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RESEARCH ARTICLE

Learning by doing, organizational forgetting, and the business cycle

Anelí Bongers

Department of Economics, University of Malaga, Campus El Ejido, Malaga, Spain

Correspondence
Anelí Bongers, Department of Economics, University of Malaga, Campus El Ejido s/n 29013, Malaga, Spain.
Email: abongers@uma.es

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Abstract

This paper supplements a learning-by-doing real business cycle model with endogenous organizational forgetting. Empirical evidence shows that the accumulated experience decay rate is not constant over the business cycle, but that forgetting is a function of economic activity. Learning reinforces the effects of productivity shocks, and organizational forgetting exacerbates their impact and increases their persistence. This is of particular interest when a negative productivity shock hits the economy, as the increasing speed of forgetting aggravates the negative shock and delays recovery.

KEYWORDS
business cycle, learning by doing, organizational forgetting

JEL CLASSIFICATION
E22, E24, E32

1 | INTRODUCTION

This paper studies the implications of learning by doing and organizational forgetting for the business cycle. Although the consequences of learning by doing are well known and have been widely incorporated into macroeconomic models (seminal paper by Arrow, 1962), the implications of organizational forgetting have been considered only at a microeconomic level, and no attempts have been made to study the connections between organizational forgetting and business cycle fluctuations at a macroeconomic level. Organizational forgetting is not simply a constant experience decay rate; empirical evidence at the firm level suggests that it is significantly affected by fluctuations in production. Empirical literature estimating organizational forgetting at the industry level shows that losses in experience can be dramatic when production is reduced (Argote et al., 1990; Benkard, 2000; David and Brachet, 2011). Benkard (2000) noted that "at a macroeconomic level, organizational forgetting implies that recessions may lead to a reduction in productivity that lasts beyond the rebound output." Therefore, organizational forgetting can be a key factor affecting the business cycle and, in particular, in explaining the size and duration of recessions.

This paper develops a simple real business cycle (RBC) model with learning by doing and endogenous organizational forgetting. learning by doing is modeled as a function of accumulated experience that affects aggregated productivity. Experience can be defined as a function of accumulated gross investment Arrow (1962) or as a function of accumulated output (Sheshinski, 1967; Wright, 1936). Forgetting is modeled as the decay process of accumulated experiences where the forgetting decay rate is a function of economic activity. Empirical evidence at the microeconomic level suggests that forgetting can be produced by labor turnover, periods of inactivity, and failure to institutionalize tacit knowledge (Besanko et al., 2010; Thompson, 2007). At an aggregate level, we find that whereas learning reinforces the effects of productivity shocks, organizational forgetting increases the persistence of shocks, reducing the experience accumulation decay rate in good economic times but increasing forgetting during bad ones. The results presented here confirm Benkard's (2000) argument that organizational forgetting increases the size and persistence of recessions and delays recovery.

Following the seminal contribution by Kydland and Prescott (1982), RBC models have proven very useful in explaining fluctuations in economic activity. The original RBC formulation has been extended in a number of ways to increase its explanatory power and accommodate a richer economic environment. Cogley and Nason (1995) show that the RBC model lacks internal propagation mechanisms, and Rebelo (2005) identifies better modeling of labor markets as an important open question in the literature. The results in this paper help to address both these issues. Other internal propagation mechanisms previously considered in the modeling of labor markets in business cycle models include labor hoarding (Burnside et al., 1993), learning by doing Chang et al. (2002), and overtime labor (Madeira, 2014, 2018).

The structure of the rest of the paper is as follows. Section 2 briefly reviews the concepts of learning by doing and organizational forgetting. Section 3 presents an RBC model extended by incorporating learning by doing and organizational forgetting. Section 4 presents the calibration of the model and the quantitative results from simulating a productivity shock. Finally, Section 5 concludes.

2 | LEARNING BY DOING AND ORGANIZATIONAL FORGETTING

Although the macroeconomic effects of learning by doing are well known, the impact of experience loss due to fluctuations in economic activity as a factor explaining the dynamics of the economy over the business cycle has been neglected in the literature. As Besanko et al. (2010) indicate, learning by doing and organizational forgetting are distinct economic forces. The basic idea behind learning by doing is simple. Workers and organizations "learn" how to perform a repeated task and, consequently, labor efficiency depends on the number of previously produced units. The learning process can take place at an individual worker level (labor learning), at a plant level (organizational learning; see Hirschmann, 1964), or at an aggregate-economy level (Arrow, 1962). The implications of learning by doing have been extensively studied through the empirical estimation of the so-called learning curves, initially developed by Wright (1936) to estimate aircraft production costs prior to World War II. This model has been applied to a large variety of industries and has thus become a key instrument for strategic management. Here, we adopt a macroeconomic perspective following the seminal work by Arrow (1962), where learning can be modeled as an additional component of total factor productivity (TFP) governing the aggregate productivity of the economy.

Organizational forgetting is a relatively recent concept, although it is related to the concept of learning by doing, which was introduced by Argote et al. (1990). Before that, learning was considered an "irreversible" process, appearing in every act of investment and continuing thereafter. Although the standard learning curve approach assumes that learning is cumulative and constant over time, Argote et al. (1990) discovered that knowledge acquired by learning by doing may depreciate rapidly. This depreciation in experience is not constant, but empirical evidence at the firm level shows that it varies greatly when changes in production occur. Depreciation of experience can be easily understood in the case of interruptions in production: after a period of interruption, when production is restarted, productivity is observed to be inferior to that of previous periods (Hirsch, 1956). This is the case, for instance, in a strike or the cessation of production after a negative shock to demand. Cabral and Riordan (1994) study the strategic implications of the learning curve in a differentiated duopoly and find that learning creates incentives for predatory pricing and may drive rivals from the market, reducing competition, and increasing market dominance. Besanko et al. (2010) extended the learning-by-doing model of Cabral and Riordan (1994) by including organizational forgetting. They illustrated that learning by doing and organizational forgetting are distinct economic forces and empirically important for industry dynamics and that forgetting can offset the effects of learning on pricing behavior by increasing competition. Here, we adopt a macroeconomic perspective and extend a learning-by-doing RBC model by considering endogenous forgetting.

3 | THE MODEL

This section presents a learning-by-doing RBC model extended with organizational forgetting. The aggregate production function of the economy is

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}, \tag{1}$$

where production of the final output, Y_t, requires labor services, L_t, and capital, K_t, where α is the capital share of output, and A_t is a measure of TFP or neutral technology. We consider that experience enters in the aggregate production function as a positive externality affecting TFP:

$$A_t = A(S_t, t), \tag{2}$$

where S_t represents accumulated experience and t is time. Following Irwin and Klenow (1994), A_t can be defined as

$$A_t = A_0 e^{\gamma t} S_t^{\theta}, \tag{3}$$

where A_0, γ, and θ are constants. That is, productivity depends on accumulated experience (interpreted as a type of dynamic returns to scale) and on calendar time, representing the standard measure of exogenous neutral or Hicks technical change. The term S_t^{θ} is a positive externality depending on accumulated experience, S_t, where θ is a parameter representing learning.

Following Wright (1936) and Sheshinski (1967), experience accumulation is a function of production. Cooper and Johri (2002) and Clarke (2006) use a three-factor production function where organization capital is accumulated with a log-linear technology depending on the output. Here, we assume that learning is a function of output and organizational forgetting, F_t:

$$S_{t+1} = S_t + \phi Y_t - F_t, \tag{4}$$

where organizational forgetting is defined as $F_t = \delta_{s,t} S_t$, where $\delta_{s,t}$ is the experience decay function representing organizational forgetting, where it is assumed to be a function of economic activity, represented as the deviations of output from the steady state,

$$\delta_{s,t} = \delta_{s,0} - \delta_{s,1}(Y_t - \overline{Y}), \tag{5}$$

where $0 < \delta_{s,0} < 1$ is the steady-state value of the experience decay rate, $\delta_{s,1} > 0$ is a parameter representing how forgetting changes in response to changes in production, and $\overline{Y}$ is the steady-state output.[1]

We consider a representative household whose preferences are represented by the following instantaneous utility function:

$$U(C, L) = \omega \ln C_t + (1 - \omega) \ln(1 - L_t), \tag{6}$$

where C_t is consumption and $1 - L_t$ is leisure where total available time has been normalized to 1, and L_t denotes the fraction of time devoted to working activities. The parameter ω $(0 < \omega < 1)$ represents the weight of consumption in the household's utility function. Household's budget constraint is given by

$$C_t + I_t = Y_t, \tag{7}$$

where I_t is an investment. Capital stock accumulation is given by

$$K_t = (1 - \delta_k)K_t + I_t, \tag{8}$$

where δ_K is the capital depreciation rate. Finally, the neutral technological change, A_t, is assumed to follow the first-order autoregressive process given by

$$\ln A_t = (1 - \rho_A) \ln \overline{A} + \rho_A \ln A_{t-1} + \varepsilon_t, \tag{9}$$

where $\overline{A} > 0$ is steady-state TFP, $\rho_A < 1$ is the persistence parameter, and $\varepsilon_t \sim N(0, \sigma_A^2)$ is an independently and identically distributed random variable.

Experience represents a positive externality, as accumulated experience positively affects productivity. This represents a market distortion, and, hence, a decentralized economy cannot reach the first best outcome. Given the existence of this positive externality, we consider a centralized economy where a central planner maximizes social welfare, that is, the expected sum of discount

[1] Alternatively, learning by doing can be assumed a function of investment, $S_{t+1} = (1 - \delta_{s,t})S_t + I_t$ as in Arrow (1962), and organizational forgetting can be defined as $\delta_{s,t} = \delta_{s,0} - \delta_{s,1}(I_t/I_{t-1} - 1)$, where forgetting accelerates when investment is below its steady state.

utility, by choosing optimal values for consumption, capital stock, labor, and experience. In a centralized economy, the externality represented by experience is internalized by the social planner, and, hence, it obtains the first best outcome. We choose a centralized economy in order to compare the results of the model with endogenous organizational forgetting with the results derived from the standard RBC model and an RBC model with learning by doing. In the case of a decentralized economy, the externality is not considered by economic agents in taking optimal economic decisions and the first best outcome cannot be reached (except in the case of the standard RBC model where there is no externality and both the centralized and the decentralized solutions are equal and first best outcomes), and, therefore, the three models are not directly comparable. The central planner maximization problem can be defined as the following Lagrange auxiliary function:

$$\max_{\{C_t,L_t,K_t,S_t\}_{t=0}^{\infty}} \mathcal{L} = E_0 \sum_{t=0}^{\infty} \beta^t \{\omega \ln C_t + (1-\omega)\ln(1-L_t)\} \tag{10}$$
$$-\lambda_t \left(C_t + K_{t+1} - (1-\delta_k)K_t - A_t S_t^{\theta} K_t^{\alpha} L_t^{1-\alpha}\right)$$
$$-\zeta\left(S_{t+1} - \left(1 - \left[\delta_{s,0} - \delta_{s,1}\left(A_t S_t^{\theta} K_t^{\alpha} L_t^{1-\alpha} - \overline{Y}\right)\right]\right)S_t - \phi A_t S_t^{\theta} K_t^{\alpha} L_t^{1-\alpha}\right),$$

where β is the discount factor, E_0 is the conditional expectation operator evaluated at time 0, and λ_t, ζ_t are associated Lagrange multipliers. From the first-order conditions, we obtain the following equilibrium expressions corresponding to the central planner's maximization problem:

$$\frac{\omega}{C_t} - \frac{\beta\omega(1-\delta_k)}{E_t C_{t+1}} = \frac{\alpha\beta E_t(1-\omega)L_{t+1}}{E_t(1-L_{t+1})(1-\alpha)K_{t+1}} \tag{11}$$

and

$$\frac{(1-\omega)L_t}{(1-L_t)\left[\phi + \delta_{s,1}S_t\right](1-\alpha)Y_t} - \frac{\omega}{\left[\phi + \delta_{s,1}S_t\right]C_t} - \frac{\omega\beta}{C_{t+1}}\theta E_t \frac{Y_{t+1}}{S_{t+1}}$$
$$= \left[\frac{\beta(1-\omega)E_t L_{t+1}}{E_t(1-L_{t+1})\left[\phi + \delta_{s,1}S_{t+1}\right](1-\alpha)E_t Y_{t+1}} - \frac{\beta\omega}{\left[\phi + \delta_{s,1}S_{t+1}\right]E_t C_{t+1}}\right]$$
$$\left[1 - \left[\delta_{s,0} - \delta_{s,1}((\theta+1)E_t Y_{t+1} - \overline{Y})\right] + \theta E_t \frac{Y_{t+1}}{S_{t+1}}\right]. \tag{12}$$

Equilibrium conditions (11) and (12) are necessary conditions for an optimal solution. These conditions, along with the accumulation equations, the technology, resource constraint, and transversality conditions for physical capital and experience, fully characterize the equilibrium of the model. Equilibrium condition (11) represents the optimal consumption-saving decision (Euler equation for the accumulation of physical capital), which is the same as that in the standard learning-by-doing model with a constant depreciation rate for the experience. Contrary to the standard RBC model, where the optimal consumption path is determined by the returns to physical capital, in this economy, the optimal consumption path also depends on labor given the effects of experience on productivity. Equilibrium condition (12) represents the optimal labor supply. Whereas in the standard RBC this is a static equation, when learning and forgetting are considered, this equilibrium condition turns out into a more complex dynamic equation, where experience and forgetting also determine optimal labor to maximize social welfare, accounting for the effects of current labor input on future experience.

4 | RESULTS

This section investigates the response of the economy to an aggregate productivity shock and compares the results with the standard RBC model and with an RBC model with learning by doing. We simulate a negative productivity shock to the calibrated economy model to better illustrate the implications of organizational forgetting for the recovery of the economy to a steady state following the shock.

4.1 | Calibration

We build an artificial economy calibrating the parameters of the model using standard values in the RBC literature for the U.S. economy. The discount factor is fixed to be $\beta = 0.985$, which represents a value standard in the literature when considering quarterly data. This value is selected to match a value for the real interest rate net of depreciation of 4%, in order to produce a capital output ratio of 3.5 (see Dixon & Jorgenson, 2013). The capital income's share of output, α, is set equal to 0.35. This share is consistent with those provided by Gollin (2002), who estimated that the capital income share should be within the [0.2, 0.4] interval in a wide set of countries under consideration. For the United States, he reported a range from 0.257 to 0.396. The physical capital depreciation rate is fixed at $\delta_K = 0.025$ (see, for instance, Smets & Wouters, 2003). The parameter ω is calibrated to produce a fraction of hours worked over total available discretionary time (which is also normalized to 1) of 0.33, a figure obtained from data of the Bureau of Labor Statistic (BLS; www.bls.gov, Table B-2) and assuming a total available discretionary time of six days by week times 52 weeks by year times 16 h by day. The resulting calibrated value is $\omega = 0.45$. The parameters driving the stochastic process for TFP are $\rho_A = 0.95$ and $\sigma_A = 0.01$, as in Kydland and Prescott (1982). Technological progress is assumed to be zero, and therefore, $\gamma = 0$, as we focus on the business cycle.

The model includes three new parameters: $(\theta, \delta_{s,0}, \delta_{s,1})$ the learning rate and the parameters governing organizational forgetting. These values are chosen using empirical estimates for learning rates and organizational forgetting. When $\theta = 0$, this is the standard case of no learning and no forgetting. When $\delta_{s,1} = 0$, forgetting is exogenous and independent of output. The empirical literature estimates a learning rate of around 20% for a number of industries. This is the case for the aircraft industry (Alchian, 1963; Benkard, 2000, 2004), the shipbuilding industry (Thompson, 2007; Thornton & Thompson, 2001), the power generation industry (Joskow & Rozansky, 1979; Zimmerman, 1982), the automobile industry (Levitt et al., 2013), semiconductors (Irwin and Klenow, 1994), etc. Liberty shipbuilders are the most studied case. The empirical literature has extended the analysis of learning by including organizational forgetting to explain how observed costs increase during certain periods. Argote et al. (1990) use the Liberty dataset to study the dynamics of learning and its depreciation and show that the measured learning in terms of accumulated output significantly overstates the persistence of learning. They calculate that from the stock of knowledge at the beginning of 1 year, only 3.2% would remain 1 year later; thus, knowledge depreciates rapidly. Thompson (2007) arrived at similar results. Argote et al. (1990) and Benkard (2000, 2004) estimate learning and forgetting in the production of the Lockheed L-1001

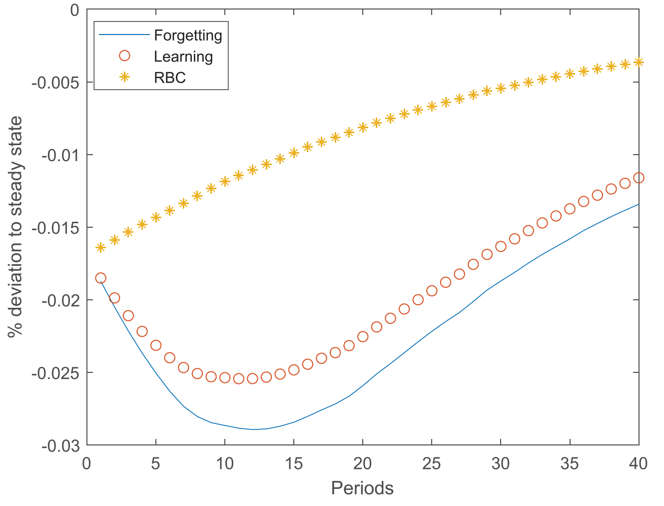

FIGURE 1 Impulse-response of output to a negative productivity shock. RBC: standard real business cycle model. Learning: the RBC model with learning by doing. Forgetting: the RBC model with learning and forgetting [Colour figure can be viewed at wileyonlinelibrary.com]

aircraft, a program characterized by wide variations in the rate of output over time. Production costs reported by Lockheed suggested that depreciation of learning was an important factor and that costs rose when the rate of production fell. Bongers (2017) finds that simultaneous production of different versions of the same aircraft accelerates forgetting. Darr et al. (1995) study the depreciation of knowledge in pizza stores and conclude that learning by doing depreciates rapidly in these stores. David and Brachet (2011) study organizational learning and forgetting for a dataset of ambulance companies and find that 62% of organizational forgetting is attributable to labor force turnover. In sum, empirical literature suggests that forgetting is quantitatively important and very sensitive to production activity conditions. Given the empirical evidence described above, we use $\theta = 0.2$, $\delta_{e,0} = 0.1$, and $\delta_{e,1} = 0.02$.

4.2 | Negative aggregate productivity shock

We study the effects of an aggregate productivity shock and compare the results with a standard RBC model without learning and forgetting. Figure 1 plots the simulated impulse-response of output to a negative TFP shock for three cases: the standard model RBC model, a learning model with a constant decay rate, and the model with both learning and forgetting as functions of output. Figure 2 plots the response of productivity. We simulate a negative TFP shock to highlight the implications in the case of a recession. When both learning and forgetting are considered, we observe a hump-shaped response of output. Forgetting amplifies the effects of the shocks, increasing the size and persistence of output deviation from the steady state. Forgetting also magnifies the loss in productivity following a negative shock, with further declines in productivity once productivity starts to recover in the learning and the standard RBC models. As the forgetting parameter increases, the response of output and productivity deviates from the standard learning model, increasing the size, and the persistence of the shock and delaying recovery to the steady state, as more experience is lost.

Table 1 compares moments for output, labor, and productivity observed from U.S. data over the business cycle with those simulated from the three alternative models. Data moments (standard deviation and the correlation coefficients) were calculated from detrended quarterly series for output, labor, and productivity taken from the Bureau of Economic Analysis (BEA, www.bea.gov) for

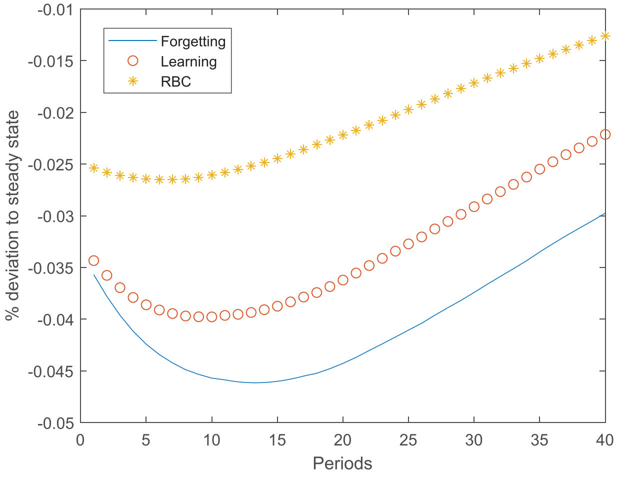

FIGURE 2 Impulse-response of productivity to a negative productivity shock. RBC: standard real business cycle model. Learning: the RBC model with learning by doing. Forgetting: the RBC model with learning and forgetting [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Cyclical properties of the United States and model-generated data

	Data	Standard RBC	Learning	Forgetting
σ_l/σ_y	0.73	0.27	0.24	0.28
σ_{pr}/σ_y	0.56	0.83	0.87	0.76
σ_l/σ_{pr}	1.29	0.32	0.28	0.37
$corr(y, l)$	0.83	0.69	0.64	0.85
$corr(y, pr)$	0.69	0.97	0.98	0.98

Note: U.S. data (HP filtered) for the period 1980:I-2019:IV.
The standard deviations and correlations are sample means of artificial data for 1000 simulations, each simulation with 180 periods, the number of quarters in the U.S. data.

the period 1980: I to 2019: IV. Cyclical components from the time series were obtained using the Hodrick–Prescott (HP) filter with a smoothing parameter of 1600 (see Cornea-Madeira, 2017, for the formula and a review of the literature). The model with endogenous forgetting performs better in predicting the relative standard deviation of productivity to output and can match the correlation between output and labor observed in the data. However, few gains are made in predicting the relative standard deviation of labor to output and the correlation between output and productivity.

5 | CONCLUSIONS

This paper studies the implications of organizational forgetting on the business cycle. Whereas learning by doing has been extensively incorporated into macroeconomic models, no attention has been paid to the implications of organizational forgetting. The empirical evidence at the firm and industry levels shows that organizational forgetting does not simply mean a constant decay rate in experience, but the loss in accumulated experience is a function of economic activity and that organizational forgetting has important consequences for industry dynamics and firms' pricing behavior. Forgetting represents not simply a loss of experience, but another economic force that interacts with learning in driving productivity. Here, we adopt a macroeconomic perspective and extend a standard learning-by-doing RBC model by including endogenous forgetting.

The paper compares an RBC model with learning and endogenous forgetting, with the standard RBC model, and an RBC with learning by doing. We find that whereas learning by doing reinforces the effects of productivity shocks, organizational forgetting exacerbates their impact and increases their persistence over the business cycle. This is of particular interest when a negative productivity shock hits the economy, as the increasing speed of forgetting due to lower economic activity reduces experience at a higher rate and aggravates the impact of the negative shock on economic activity and delays recovery.

The results presented in this paper offer a new perspective regarding the implications of human capital accumulation for productivity. In standard models, human capital is accumulated through investment in education, either formal education or on-the-job training programs. With learning-by-doing workers learn automatically when they spend time producing, as an additional source of human capital. With forgetting, organizations and workers can forget at a variable speed the accumulated experience gained by the learning-by-doing process due to a decline in production activities and labor turnover. This implies the existence of a new mechanism driving the stock of human capital of an economy, where downturns in economic activity accelerate forgetting, depreciating human capital.

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ORCID

Anelí Bongers https://orcid.org/0000-0002-4063-2585

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