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by Dennis Wesselbaum

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What drives Endogenous Growth in the United States?*

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1 Introduction

The traditional separation between business cycle fluctuations and growth suggests that the latter is driven by productivity progress, whereas the former are caused by aggregate spending or monetary shocks. This classical dichotomy was challenged by Nelson and Plosser (1982), showing that movements in GNP reveal a unit root. In addition, the Real Business Cycle literature combined growth and business cycle theory. According to this stream, stochastic productivity shocks generate business cycle fluctuations. This view of the relationship between growth and cycles can be traced back to Schumpeter (1911), who perceived that both phenomena are driven by innovation. In a steady state firms earn no profits and innovations would cause an expansion. This boom necessarily turns to bust by reason of structural adjustments, though still reaching a higher equilibrium due to increased productivity. In addition. developments in growth theory proposed the endogenous nature of productivity growth. Starting with Lucas (1988), the accumulation of knowledge or human capital is subject to the current state of the economy. Therefore, even temporary shocks may have permanent effects due to changes in the incentive structure. Booms may increase growth due to learning-by-doing effects (LBD, henceforth)[1] or it might be recessions that increase productivity.[2] Galí and Hammour (1991) use a very illustrative and intuitive model to scrutinize the interaction between productivity and business cycles. They explain productivity growth by introducing two components, (i) an exogenous and (ii) an endogenous component. The latter component accounts for LBD effects, and cleansing effects of recessions. We estimate the structural parameters governing the endogenous growth component using macro data, such that we can identify whether LBD effects or cleansing effects of recessions dominate.[3]
We find evidence that external and internal LBD clearly dominate over cleansing effects of recessions. The remainder is structured as follows. The next section develops the model. Section 3 estimates the model and section 4 concludes.

2 Model Derivation

2.1 Demand and Supply

Our economy is populated by a representative household, who consists of a continuum of infinitely-lived members. Households equally share income and risk among all family members. Then, the household maximizes its intertemporal utility

$$U = E_0 \sum_{t=0}^{\infty} \beta^t U(C_t) e^{\mathcal{P}_t}, \tag{1}$$

[1]Stadler (1990) introduced learning-by-doing based on Arrow's (1962) approach.
[2]Caballero and Hammour (1994) show that a selection process increases average productivity, by closing inefficient production units.
[3]As an example for micro studies, Cooper and Johri (2002) find substantial and significant effects of LBD.

where C_t is consumption and $U(C_t) = \frac{C_t^{1-\sigma}}{1-\sigma}$. Here, $\sigma \geq 0$ denotes the degree of risk aversion, the discount rate is given by β, and the stochastic term $\mathcal{P}_t$ is an exogenous preference shifter. Solving the households problem, using that in equilibrium $Y_t = C_t$, yields the first-order condition,

$$U'(Y_t)e^{\mathcal{P}_t} = \beta E_t \left[U'(Y_{t+1})e^{\mathcal{P}_{t+1}} \left(\psi + \tau N_{t+1}\right) A_{t+1}\right], \tag{2}$$

by using the Cobb-Douglas production function,

$$Y_t = \mathcal{A}_t \mathcal{B}_t N_t^{\alpha}, \tag{3}$$

with $\alpha < 1$ and $\mathcal{A}_t$ is the exogenous component of productivity. We assume, that it follows

$$\frac{\mathcal{A}_t}{\mathcal{A}_{t-1}} = e^{X_t}, \tag{4}$$

where X_t is an AR(1) process.
$\mathcal{B}_t$ is the endogenous component of productivity that can be either embodied or disembodied. It evolves over time according to $\frac{\mathcal{B}_{t+1}}{\mathcal{B}_t} = \psi + \tau\tilde{N}_t - \theta N_t$, where $\tilde{N}_t$ denotes aggregate employment, which is an indicator for aggregate activity, that is observed by the household. In the symmetric equilibrium, $\tilde{N}_t = N_t$, such that

$$\frac{\mathcal{B}_t}{\mathcal{B}_{t-1}} = \psi + (\tau - \theta)N_{t-1}. \tag{5}$$

Then, we can make the following propositions

- **Proposition 1**
  If $\theta = \tau = 0$ and $\psi \geq 1$, we obtain an exogenous growth model.
- **Proposition 2**
  If $\tau > 0$, the model features external learning-by-doing effects.[4]
- **Proposition 3**
  If $\tau > 0$ and $\theta < 0$, internal and external learning-by-doing effects exist.
- **Proposition 4**
  If $\tau = 0$ and $\theta > 0$, the model accounts for cleansing effects of recessions.

2.2 Equilibrium

The stochastic processes for $\{\mathcal{P}_t, X_t\}$ evolve as

$$\mathcal{P}_t = \mathcal{P}_{t-1}^{\rho_\mathcal{P}} e^{\epsilon_t^\mathcal{P}}, \tag{6}$$
$$X_t = X_{t-1}^{\rho_X} e^{\epsilon_t^X}. \tag{7}$$

[4]Which is equivalent to $\theta < 0$, i.e. creating internal learning-by-doing effects.

Here, $\epsilon_t^{\mathcal{P},X} \sim N(0, \sigma_{\mathcal{P},X})$ and $0 < \rho_{\mathcal{P},X} < 1$.
In addition, we assume that the growth rate of productivity is

$$\Delta s_t = s_t - s_{t-1}, \tag{8}$$

where

$$s_t = ln(\mathcal{A}_t \mathcal{B}_t). \tag{9}$$

The symmetric equilibrium of our economy is characterized by the system of equations (2), (3), (4), (5), (6), (7), (8), and (9).
If we consider the model without exogenous shocks, it growths along the balanced growth path, with constant growth rate $\gamma = \psi + (\tau - \theta)\bar{N}$ for Y and B. Stochastic shocks generate deviations from that balanced growth path and the corresponding model is solved by log-linearizing the equation system.
We calibrate our model to match quarterly data for the United States.
Risk aversion σ is set to 2 as in Krause and Lubik (2007) and the discount factor β is set to 0.99. Steady state unemployment is set to 6%. The autocorrelation parameters for the three shocks are all set to 0.9. We set α in the production function to a standard value of 2/3.

3 Estimation

3.1 Methodology

Recent research has made it possible to estimate even large-scale DSGE models by particularly applying full information Bayesian techniques, see for instance del Negro et al. (2004) and Smets and Wouters (2007). However, there exists a trade-off between the estimation of small structural models and the estimation of large structural models. The estimation of small and therefore stylized models may lead to misspecifications, while estimating large models could lead to identification problems. The Bayesian method is capable of dealing with both problems. One of the main advantages of Bayesian methods is the fact that the estimation fits the entire model. In addition, the assumption of priors avoids that the posterior distribution peaks at strange points where the likelihood peaks.
Due to the lack of evidence and research on the (Bayesian) estimation of the structural parameters governing the endogenous growth component in our specification, we are faced with the problem of setting the posterior means, variances as well as the distribution function. Since we are exclusively interested in the parameters driving the endogenous growth component, eq. (5), we stick to the calibration presented in section 2.2 for the other parameters. For α we impose a mean of 1 and a standard deviation of 1. The prior mean of τ is set to 1, while its standard deviation of 0.5. Finally, θ has a mean of 0.5 and also a standard deviation of 0.5. Furthermore, we assume that all parameters follow a standard normal distribution.

We use U.S. time series of employment and TFP for our estimation. Both time series are on a quarterly basis from 1970:Q1 to 2009:Q3. The time series for output is taken from the OECD database. We construct the TFP time series by deviding output by total labor input (hours per worker times employment) and divide this fraction by the labor share. Time series for hours per worker, employment, and the labor share are taken from the Bureau of Labor Statistics. Then, all time series are written in log deviations and are detrended using a Hodrick-Prescott filter with smoothing parameter $\lambda = 10^5$.

3.2 Results

We use five chains of 50.000 draws for our MCMC results. The posterior estimates of the two parameters of interest can be found in Table 1 and Figure 1. We find that all three parameters are considerably shifted away from their respective priors, i.e. the data is informative. Furthermore, we find that τ is 2.20 and tightly estimated. This value implies that external learning-by-doing effects are very important in our dataset. In addition, θ is also tightly estimated to be -0.68, which implies that there are also internal learning-by-doing effects. So, the external learning-by-doing effect dominates the internal one and we find no evidence for cleansing effects of recessions (which would imply a positive value of θ). In addition, the exogenous growth component, α, is estimated to be 2.21, which is in line with empirical evidence on long-term grwoth in the United States.

4 Conclusion

We use the Galí and Hammour (1991) model to estimate whether LBD or cleansing effects of recessions drive the endogenous component of productivity in the United States. Using quarterly data for employment and TFP, and applying a Bayesian estiamtion, we find that there is no support for cleansing effects of recessions. In contrast, external and internal LBD are important and the exogenous component of productivity growth is close to the 2 % pace. This results suggests to endogenously derive a model of LBD effects. We leave this to the future.

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Tables and Figures

Table 1: Posterior Estimates.

	Prior Mean	Posterior Mean	5%	95%
τ	1	2.20	2.09	2.43
θ	0.5	-0.68	-0.73	-0.53
α	1	2.21	1.94	2.32

Notes: Results from Bayesian Estimation. Details can be found in the text.

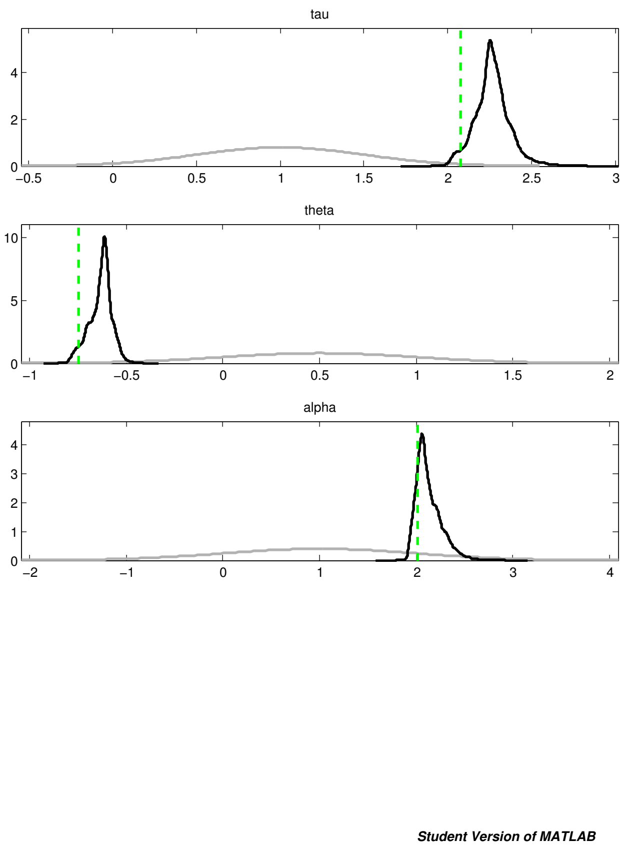

Figure 1: Posteriors.