ | 100 |
| Initial Debt | $B(0)$ | 80 |
| Initial Production | $Y(0)$ | 100 |
| Productivity of First Vintage | $\theta(0)$ | 1.5 |
| Initial Interest Rate | $r(0)$ | 0.053 |

Table 2: Initial Conditions.

| | Output | Aggr.Inv. | Empl. | Avg.Prod. | Net Worth |
|---|---|---|---|---|---|
| DF Test (logs) | -0.475 | -1.173 | -0.468 | 5.148 | -0.474 |
| | (1.000) | (1.000) | (1.000) | (1.000) | (1.000) |
| DF Test (Bpf) | -5.360 | -8.096 | -6.066 | -5.433 | -5.461 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Std.Dev. (Bpf) | 0.356 | 1.616 | 0.430 | 0.018 | 0.358 |
| Rel. Std. Dev. | 1.000 | 4.543 | 1.210 | 0.051 | 1.008 |

Table 3: First two rows: Dickey-Fuller Tests for Log of Output (first row) and Band-Pass Filtered (6,32,50) Output Series. Significance levels in parentheses. Third Row: Standard Deviations of Band-Pass Filtered (6,32,50) Output Series. Fourth Row: Standard Deviations Relative to Band-Pass Filtered (6,32,50) Output Series.

| Output Leads | Output | Aggr.Inv. | Empl. | Avg.Prod. | Net Worth |
|---|---|---|---|---|---|
| -6 | -0.221 | -0.239 | -0.211 | 0.416 | -0.194 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| -5 | -0.087 | -0.252 | -0.085 | 0.312 | -0.058 |
| | (0.034) | (0.000) | (0.032) | (0.000) | (0.141) |
| -4 | 0.117 | -0.248 | 0.103 | 0.174 | 0.142 |
| | (0.003) | (0.000) | (0.009) | (0.000) | (0.000) |
| -3 | 0.385 | -0.192 | 0.359 | 0.031 | 0.409 |
| | (0.000) | (0.000) | (0.000) | (0.435) | (0.000) |
| -2 | 0.678 | -0.053 | 0.638 | -0.093 | 0.696 |
| | (0.000) | (0.183) | (0.000) | (0.018) | (0.000) |
| -1 | 0.911 | 0.163 | 0.854 | -0.185 | 0.917 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 0 | 1.000 | 0.396 | 0.924 | -0.242 | 0.990 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 1 | 0.911 | 0.562 | 0.821 | -0.266 | 0.886 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2 | 0.678 | 0.594 | 0.586 | -0.263 | 0.642 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 3 | 0.385 | 0.484 | 0.309 | -0.238 | 0.345 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 4 | 0.117 | 0.282 | 0.070 | -0.199 | 0.078 |
| | (0.004) | (0.000) | (0.075) | (0.000) | (0.047) |
| 5 | -0.087 | 0.066 | -0.096 | -0.154 | -0.116 |
| | (0.028) | (0.096) | (0.015) | (0.000) | (0.003) |
| 6 | -0.221 | -0.098 | -0.209 | -0.111 | -0.246 |
| | (0.000) | (0.013) | (0.000) | (0.005) | (0.000) |

Table 4: Cross-Correlations between Aggregate Variables at Lead Zero and Output at various Leads and Lags. P-values in parentheses.

| Quintiles | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | 0.3520 | 0.2148 | 0.1651 | 0.1388 | 0.1250 |
| | (-0.1258) | (0.1106) | (0.0967) | (0.1156) | (0.1367) |
| 2 | 0.3252 | 0.2885 | 0.1691 | 0.1138 | 0.1009 |
| | (0.0943) | (0.1253) | (0.1112) | (0.0839) | (0.1210) |
| 3 | 0.17202 | 0.34432 | 0.26494 | 0.13867 | 0.07949 |
| | (0.0855) | (0.1452) | (0.1433) | (0.0936) | (0.0925) |
| 4 | 0.0964 | 0.1289 | 0.3426 | 0.3287 | 0.1026 |
| | (0.0596) | (0.1286) | (0.1612) | (0.1771) | (0.0837) |
| 5 | 0.0553 | 0.0224 | 0.0577 | 0.2861 | 0.5753 |
| | (0.0432) | (0.0345) | (0.0802) | (0.2003) | (0.2583) |

Table 5: Forward Productivity Transition Matrix. Time-series standard deviations in parentheses. Each $(h, k)$ entry represents the estimated average fraction of firms that belong at the beginning of a 20-period interval to the $h$-th quintile of the productivity distribution and end up in the $k$-th quintile at the end of the interval.

| Quintiles | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | 0.3512 | 0.21427 | 0.1641 | 0.1374 | 0.1271 |
| | (0.1257) | (0.1101) | (0.0955) | (0.1144) | 0.1393 |
| 2 | 0.3255 | 0.2892 | 0.1700 | 0.1134 | 0.1034 |
| | (0.0932) | (0.1262) | (0.1132) | (0.0836) | (0.1246) |
| 3 | 0.1721 | 0.3457 | 0.2644 | 0.1384 | 0.0810 |
| | (0.0855) | (0.1476) | (0.1409) | (0.0939) | (0.0939) |
| 4 | 0.0961 | 0.1286 | 0.3436 | 0.3288 | 0.1047 |
| | (0.0587) | (0.1283) | (0.1636) | (0.1793) | (0.0852) |
| 5 | 0.0544 | 0.0221 | 0.0577 | 0.2806 | 0.5747 |
| | (0.0428) | (0.0348) | (0.0821) | (0.1984) | (0.2580) |

Table 6: Backward Productivity Transition Matrix. Time-series standard deviations in parentheses. Each $(h, k)$ entry represents the estimated average fraction of firms that belong at the end of a 20-period interval to the $h$-th quintile of the productivity distribution and started in the $k$-th quintile at the beginning of the interval.

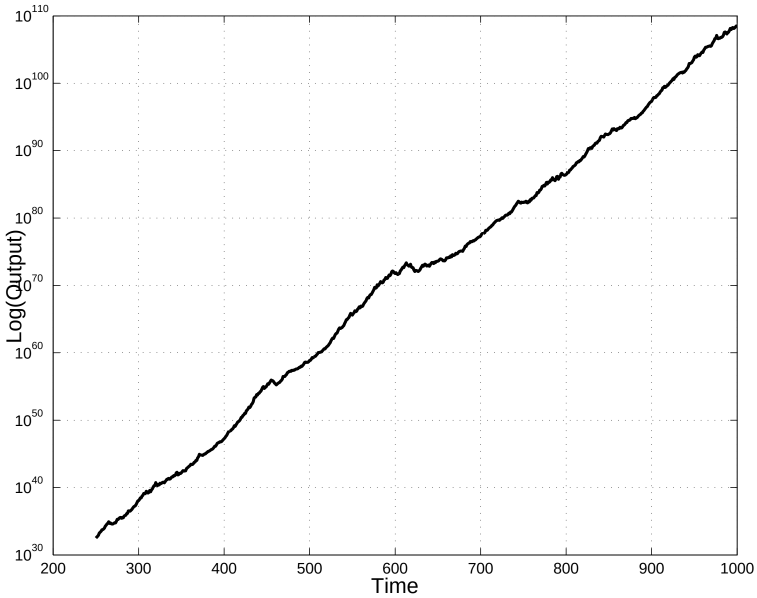


Figure 1: Output Time-Series.

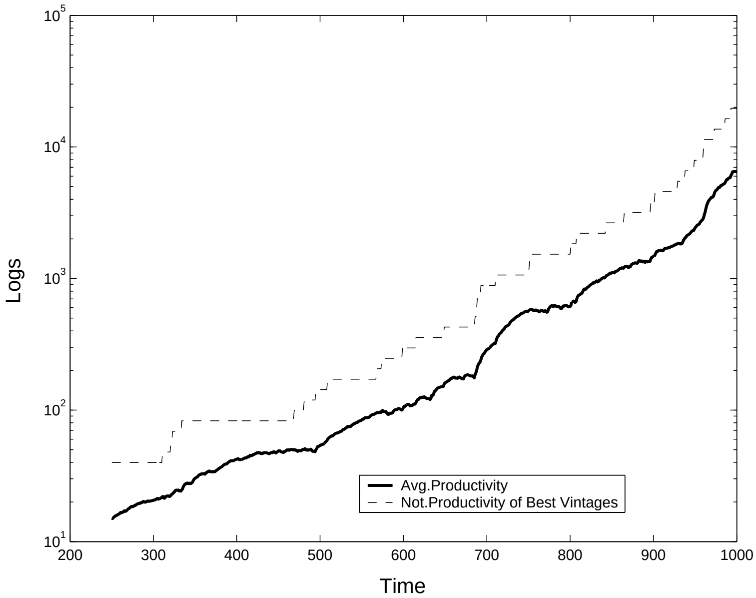


Figure 2: Productivity Trend. Solid line: Average Productivity. Dashed Line: Notional Productivity of Best Vintages.

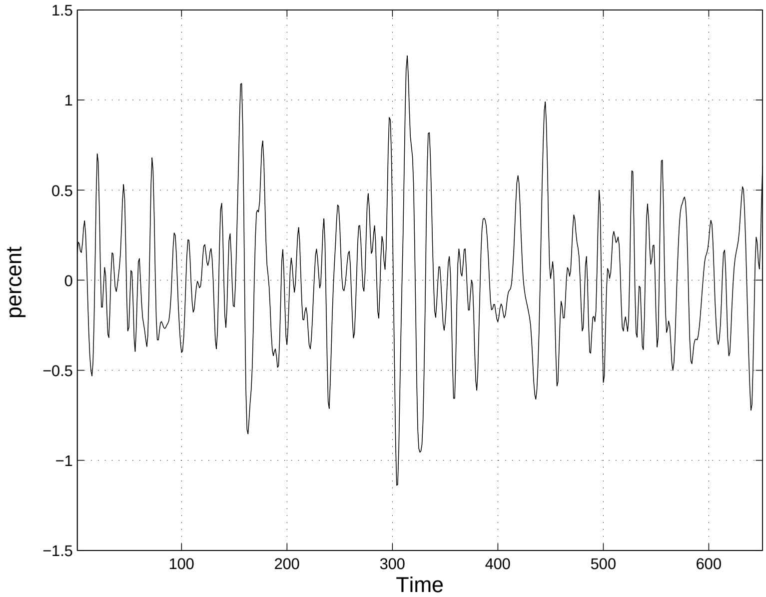


Figure 3: Band-Pass Filtered Aggregate Output.

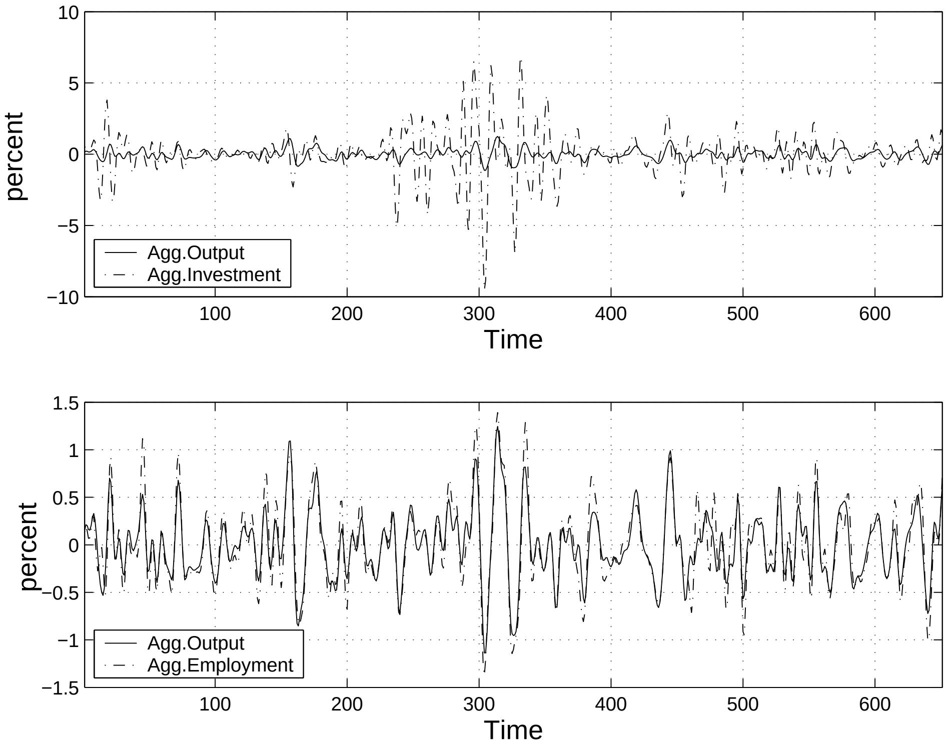


Figure 4: Output, Investment and Employment (Band-Pass Filtered) Time-Series. Top Panel: Output vs. Aggregate Investment. Bottom Panel: Output vs. Aggregate Employment.

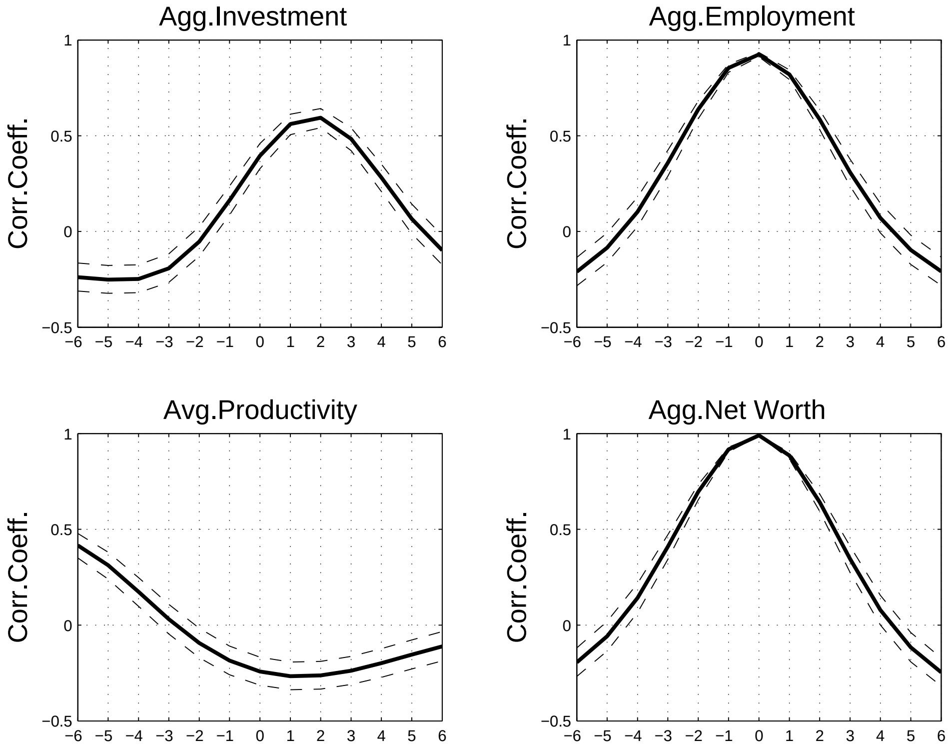


Figure 5: Output Correlation Structure. Cross-correlation between Aggregate Variables at lead zero and output at various leads and lags (solid line). Dashed lines: confidence bands. X-axis: leads of output. Band-Pass Filtered Series.

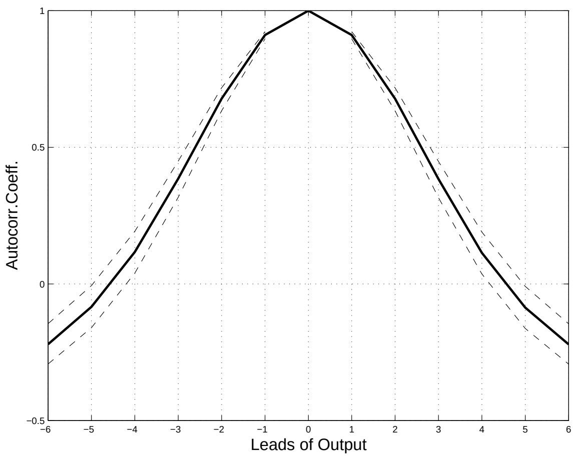


Figure 6: Output Autocorrelation (solid line). Dashed lines: confidence bands. X-axis: leads of output. Band-Pass Filtered Series.

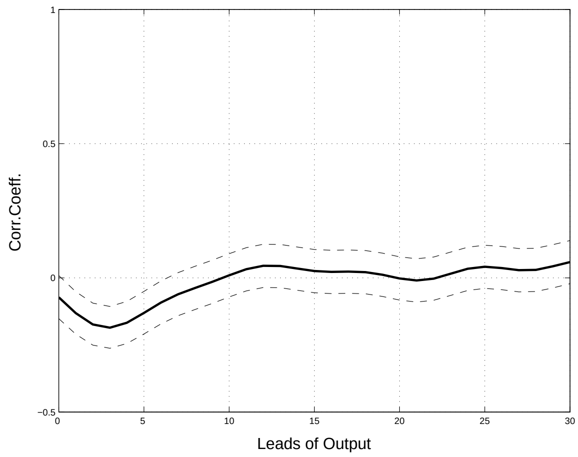


Figure 7: Technological Shocks and Aggregate Output. Cross-correlation between technology shocks at lead zero and output at positive leads (solid line). Dashed lines: confidence bands. X-axis: leads of output. Band-Pass Filtered Series.

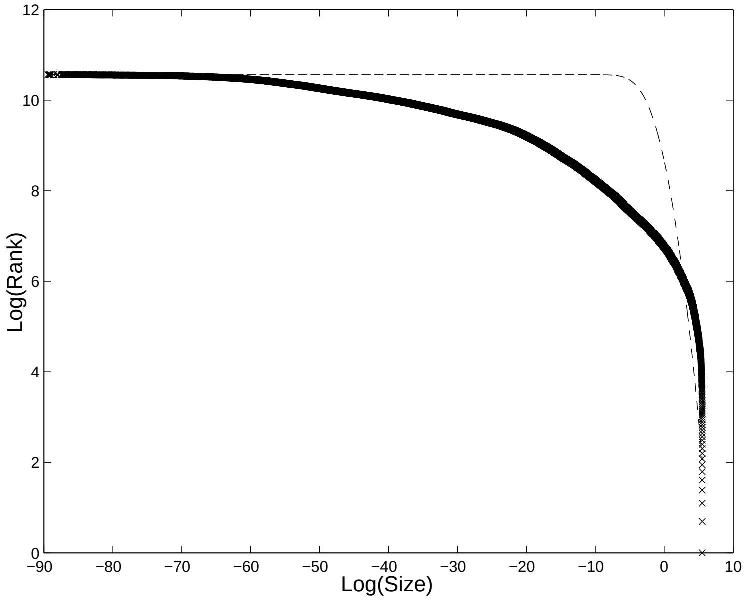


Figure 8: Firm Size Distribution. Pooled Rank-Size Plot (solid line) vs. Log-Normal Fit (dashed line).

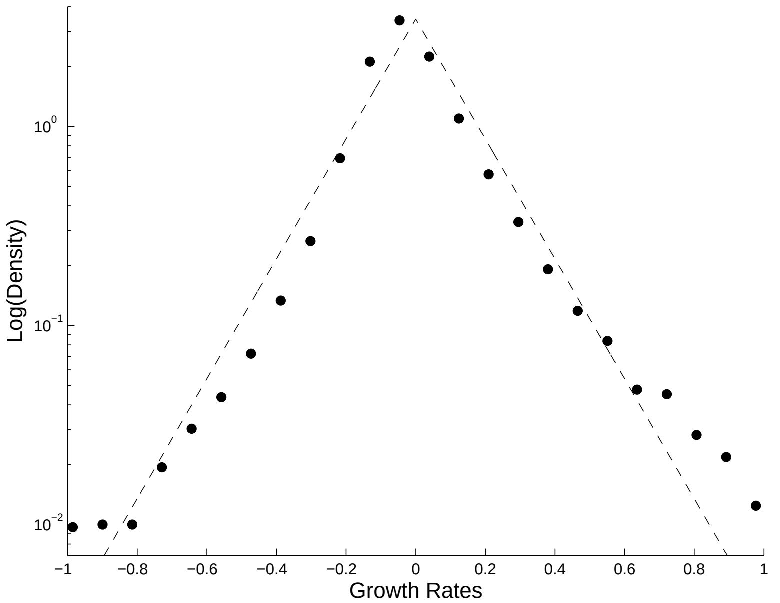


Figure 9: Firm Growth Rate Distribution. Pooled Growth-Rate Density (circles) vs. Laplace Fit (dashed line).

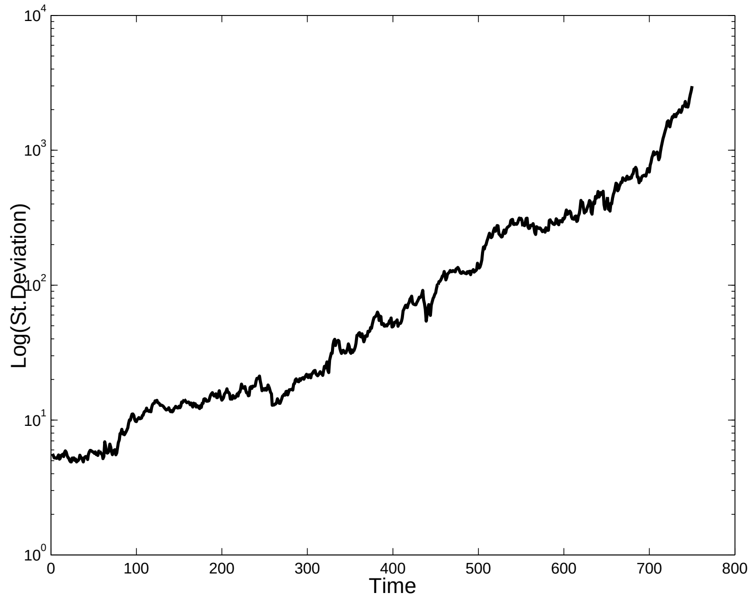


Figure 10: (Log of) Time-Series Productivity Standard Deviation.

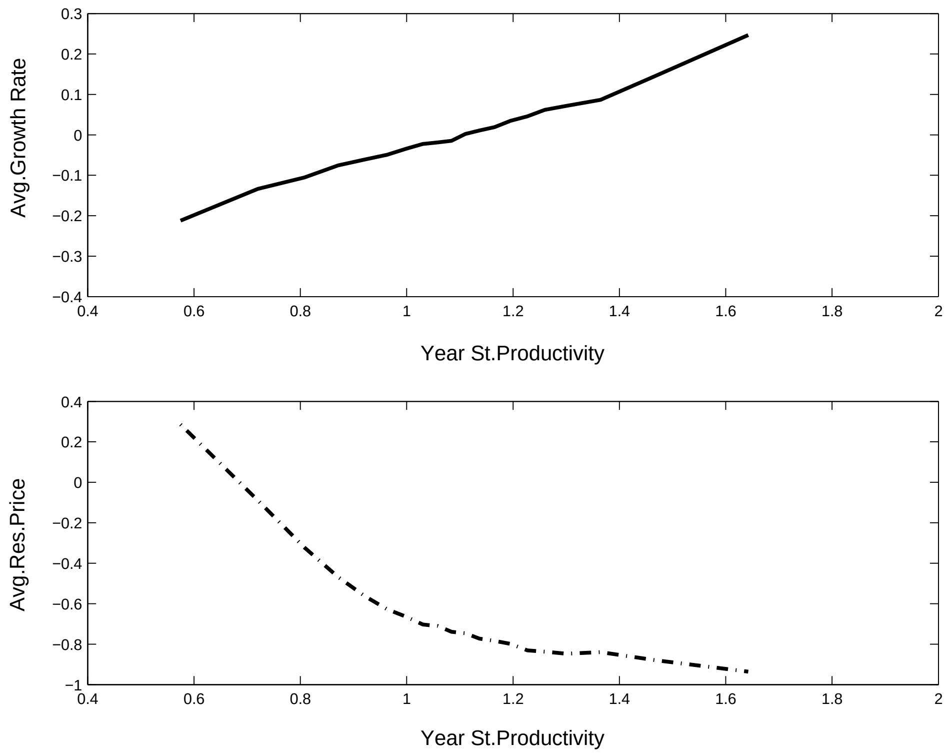


Figure 11: Productivity, Firm Growth and Exit. Top-panel: Within-bin average firm growth rates vs. within-bin average labour productivity. Bottom-Panel: Within-bin average firm reservation prices vs. within-bin average labour productivity. Bins computed as 5%-percentiles.