On the integration of growth and business cycles*

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1 Introduction

This paper presents evidence on the relevance of macro models where endogenous technological change mechanisms are responsible both for long-run growth and the propagation of low-persistence shocks. Section 2 presents evidence on the persistence of macro series. Section 3 presents three different strategies to modeling this persistence. Section 4 presents evidence that supports the view that high and medium term fluctuations are connected. Section 5 provides evidence in favor of models where the persistence of macro series originates from endogenous technological change mechanisms such as endogenous research and development (R&D) and/or endogenous diffusion of technologies. This evidence includes new estimates of the effect of medium term fluctuations of GDP on the speed of diffusion of over 20 specific technologies in the UK. Section 6 presents a simple model of endogenous technological change and diffusion that is consistent with the evidence presented before.

2 On the persistence of macro variables

Most macroeconomic variables are very persistent. Column 1 in Table 1 reports the first order auto-correlation of several macro variables after being filtered using the Hodrick-Prescott (HP) filter. In particular, we focus on a measure of GDP per capita (specifically non-farm private business output per person between the ages 16 and 65), hours worked, total factor productivity (TFP), labor productivity measured by output per hour in the non-farm private business sector (the BLS measure), the relative price of new capital (the Gordon series), private R&D, the

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markup, measured as the difference between the marginal product of labor and the representative household's marginal rate of substitution between consumption and leisure, capacity utilization and a second measure of capacity utilization, namely, electricity consumption divided by the stock of capital. The first-order auto-correlation of each of these variables, with the exception of capacity utilization, is over 0.4 at the annual frequency.

An alternative way to show the persistence of macro time series is to compute the standard deviation of the variables at some medium frequency and to compare it to its standard deviation at the high frequencies. Following Comin and Gertler (2006), I take the medium frequency as representing cycles with periods between 8 and 50 years while the high frequency corresponds to cycles with periods smaller than 8 years. Note that the high frequency is very similar to what remains after applying the HP filter. Columns 2 and 3 in Table 1 presents the standard deviation of the medium and high frequency of various macro series. We can observe how in all the cases (except for capacity utilization), the macro series have more variance at the medium than in the high frequencies. This, again, indicates the significance of very persistent fluctuations.

3 Three views on persistence

There are three ways to accounting for the persistence of macro variables. The first approach is the RBC approach. As shown by Cogley and Nason (1995) the persistence of the RBC models is basically the persistence of their shocks. Hence, the RBC approach consists in introducing the persistence through the persistence of the shocks that cause the fluctuations in the economy.

A second approach proposed by Rotemberg (2005) consists in modeling separately the low and high frequency fluctuations in the macro variables. According to Rotemberg, the high frequency fluctuations in macro variables result from low persistence markup shocks while the medium term fluctuations result from the exogenous diffusion of new technologies. Importantly for Rotemberg, (i) the high and medium frequency realities are orthogonal and (ii) the medium term fluctuations, which generate the persistence of macro variables, are also exogenous.

Comin and Gertler (2006) present a third approach to modeling persistence. Unlike Rotemberg (2005), Comin and Gertler argue that the high and medium term fluctuations in macro variables are part of a same reality. That is, they both result from low persistence shocks which are endogenously propagated into the medium term by the mechanisms of the model. Unlike the RBC approach, the persistence of the macro variables is not assumed but is generated by the propagating power of the

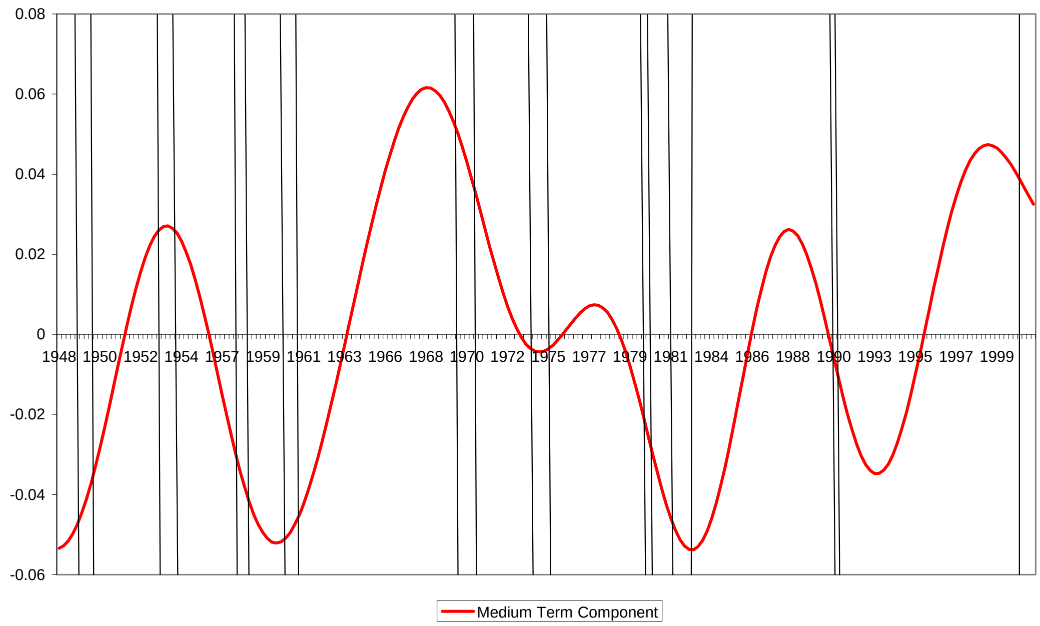

Figure 1: Non-farm Business Output per person 16-65

model.

4 Evidence on the connection between high and medium term components

We start by plotting in Figure 1 the medium term component of the cycle for non-farm business output per person between 16 and 65 along with the NBER business cycle dates. There is sustained upward movement in the medium term component of output over the 1960s. Output reverses course in the 1970s through the early 1980s. There is again a sustained upward movement beginning in the mid 1990s.

On the surface it appears there may be some connection between the high frequency output fluctuations normally associated with the business cycle and the medium frequency oscillations that we have just described. The long U.S. expansion of the 1960s was free of any significant recession. By contrast, the stagnation of the 1970s and early 1980s was accompanied by a number of major recessions, including the two considered the worst of the post-war. In turn, the high growth period over the past ten years has been interrupted by only one recession, considered modest by post-war standards.

If the high and medium term fluctuations in macro variables result from different (and unrelated) forces, we should observe (i) that the variables that drive the high frequency have an insignificant medium term component and (ii) that the variables that drive the medium term have an insignificant high frequency component. According to Rotemberg (2005), the high frequency fluctuations are caused by fluctuations in markups, which capture the efficiency of factor allocation in the economy, while the medium term is driven by the arrival and diffusion of technologies.

Comin and Gertler (2006) provide three variables that measure the efficiency of operation of the economy. These are the total markup (defined above), the Board measure of capacity utilization and electricity consumption per unit of capital. As observed in Table 1, these three variables have very large medium term components. Indeed, in the first two, the medium term component is more variable than the high frequency and in the third it is about the same. Hence, it is hard to argue that the forces that Rotemberg and many others[1] identify as driving high frequency fluctuations, are orthogonal to medium term fluctuations.

A proxy for the intensity of arrival of new technologies is the private R&D expenses deflated by the GDP deflator. Table 1 shows that the high frequency component of this variable is fifty percent more volatile than the high frequency component of output. R&D is not only highly variable in the high frequency, but also commoves strongly with output in the high frequency. As Comin and Gertler show, the contemporaneous correlation of R&D with output at the high frequency is significant with a point estimate of 0.42. Hence, one of the forces that surely drive medium term fluctuations seems to be connected to high frequency fluctuations in output.

Both of these observations constitute, in my opinion, significant challenges for the view that high and medium term fluctuations result from two orthogonal realities.

5 Evidence on the propagation mechanisms

Comin and Gertler (2006) propose two endogenous technology mechanisms by which (non-technological) high frequency shocks are propagated into the medium term. These are pro-cyclical R&D expenses and pro-cyclical speed of diffusion of technologies. For R&D, the contemporaneous relationship with output is similarly positive over the medium term cycle and at the high frequencies alone. Comin and Gertler show

[1] Comin and Gertler (2006) among them.

that when including the medium term frequencies in the analysis the timing of the cross-correlogram changes. In particular, there is a lead of R&D over output. For example, R&D at $t-5$ has correlation of nearly 0.4 with output at t. This lead of R&D over output is absent at the high frequency.

To the extent that new technologies are embodied in new capital and they improve the quality of capital relative to consumption, the relative price of (quality-adjusted) capital should provide a good measure of the rate at which innovations are introduced in the market. When incorporating medium term frequencies to the analysis of the relative price of capital, Comin and Gertler find that the co-movement of the relative price of capital and output is significantly strengthened. At the high frequency there is only a relatively weak negative correlation between annual movements in the relative price of capital (-0.24) and output. This negative relation is clearly stronger over the medium term cycle (-0.56).

Next I provide new evidence on the pro-cyclicality of the speed of diffusion of new technologies.

5.1 The pro-cyclicality of diffusion

The diffusion literature has long recognized the good fit provided by S-shaped curves to the diffusion processes. Mansfield (1961) seminal analysis shows that the logistic is a good first order approximation to very general diffusion patterns. Based on this, I take the logistic as starting point of my analysis of diffusion.

Let m_{jt} be the number of firms that have adopted the j^{th} technology at time t, and let n_{jt} be the total number of firms that potentially can adopt the j^{th} technology. Suppose that

$$\frac{m_{jt}}{n_{jt}} = \frac{1}{1+e^{-\alpha_j-\beta_j t_j}}$$

Simple algebraic manipulation allows us to derive the following expression for the ratio of adopters to non-adopters:

$$r_{j_t} \equiv \ln(m_{jt}/(n_{jt}-m_{jt})) = \alpha_j + \beta_j t_j,$$

where t_j is the time (in years) since the development of the j^{th} technology.

By taking first differences, we can gain further insight on the restrictions imposed by a logistic specification.

$$\triangle r_{j_{t+1}} \equiv \ln(m_{jt+1}/(n_{jt+1}-m_{jt+1})) - \ln(m_{jt}/(n_{jt}-m_{jt})) = \beta_j.$$

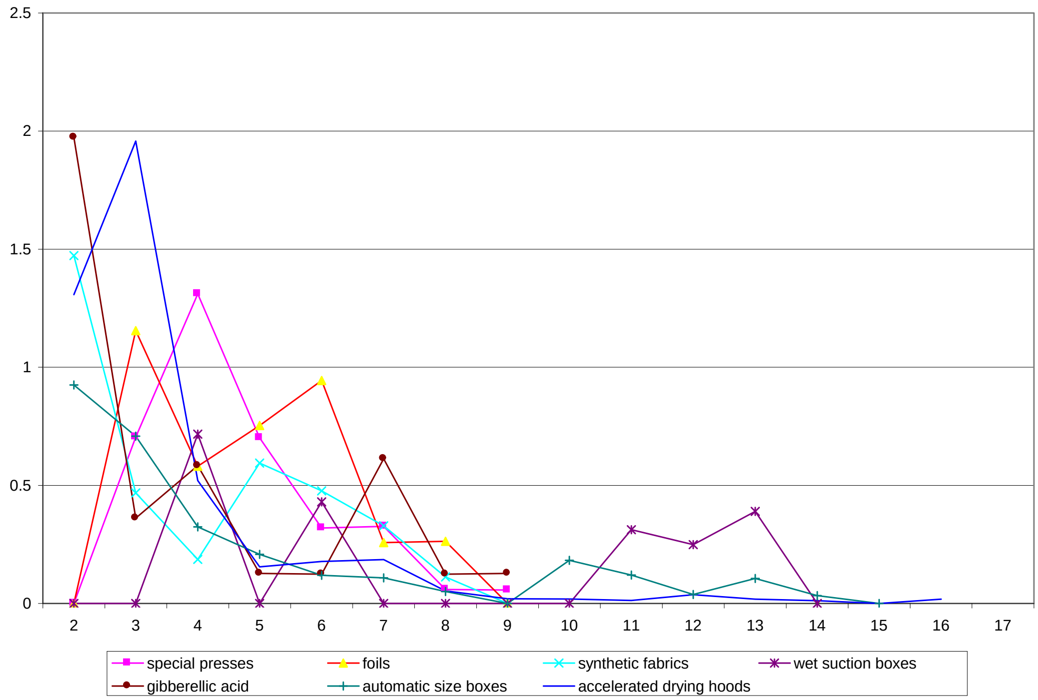

Figure 2: Evolution of $\triangle r_{j_{t+1}}$for seven technologies.

This means that the change in the log ratio of adopters vs. non-adopters is constant over the diffusion process.

To explore this property we focus on a sample of 22 manufacturing technologies diffused in the UK during the post-war period from Davies (1979).[2] Figure 2, plots this ratio for several of the technologies in our sample. It is quite clear from this figure that this implication of the logistic specification is not borne by the data. Many of these technologies display a decline in $\triangle r_{j_{t+1}}$ over time which eventually converges to a constant level. To accommodate this observation, we need to include time-variation in the evolution in $\triangle r_{j_{t+1}}$.

In addition, since I am interested in exploring the relationship between the speed of diffusion and the business cycle, I allow $\triangle r_{j_{t+1}}$ to depend on the medium term cycle British GDP in the UK (y_{2200t}). That

[2] These include special presses, foils, wet suction boxes, gibberellic acid, automatic size boxes, accelerated drying hoods, electrical hygrometers, basic oxygen process, vacuum degassing, vacuum melting, continuous casting, tunnel kilns, process control by computer, tufted carpets, computer typesetting, photo-electrically controlled cutting, shuttleless looms, numerical control printing presses, numerical control turning machines and numerical control turbines.

is the sum of the high and medium term components of the cycle. The view that demand drives the adoption of innovations was first presented by Schmookler (1962). Here, we look for evidence by estimating the following reduced form specification:

$$\triangle r_{j_{t+1}} = \tilde{\beta}_j + \tilde{\gamma}_2 t_j + \tilde{\gamma}_3 t_j^2 + \varrho y_{2200t}.$$

This specification yields the following law of motion for the ratio r_j :

$$r_j = \alpha_j + \beta_j t_j + \gamma_2 t_j^2 + \gamma_3 t_j^3 + \varrho c y_{2200jt} \tag{1}$$

where cy_{2200jt} is the cumulative medium term business cycle component of UK GDP at year t since technology j was introduced. Table 2 displays the estimates of the average β_j across technologies (denoted as β), γ_2, γ_3 and ϱ together with their 95 percent confidence intervals.

I want to emphasize two conclusions from Table 2. First, the estimates of γ_2 and γ_3 are statistically significant. Hence, as suggested by Figure 2, the technologies in our sample do not follow a logistic diffusion pattern. There is a second reason why the logistic is not a good characterization of the diffusion of our technologies. Namely, that the medium term cycle is significantly related to the speed of diffusion of technologies (i.e. $\varrho > 0$). One interpretation of this fact is that in booms agents have more incentives to adopt new technologies, hence the acceleration in the speed of diffusion.

Regardless of whether we accept this plausible interpretation of the correlation reported in Table 2, it is important to emphasize that this effect is quantitatively strong. Figure 3 shows this for one particular technology, numerical control turning machines, that constitutes a representative case of our sample of 22 technologies. Specifically, in the figure we can see the diffusion path of numerical control turning machines in the UK (black solid line) together with the diffusion path predicted by equation (1) (line with triangles), the evolution of cy_{2200j} (line with stars), and the diffusion path predicted by equation (1) when the effect of the cycle on diffusion is ignored (line with squares). Ignoring the business cycle component in equation (1) has important consequences. Eight years after the introduction of of numerical control turning machines in the UK only seven percent of potential adopters had adopted the technology. The model without the cycle component predicts that over 30 percent of potential adopters should be using the technology. One explanation for the slow diffusion of numerical control turning machines in the UK is that at that point it had been for eight consecutive years below trend. As a result producers faced a low demand and had few incentives to invest in the new technology. Once this effect is taken

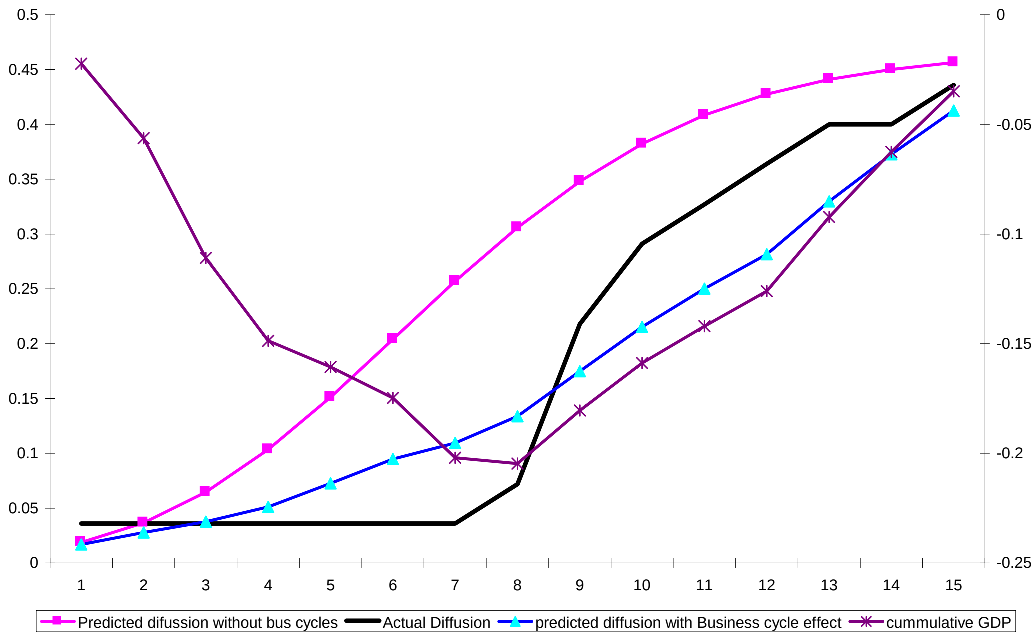

Figure 3: Diffusion of Numerical Control Turning Machines in the UK

into account, equation (1) predicts that after eight years the diffusion of numerical control turning machines in the UK should have been 13 percent, much closer to the actual seven percent.

6 How to model these mechanisms

I conclude this paper by writing a simple model of the propagation mechanisms described above.

Final Goods Firms:

Final output is produced competitively according to

$$Y_t = \left((U_t K_t)^{\alpha} L_t^{1-\alpha} \right)^{\gamma} M_t^{1-\gamma} \tag{2}$$

where U_t denotes the intensity of utilization of capital, K_t, L_t denotes hours worked and M_t denotes the materials used in production. Utilization comes at the cost of a faster depreciation of capital. Materials are produced competitively combining differentiated intermediate goods according to

$$M_t = \left(\int_0^{A_t} x_{it}^{1/\theta} \right)^{\theta}$$

where $\theta > 1$ will also be the markup charged by the producer of intermediate good i. It takes one unit of final output to produce one unit of any intermediate good. A_t denotes the number of intermediate goods available for production at time t.

Adoption

Intermediate goods are invented and then are adopted for production. We first characterize the adoption process conditional on the available set of technologies. We then describe the research and development process that leads to new technologies.

Our goal is to introduce an adoption process that is pro-cyclical in equilibrium, consistent with the evidence presented in Section 5. At the same time, we would like to capture the notion that the adoption process takes time. Finally, we would like to capture these aggregate patterns of adoption in a way that minimizes complications from aggregation. In particular, we would like to avoid having to keep track for every available technology of the fractions of firms that have and have not adopted it.

These considerations lead us to the following formulation: at each point in time a continuum of unexploited technologies is available to adopt. At each period a fraction of the available new technologies become usable. Whether a technology becomes usable is a random draw with success probably λ_t. Once a technology is usable, all firms are able to employ it immediately. Note that under this setup there is slow diffusion of new technologies on average (as they are slow on average to become usable) but aggregation is simple as once a technology is in use, all firms have it. We will obtain a pro-cyclical adoption behavior by endogenizing the probability λ_t that a new technology becomes usable and making it increasing in the amount of resources devoted to adoption at the firm level.

More formally, let Z_t be the stock of invented technologies. Then

$$A_t = \lambda_t[Z_{t-1} - A_{t-1}] + \phi A_{t-1} \tag{3}$$

with $0 < \phi < 1$ representing the probability that the technology has not become obsolete in one period, $0 < \lambda_t < 1$ and

$$\lambda_t = \lambda(\Gamma_t x_t)$$

with $\lambda' > 0$, $\lambda'' < 0$, where the time-varying slope parameter Γ_t^z is exogenous to the adopter and x_t are the resources devoted to adopting a technology in time t.[3]

[3] The term Γ_t is necessary to ensure the existence of a balanced growth path. On reasonale way to model it consists in making it inversely proportional to the (wholesale) value of capital over the stock on developed technologies. This is the approach followed by Comin and Gertler (2006).

The value to the adopter of successfully bringing a new technology into use, v_t, is given by the present value of profits from operating the technology. Profits each period π_t arise from the fact that the producer of the new good is a monopolistic competitor. Accordingly, given that R_{t+1} is the one period discount rate between $t+1$ and t, we can express, v_t, as

$$v_t = \pi_t + (1-\phi)E_t\left[\frac{v_{t+1}}{R_{t+1}}\right]. \tag{4}$$

If an adopter is unsuccessful in the current period, he may try again in the subsequent period to make the technology usable. Let w_t be the value of acquiring an innovation that has not yet been adopted. w_t is given by

$$w_t = \max_{x_t} -x_t + (1-\phi)E_t\left[\frac{[\lambda\left(\Gamma_t x_t\right)v_{t+1} + \left(1-\lambda\left(\Gamma_t x_t\right)\right)w_{t+1}]}{R_{t+1}}\right], \tag{5}$$

At the margin, adopters determine how much to spend in adopting a technology by equalizing the marginal cost and the expected marginal benefit from adoption:

$$1 = E_t\left[R_{t+1}^{-1}\Gamma_t(1-\phi)\lambda'\left(\Gamma_t x_t\right)\left(v_{t+1} - w_{t+1}\right)\right] \tag{6}$$

Innovation

Now that we have solved for the adoption process given the number of available technologies, we need to derive the equations that determine the number of available innovations, Z_t.

New technologies are developed through R&D. Each innovator, indexed by p, faces the following technology to develop new intermediate goods:

$$Z_{t+1}\left(p\right) - Z_t\left(p\right) = \varphi_t S_t(p) - \phi Z_t(p) \tag{7}$$

where $Z_t(p)$ denotes the stock of (non-obsolete) intermediate goods she has developed up to time t, $S_t(p)$ is the number of units of output she devotes to R&D and φ_t is the productivity of the R&D as perceived by the individual innovator. As in Romer (1990), the linear formulation permits a simple decentralization of the innovation process. We differ from Romer, however, by having the innovation technology use as input a final good composite of capital and labor, as opposed to just labor.

We assume that φ_t depends on the aggregate values of the stock of innovations, Z_t, the wholesale value of the capital stock $P_t^I K_t$, and research and development S_t, and the stock of innovations as follows:

$$\varphi_t = \chi Z_t (\frac{S_t}{P_t^I K_t})^{\rho-1} (P_t^I K_t)^{-1} \tag{8}$$

with $0 < \rho \leq 1$ and where χ is a scale parameter. As with Romer, there is a positive spillover of the current stock of innovations on the creation of new products, i.e. φ_t increases linearly in Z_t. The formulation differs from Romer in two respects, however. First, the productivity of the R&D technology is scaled by the wholesale value of the capital stock (i.e. $P_t^I K_t$). Intuitively, cost of producing new inventions rises proportionately over time with the scale of economic activity, as measured by the value of the capital stock. This scaling factor ensures that the equilibrium growth rate of new projects is stationary. Secondly, we introduce an aggregate congestion to R&D conducted through the factor $(S_t/P_t^I K_t)^{\rho-1}$. This permits us flexibility in calibrating the impact of R&D on innovation in a way that is consistent with the evidence.

The linearity of the R&D technology as perceived by the individual researchers together with a free entry assumption implies that each new product developer p must break even. As a result, the resources invested in R&D by the p^{th} innovator satisfy the following arbitrage condition:

$$E_t \left[\frac{w_{t+1}}{R_{t+1}} \right] - 1/\varphi_t = 0,$$

where the first side is the discounted marginal benefit from an innovation and the left side is the marginal cost in units of final output.

In equilibrium, the law of motion for the number of intermediate goods, Z_t, is

$$Z_{t+1} - Z_t = Z_t \chi (S_t/P_t^I K_t)^{\rho} - \phi Z_t$$

Households

There is a representative household that consumes, supplies labor and saves. It may save by either accumulating capital or lending to innovators. The household also has equity claims in all monopolistically competitive firms. It makes one period loans to innovators and also rents capital that it has accumulated directly to firms.

Let C_t be consumption and μ_t^w a preference shifter. Then the household maximizes the present discounted utility as given by the following expression:

$$E_t \sum_{i=0}^{\infty} \beta^{t+i} \left[\ln C_t - \mu_t^w \frac{(L_t)^{\zeta+1}}{\zeta+1} \right] \tag{9}$$

Fluctuations may be introduced by shocking the parameter μ_t^w. This parameter can be interpreted as a preference parameter but also as a measure of the distortions in the labor market such as labor market frictions, labor income taxes, etc. It is important to stress that my interest here is more on the propagation mechanisms than on the specific shock that drives them.

Intuition

This model is consistent with the facts described in Section 5. Next, we describe intuitively how the model can account for them. A positive shock to μ^w causes a contraction in labor supply. This causes a recession which reduces aggregate output. This reduction in output, compresses the demand for intermediate goods and as a result there is a decline in their expected profits. This reduces the value of firms that sell adopted technologies leading to a decline in the equilibrium intensity of technology adoption and on the number of adopted technologies for a given number of available intermediate goods. In addition, the decline in the value of adopted technologies also leads to a decline in the value of not-adopted technologies. This causes a decline in the private return to R&D and as a result in the number of intermediate goods developed in equilibrium.

It is interesting to stress that, since the adoption and innovation mechanisms affect the stock of technologies, temporary fluctuations in the intensity of adoption or innovation are going to lead to very persistent effects on the stock of available technologies and on productivity. Furthermore, the persistence added by endogenous adoption and innovation, amplifies the fluctuations in the value of adopted technologies and this amplifies the effect of the shock. Comin and Gertler (2006) provide a quantitative evaluation of these mechanisms.

7 Conclusions

This paper has described an approach to integrate growth and business cycles. Namely, by changing the workhorse growth model used to conduct business cycle analysis from the Neoclassical growth model to a model of endogenous technological change. This innovation introduces a mechanism that generates endogenously the persistence observed in the data as well as a theory of endogenous TFP at the high and medium term frequencies. It also introduces an explanation for the observed relationship between fluctuations ate high and medium term frequencies.

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TABLE 1 -- Persistence of Macro Variables

	First-order autocorrelation of HP-filtered series	Standard Deviation of High frequency component	Standard Deviation of Medium term component
Non-Farm Business output per person with 16-65	0.47	0.022	0.032
Labor Productivity	0.48	0.01	0.021
Hours worked	0.40	0.016	0.021
TFP	0.45	0.012	0.02
Investment	0.57	0.0488	0.082
Consumption	0.55	0.012	0.021
R&D	0.52	0.034	0.059
Markup	0.47	0.024	0.036
Relative price of capital (quality adjusted)	0.54	0.014	0.041
Capacity utilization	0.34	0.0308	0.0296
Electricity consumption over capital	0.40	0.021	0.05

TABLE 2 -- Estimates of Diffusion Equation

β	0.8 (0.47 , 1.12)
γ_2	-0.05 (-0.08 , -0.02)
γ_3	0.0011 (0 , 0.0023)
ϱ	5.12 (1.9 , 8.34)

Note: 95 percent confidence interval in parenthesis