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by Dennis Wesselbaum

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What drives Endogenous Growth in the United States?*

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June 7, 2011

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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. According to this "classical" dichotomy empirical business cycle analysis identifies a trend in GNP and interprets deviations from this trend as business cycles.

This classical dichotomy was challenged by Nelson and Plosser (1982), showing that movements in GNP reveal a unit root and are hence permanent. In addition, Kydland and Prescott (1982) and Long and Plosser (1983) amongst others mainly contributed to the Real Business Cycle literature, that combined growth and business cycle theory. According to the RBC stream in macroeconomic modelling, 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. To be precise, assume that the economy is in a steady state. Then, 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.

Besides the revolutionary changes in the design of macroeconomic models, 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. Stadler (1990) introduced learning-by-doing based on Arrow's (1962) approach.[1] He shows that, if productivity is endogenous, real and monetary models of the business cycle generate similar output patterns and aggregate demand changes cause permanent effects on productivity, employment, and output.

So far, we have seen three explanations for the relationship between productivity growth and cycles. At first, productivity growth can be entirely exogenous and the classical dichotomy holds. In contrast, booms may increase growth due to learning-by-doing effects or - in turn - it might be recessions that increase productivity. Caballero and Hammour (1994) show, that the process of innovation on the one hand causes destruction of production units that embody outdated techniques. On the other hand, new units that feature new techniques are created. This process increases average productivity in the economy by a selection process, that identifies inefficient production units and shuts them down. A different interpretation for this result can be found in Saint-Paul

[1] A different approach can be found in Eltis (1971), stressing the role of research and development (R&D) for growth.

(1997), where a recession is the time for firms to substitute productivity-enhancing activities for regular production activities, hence increasing productivity.

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 an exogenous and an endogenous component. The latter is determined by learing-by-doing effects, driven by employment. If endogenous productivity is driven by employment, then, perfect labor markets imply that the accumulation process is purely (labor) demand driven. We estimate the model for the United States using Bayesian estimation techniques to address the question whether learning-by-doing effects or cleansing effects of recessions dominate. Therefore, this paper's main contribution is the estimation of structural parameters governing the endogenous growth component, where we can identify whether learning-by-doing effects or cleansing effects of recessions dominate.

We find significant evidence that external and internal learning-by-doing effects clearly dominate the cleansing effects of recessions. The remainder is structured as follows. The next section develops the model. Section 2 estimates the model and section 3 briefly concludes.

2 Model Derivation

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. We further assume that the economy begins with all households having identical financial wealth and consumption histories. This assumption assures that together with the optimal use of the available contingent claims markets, this homogeneity will continue. Then, the household maximizes its intertemporal utility

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

where C_t is consumption and the function characterizing utility is $U(C_t) = \frac{C_t^{1-\sigma}}{1-\sigma}$. Here, $\sigma \geq 0$ denotes the intertemporal elasticity of substitution, the discount factor is given by $\beta > 0$, and the stochastic term $\mathcal{P}_t$ is an exogenous preference shifter. It is assumed to follow a first-order autoregressive process

$$\mathcal{P}_t = \mathcal{P}_{t-1}^{\rho_{\mathcal{P}}} e^{\epsilon_t^{\mathcal{P}}}, \tag{2}$$

where $0 < \rho_{\mathcal{P}} < 1$ determines the degree of autocorrelation and its innovation is i.i.d. over time and normally distributed,

$$e_t^{\mathcal{P}} \sim N(0, \sigma_{\mathcal{P}}). \tag{3}$$

Solving the households problem by using that in equilibrium $Y_t = C_t$ holds, yields the first-order condition,

$$U'(Y_t)e^{\mathcal{P}_t}\mathcal{A}_t = \beta E_t\left[U'(Y_{t+1})e^{\mathcal{P}_{t+1}}\left(\psi + \tau N_{t+1}\right)\mathcal{A}_{t+1}\right], \tag{4}$$

where we also make use of the linear production function,

$$Y_t = \mathcal{A}_t\mathcal{B}_t N_t, \tag{5}$$

used by the representative producer of a single good. Moreover, $\mathcal{A}_t$ is the exogenous component of productivity. We assume that it evolves according to

$$\frac{\mathcal{A}_t}{\mathcal{A}_{t-1}} = e^{X_t}, \tag{6}$$

where X_t is a first-order autoregressive process

$$X_t = X_{t-1}^{\rho_X} e^{\epsilon_t^X}, \tag{7}$$

where $0 < \rho_X < 1$ determines the degree of autocorrelation and its innovation is i.i.d. over time and normally distributed,

$$e_t^X \sim N\left(0, \sigma_X\right).$$

In addition, $\mathcal{B}_t$ 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

$$\frac{\mathcal{B}_t}{\mathcal{B}_{t-1}} = \psi + (\tau - \theta)N_{t-1}. \tag{8}$$

Here, we define the growth rate of productivity as

$$\Delta s_t = s_t - s_{t-1}, \tag{9}$$

where

$$s_t = ln(\mathcal{A}_t\mathcal{B}_t). \tag{10}$$

Then, we can make the following propositions

Proposition 1

If $\theta = \tau = 0$ and $\psi \geq 1$, we obtain an exogenous growth model. In this case, the total productivity growth rate is given by $\psi + X_t$.

Proposition 2

If $\tau > 0$, the model features external learning-by-doing effects.[2]

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.

Finally, the symmetric equilibrium of our economy is characterized by the system of equations (2), (4), (5), (6), (7), (8), (9), and (10). 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 around the non-stochastic steady state.

3 Estimation

3.1 Methodology and Data

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 Justiniano and Preston (2010). 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.

We follow the strategy discussed in Campbell et al. (2010) and describe the log-linear solution to our DSGE model by a first-order autoregression, given the model's parameters θ

$$\zeta_t = \Upsilon(\theta)\,\zeta_{t-1} + \varepsilon_t, \tag{11}$$

where the vector y_t stacks all date t values of our variables and vector ζ_t contains all date t states. Furthermore, $\varepsilon_t \sim N(0, \Sigma(\theta))$ contains the innovations. Then, the model analogues to the variables

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

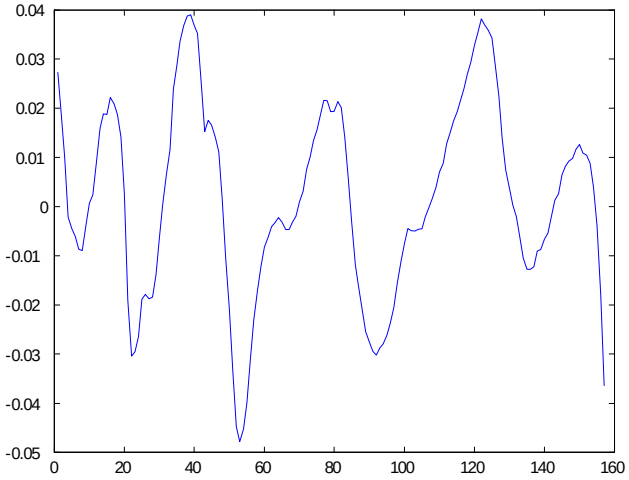

Figure 1: Employment, cycle component.

in y_t can be derived as linear functions of ζ_t and ζ_{t-1}, according to

$$y_t = G(\theta)\zeta_t + H(\theta)\zeta_{t-1} + v_t, \tag{12}$$

$$v_t = \Lambda(\varphi)v_{t-1} + e_t, \tag{13}$$

$$e_t \sim N(0, D(\varphi)). \tag{14}$$

Vector φ parameterizes the stochastic processes for v_t. Finally, we denote the prior density for the parameters governing the data collection $\Theta = (\theta, \varphi)$ by $\Pi(\Theta)$. Let us call Y the sample of all observed data. Given Θ and a prior distribution for ζ_0, we can calculate the conditional density of Y, $F(\Theta|Y)$. Then, Bayes rule links data and priors to the posterior density according to

$$P(\Theta|Y) \propto F(Y|\Theta)\Pi(\Theta). \tag{15}$$

For the variables in the vector y_t we use U.S. time series for employment and TFP. 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 $\lambda = 10^5$. Figure 1 and 2 show the detrended time series of employment and TFP.

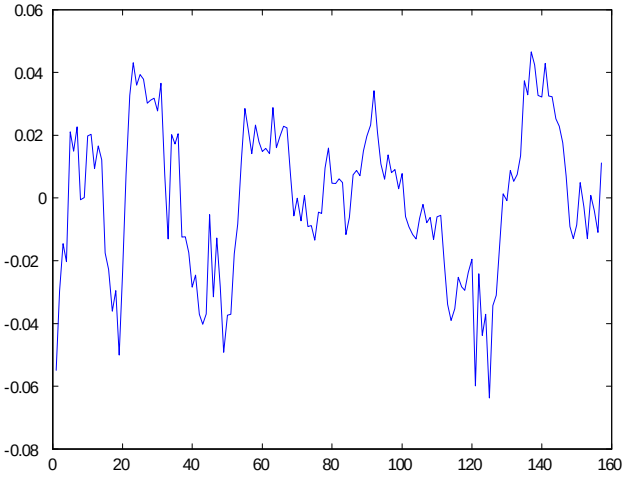

Figure 2: Total factor productivity, cycle component.

3.2 Priors

We only estimate the three parameters driving the endogenous growth component, eq. (8). Therefore, we do have to calibrate the remaining five parameters to match quarterly data for the United States. The intertemporal elasticity of substitution, σ, is set to 2 as e.g. in King et al. (1988) and the discount factor β is set to 0.99, which equals an average real rate of 4 % p.a. found in the data. Steady state unemployment is set to 6 %, which is the long run unemployment rate in the United States. Following King et al. (1988), the autocorrelation parameters for the two shocks are set to 0.9. Finally, we set α, the labor share, in the production function to a standard value of 2/3, also as discussed in King et al. (1988).

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 imposing the required posterior means, variances as well as the underlying distribution of those three parameters. The exogenous component of productivity, ψ, is assumed to follow a gamma distribution with means of 1 and a standard deviation of 0.5. The prior mean of τ, the endogenous productivity component governing the external learning-by-doing effects, is set to 1, while its standard deviation is set to 0.5. We further assume, that its density distribution follows a gamma distribution.

Finally, the prior density of θ, the parameter that indicates the degree of cleansing effects, belongs to the normal family and has a mean of 0.5 and a standard deviation of 0.5.

3.3 Results

We use five chains, each with a length of 100.000 draws for our MCMC results. Table 1 summarizes the estimation results for the three structural parameters and presents the median estimation and the 5th and 95th percentiles. At a first glance, we infer that the parameters are considerably shifted away from their respective priors, i.e. the data is informative. In addition, given our quite loose priors all parameters are tightly estimated.

Table 1: Parameter Estimates.

	Prior Mean	Posterior Mean	5%	95%
τ	1	2.33	2.16	2.44
θ	0.5	-0.52	-0.62	-0.44
ψ	1	2.54	2.33	2.80

Our estimate for the parameter governing the external learning-by-doing effects, τ, has a median value of 2.33, with the 5th and 95th percentiles of 2.16 and 2.44, respectively. This indicates quite strong external learning-by-doing effects over our sample period.

Furthermore, θ, the parameter that drives the cleansing effects of recession is negative. We find a mean value of -0.52 with the 5th and 95th percentiles corresponding to -0.62 and -0.44, respectively. This negative value, according to proposition 3, indicates that we do find significant evidence for external and internal learning-by-doing effects. This directly implies that there is no support for the existence of cleansing effects of recessions in our dataset.

Finally, the exogenous growth component, ψ, is estimated to be 2.54, which is in line with empirical evidence on long-term growth in the United States. The 95 percent posterior density interval lies between 2.33 and 2.80.

4 Final Remarks

This paper estimates the endogenous component of productivity in the United States. We use the tractable Galí and Hammour (1991) model that allows to disentangle between learning-by-doing effects and cleansing effects of recessions. Employing quarterly data for employment and TFP, we estimate the model by applying Bayesian estimation techniques. Our findings strongly reject the hypothesis of cleansing effects of recessions. In contrast, external and internal learning-by-doing effects are the main driver of endogenous productivity in the United States over the period from 1970 to 2009.

We therefore find, that a positive technology shock increases employment temporarily and increases productivity in the long-run according to the finding by the VAr estimation from Galí and Hammour (1991). On the other hand, we find that a positive temporary demand shock will increase employment temporarily but increase productivity very persistently. This contradicts the estimation results by Galí and Hammour (1991), as they find a negative impact on productivity in the long-run. They conclude that cleansing effects of recessions are driving this result. However, our findings indicate that learning-by-doing effects dominate and therefore, we do find a different reaction over the cycle. While in the Galí and Hammour (1991) model demand-driven recessions are beneficial in terms of increasing productivity, our model clearly shows that recessions are in no way desirable, as they would always be at the cost of lower productivity. Here, we could also conclude that policy measures addressed to counter the deterioration of economic activity in a recession might be beneficial, as they would reduce the negative impact on long-run productivity.

In addition, we simulate a version of the model using the search and matching approach to model - labor - market imperfections. We do find similar results, though a stationary technology shock would reduce employment over the cycle. However, there is still room for active policy measures to work against the negative consequences of recessions.

References

[1] Arrow, Kenneth J. 1962. "The Economic Implications of Learning by Doing." *Review of Economic Studies*, 29: 155-173.

[2] Caballero, Ricardo J. and Mohamad L. Hammour. 1994. "The Cleansing Effect of Recessions." *American Economic Review*, 84(5): 1350-1368.

[3] Campbell, Jeffrey R., Jonas D. M. Fisher, and Alejandro Justiniano. 2010. "The Chicago Fed DSGE Model." mimeo.

[4] Cooper, Russell and Alok Johri. 2002. "Learning-by-doing and Aggregate Fluctuations." *Journal of Monetary Economics*, 49(8): 1539-1566.

[5] del Negro, Marco, Frank Schorfheide, Frank Smets, and Rafael Wouters. 2004. "On the Fit and Forecasting Performance of New Keynesian Models." Federal Reserve Bank of Atlanta Working Paper 2004-37.

[6] Galí, Jordi and Mohamad L. Hammour. 1991. "Long Run Effects of Business Cycles." mimeo.

[7] Justiniano, Alejandro and Bruce Preston, 2010. "Monetary policy and uncertainty in an empirical small open-economy model." *Journal of Applied Econometrics,* 25(1): 93-128.

[8] King, Robert G., Charles I. Plosser, and Sergio T. Rebelo. 1988. "Production, Growth and Business Cycles. I. The Basic Neoclassical Model." *Journal of Monetary Economics*, 21: 195-232.

[9] Lucas, Robert E.. 1988. "On the Mechanics of Economic Development." *Journal of Monetary Economics*, 22(1): 3-42.

[10] del Negro, Marco, Frank Schorfheide, Frank Smets, and Rafael Wouters. 2004. "On the Fit and Forecasting Performance of New Keynesian Models." Federal Reserve Bank of Atlanta Working Paper 2004-37.

[11] Nelson, Charles R. and Charles I. Plosser. 1982. "Trends and random walks in macroeconomic time series." *Journal of Monetary Economics*, 10: 139-162.

[12] Schumpeter, Joseph A.. 1911. "Theorie der wirtschaftlichen Entwicklung." Duncker & Humolt, Berlin.

[13] Smets, Frank and Rafael Wouters. 2007. "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach." *American Economic Review*, 97(3): 586-606.

[14] Stadler, George W.. 1990. "Business Cycle Models with Endogenous Technology." *American Economic Review*, 80(4): 763-778.