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Technology shocks, structural breaks and the effects on the business cycle

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Abstract

This paper contributes to the literature on the role of technology shocks as source of the business cycle in two ways. First, we document that time-series of US productivity and hours are apparently affected by a structural break in the late 60's, which is likely due to a major change in the monetary policy. Second, we show that the importance of demand shocks over the business cycle has sharply increased after the break.

Keywords: Business cycle, technology shocks, structural breaks.
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1. Introduction

Determining what are the driving forces of aggregate fluctuations is a highly debated research topic in macroeconomics. While real business cycle (RBC) models predict that technological shocks generate most of business cycles (see, e.g., Kydland and Prescott, 1982), new-keynesian theorists focus on the relevance of nominal shocks. The second viewpoint has recently gained empirical consensus on the basis of an influential paper by Galí (1999), whose main finding is to reject a key prediction of the RBC paradigm, namely the existence of positive comovements between output, employment and productivity in response to technology shocks.

We contribute to this literature in two ways. First, we question that the data generating process (DGP) of labor productivity and hours is stable over time, as implicitly assumed in most of previous analyses. In particular, we test for structural changes with unknown break dates in a vector auto-regressive (VAR) model of these variables. Second, we resort to a measure of the sources of the business cycles *via* a parametric spectral analysis as proposed by Centoni and Cubadda (2003). Since this measure is directly derived from the structural VAR parameters, it is possible to evaluate its sample variability through bootstrap techniques. This peculiarity is appealing when evaluating changes in the determinants of the business cycle across sub-periods.

The paper is organized as follows. After shortly reviewing the Galí's approach (1999) in Section 2, in Section 3 we apply the parameter stability test by Bai *et al.* (1998) to the Galí's bivariate VAR model (1999, 2004), and find a single break in the late sixties. In Section 4, we link this break to a decrease in the short-run response of monetary policy to technology shocks. In section 5, we show that the conditional correlation between hours and productivity on technology shocks changed over time. In section 6 we document that the break had a strong impact on the importance of sources of cyclical fluctuations.

2. The Galí's approach

The Galí's (1999) key identifying assumption is that labor productivity is permanently affected only by technology innovations. Formally, let n_t, y_t, and $x_t \equiv y_t - n_t$ denote, respectively, the logarithms of hours, output, and labor productivity. The bivariate time series $u_t \equiv (\Delta x_t, \Delta n_t)'$ is supposed to be generated by the following stationary stochastic process

$$u_t = \delta + C(L)\varepsilon_t, \tag{1}$$

where δ is a 2-vector of constant terms, $\varepsilon_t \equiv (\varepsilon_t^z, \varepsilon_t^m)'$ are i.i.d. $N_2(0, I_2)$, ε_t^z and ε_t^m denote, respectively, technology and non-technology shocks, $C(L) = \sum_{i=0}^{\infty} C_i L^i$ is such that $\sum_{j=1}^{\infty} j\,|C_j| < \infty$ and $C(1)$ is a lower-triangular matrix. Hence, only technology shocks ε_t^z have permanent effects on labor productivity.

For statistical inference, we assume that series u_t admits the following VAR(p) representation:

$$A(L)u_t = \mu + \nu_t, \quad t = 1, \dots, T, \tag{2}$$

where μ is a 2-vector of constant terms, ν_t are i.i.d. $N_2(0, \Omega)$, and $A(L) = I_n - \sum_{i=1}^{p} A_i L^i$ is such that the roots of $\det[A(L)]$ are outside the unite circle.

Since the structural shocks ε_t are linked to reduced form VAR innovations ν_t by the relation $\nu_t = S\varepsilon_t$, where $S = A(1)C(1)$, and $C(1) = \text{chol}\left[A(1)^{-1}\Omega(A(1)^{-1})'\right]$, consistent estimates of the coefficients of model (1) are obtained from the estimated parameters of model (2) through the relation $C(L) = A(L)^{-1}S$.

3. Testing for structural breaks

The previous empirical model is specified assuming that the DGP of the time series $\{u_t, t = 1, \dots, T\}$ is constant over time. As this assumption is rather questionable, we test for the presence of structural breaks in model (2).

Let first test for one break at time $\tau = \pi T$, where $\pi \in (0, 1)$, and its date τ is unknown. Model (2) is then generalized by the following sub-sample VAR models:

$$A^-(L)u_t = \mu^- + \nu_t, \quad t = 1, \dots, \tau, \tag{3}$$

$$A^+(L)u_t = \mu^+ + \nu_t, \quad t = \tau + 1, \dots, T, \tag{4}$$

where μ^- and μ^+ are 2-vectors of constant terms, and $A^-(L) = I_n - \sum_{i=1}^{p} A_i^- L^i$ and $A^+(L) = I_n - \sum_{i=1}^{p} A_i^+ L^i$ are such that the roots of $\det[A^-(L)]$ and $\det[A^+(L)]$ are outside the unite circle.

Under the null hypothesis that the model is stable over time we have

$$\text{H}_0\text{: } [A^-(L) = A^+(L)] \cap [\mu^- = \mu^+]. \tag{5}$$

Since the break date is unknown, we must resort to a testing procedure that allows us to treat τ as a parameter to be estimated. A standard solution is to perform a sequence of Chow tests, and date the break when the test statistic takes the largest value. Formally, the test statistic is the following:

$$LR(\widehat{\tau}) = \sup_{\tau \in [\underline{\tau}, \overline{\tau}]} LR(\tau), \tag{6}$$

where $LR(\tau)$ is the likelihood ratio test for the null hypothesis (5) having fixed the break date at time τ, and $[\underline{\tau}, \overline{\tau}]$ is the trimming region, which is usually set to $[0.15T, 0.85T]$.

Since the asymptotic distribution, which was provided by Bai *et al.* (1998), is often a poor approximation of the exact distribution of parameter stability tests when applied to

Table 1: Structural break test

Sample period	Break date	Test statistic	Asymptotic p-value	Bootstrap p-value
1947:1-2004:4	1968:2	32.37	0.071	0.014
1947:1-1968:2	1952:2	12.39	0.997	0.853
1968:3-2004:4	1985:1	19.78	0.758	0.365

Note: p-values are obtained by 5000 bootstrap replications

multivariate dynamic models (Candelon and Lütkepohl, 2001), we also use a bootstrap procedure to evaluate the significance of the test statistics (6).[1]

Finally, we investigate the existence of multiple breaks by the Bai and Perron (1998) sequential method. Having found a significant break at date $\widehat{\tau}$, we test for an additional break in each of the segments $(1, \widehat{\tau})$, $(\widehat{\tau}+1, T)$. If no additional significant break is found, the procedure stops. Otherwise, test again for the presence of another break in each pair of adjacent segments that are separated by an additional significant break. The rationale of this testing procedure is that the fraction τ/T will be consistently estimated for the break that allows for the greatest reduction in the sum of residuals, even if several breaks exist.

We use U.S. quarterly seasonally adjusted indexes of labor productivity and hours of the business sector for the period 1947:1–2004:4. Having fixed $p = 3$ according to the AIC, the testing results, reported in Table 1, favor the existence of a single break in the second quarter of 1968, thus supporting previous empirical findings in studies of the postwar productivity slowdown (Bai et al. (1998), and Candelon and Cubadda (2006)).

In order to separate more clearly the two regimes, the rest of the analysis excludes the 95% asymptotic confidence interval of the significant break date, namely 1967:2–1969:2. Hence, we focus on the two sub-samples 1947:1–1967:1 and 1969:3–2004:4.

4. Changes in the conditional variances and deep parameters

The evidence of a structural break in the DGP calls for an economic interpretation. Hence, we refer to the Galí's stylized model (1999), which admits the following solutions for output and hours:

$$\Delta y_t = \Delta\xi_t + \gamma\eta_t + (1-\gamma)\eta_{t-1}, \tag{7}$$

[1] This procedure is based on three steps. First, estimate model (2) and store the estimated parameters and the residuals $\widehat{\nu}_t$. Second, sample with replacement from $\widehat{\nu}_t$ 5000 times, and take the estimated parameters in (2) to rebuild the data that are used to bootstrap $LR(\widehat{\tau})$. Third, compute the bootstrap p-value as the percentage of the simulated statistics that are larger than the actual statistic.

Table 2: Estimates and confidence intervals of conditional variances

Variance	Sample: 1947:1-1967:1	Sample: 1969:3-2004:4
$\mathrm{Var}(\Delta y_t \vert z)$	7.253 [2.557,15.228]	1.357 [0.669,3.979]
$\mathrm{Var}(\Delta y_t \vert m)$	15.031 [7.783,21.693]	10.871 [7.598,13.022]
$\mathrm{Var}(\Delta n_t \vert z)$	2.512 [1.283,5.630]	1.638 [0.612,3.401]
$\mathrm{Var}(\Delta n_t \vert m)$	9.116 [5.556,11.890]	5.011 [3.235,6.539]

$$n_t = \frac{1}{\varphi}\xi_t + \frac{\gamma - 1}{\varphi}\eta_t, \tag{8}$$

where $\xi_t = \sigma_\xi \varepsilon_t^m$, $\eta_t = \sigma_\eta \varepsilon_t^z$, $\sigma_\eta > 0$, $\sigma_\xi > 0$, $\varphi > 0$ denotes the short-run return to labor, and $\gamma = \partial(\Delta m_t)/\partial \eta_t > 0$ measures the short-run response of monetary policy to technology shocks.

From equations (7) and (8), we derive the following conditional variances:

$$\mathrm{Var}(\Delta y_t|z) = (2\gamma^2 + 1 - 2\gamma)\sigma_\eta^2, \tag{9}$$

$$\mathrm{Var}(\Delta y_t|m) = 2\sigma_\xi^2, \tag{10}$$

$$\mathrm{Var}(\Delta n_t|z) = \frac{2}{\varphi}(\gamma^2 + 1 - 2\gamma)\sigma_\eta^2, \tag{11}$$

$$\mathrm{Var}(\Delta n_t|m) = \frac{2}{\varphi^2}\sigma_\xi^2, \tag{12}$$

where $\mathrm{Var}(\cdot|m)$ and $\mathrm{Var}(\cdot|z)$ denote, respectively, the conditional variances on monetary and technology shocks being the only source of fluctuations.

Interestingly, equation (9) is an increasing function of γ for $\gamma > 0$, equation (11) is an increasing function of γ for $\gamma > 0$ and $\varphi > 0$, and, finally, equation (12) is a decreasing function of φ, for $\varphi > 0$. In Table 2 we report the values of the conditional variances in each sub-period, along with their bootstrap 90% confidence limits.[2] The largest percentage reduction is recorded for $\mathrm{Var}(\Delta y_t|z)$, thus suggesting that a statistically significant change occurred on the parameter γ across the two sub-periods.

In order to have further economic insights, it is necessary to estimate the parameters φ and γ. We do this in two steps. First, we compute the parameter φ as the square root of the ratio of the estimates of $\mathrm{Var}(\Delta y_t|m)$ to $\mathrm{Var}(\Delta n_t|m)$. Second, we substitute the estimate of φ into the ratio of the estimates of $\mathrm{Var}(\Delta y_t|z)$ to $\mathrm{Var}(\Delta n_t|z)$ to obtain a numerical value of γ as a root of the resulting second degree polynomial. Based on Galí's (1999) theoretical assumptions, we expect to find a unique root that falls within the interval $[0, 1)$. Remarkably, this estimation strategy has the appealing property of canceling out the nuisance parameters σ_ξ^2 and σ_η^2.

[2] Hereafter, all confidence bounds are obtained by 5000 bootstrap replications.

Table 3: Estimates and confidence intervals of deep parameters

Parameter	Sample: 1947:1-1967:1	Sample: 1969:3–2004:4
φ	1.284 [0.921,1.765]	1.473 [1.187,1.839]
γ	0.652 [0.275,0.779]	0.261 [0.093,0.686]

Table 3 reports both point and interval estimates of γ and φ in the two sub-samples. Interestingly, all the estimated parameters fall in the value ranges suggested by Galí (1999), namely $\varphi \in (1, 2)$ and $\gamma \in [0, 1)$.[3] Moreover, the break seems to have more significantly affected the coefficient γ, and its large decrease indicates that the monetary authority became less reactive to technological shocks.

These results accord well with the economic events around 1968. Up to 1968 "the Fed did not attach much significance to changes in the inflation rate from its target value" (Duffy and Engle-Warnick, 2006). Similar conclusions have been reached by Meulendyke (1990) and Mayer (1999). Indeed, the monetary authority was satisfied with the monetary course as price stability had been achieved, while recessions did not represent a major problem. This situation ended in late sixties, when the Fed policy witnessed a shift toward inflation control in response to the Vietnam war deficit financing and Great Society programs. Based on the FOMC minutes, Romer and Romer (1989) provide further evidence along this direction by stating that "...at roughly the end of 1968 there appears to have been a change in the goals of policy: the Federal Reserve began to feel that it should act to reduce inflation". Moreover, "The intent to do more than offset expected increases in aggregate demand is clear".

However, despite this change in policy, inflation control was not fully achieved until Paul Volcker's appointment as Fed chairman, as forcefully stressed by the literature on empirical interest rate rules (see, among others, Clarida *et al.*, 2000, and Galí *et al.*, 2003). In order to check if our analysis fails to detect another major change in the deep parameters, we split our second sub-sample into two segments, before and after the reorientation of monetary policy on October 1979 (Romer and Romer, 1989). From Table 4 we see that, although the estimate of γ appears slightly upward biased due to the limited sample sizes, there is no evidence of significant changes of the deep parameters between the two segments.

[3] Interestingly, we obtained a unique bootstrapped value for γ that falls in $[0, 1)$ in about 81% of the replications. In the remaining cases, we obtained complex roots and we took the real part of them, which always belonged to the same interval.

Table 4: Estimates and confidence intervals of deep parameters after 1969:2

Parameter	Sample: 1969:3-1979:3	Sample: 1979:4–2004:4
φ	1.537 [0.999, 2.389]	1.415 [1.040, 1.884]
γ	0.364 [0.119, 0.741]	0.305 [0.122, 0.773]

Table 5: Estimates and confidence intervals of conditional correlations

Correlation	Sample: 1947:1–1967:1	Sample: 1969:3–2004:4
$\text{Corr}(\Delta x_t, \Delta n_t \vert z)$	-0.483 $[-0.818, 0.079]$	-0.825 $[-0.907, -0.516]$
$\text{Corr}(\Delta x_t, \Delta n_t \vert m)$	0.519 $[-0.037, 0.611]$	0.490 $[0.296, 0.628]$

5. Changes in the conditional correlations

Table 5 reports the estimates and 90% confidence intervals of the correlations between productivity and hour growth rates conditional to technology shocks, $\text{Corr}(\Delta x_t, \Delta n_t|z)$, and non technology shocks, $\text{Corr}(\Delta x_t, \Delta n_t|m)$, for the two sub-samples. Although the main finding in Galí (1999) is confirmed, since the estimates of $\text{Corr}(\Delta x_t, \Delta n_t|z)$ and $\text{Corr}(\Delta x_t, \Delta n_t|m)$ are, respectively, negative and positive in both periods, the sample conditional correlation on technological shocks has almost doubled in magnitude after the break. On the contrary, the correlation conditional on non technology shocks has almost remained unaltered.

6. Changes in the business cycle effects of technology shocks

Based on Centoni and Cubadda (2003), we use a parametric measure of the contribution of technological shocks to the spectral mass of output in the 6-32 quarter period range. If the data are generated by model (2), the power spectrum of the process Δy_t is

$$F(\omega) = \frac{1}{2\pi} C_y'(e^{-i\omega}) C_y(e^{i\omega})$$

where $C_y'(L) = (1, 1)C(L)$, and $C(e^{-i\omega}) = A(e^{-i\omega})^{-1}S$. We can measure the business cycle effects of technology shock on output through the following statistic:

$$R_z(\pi/16, \pi/3) = \frac{\int_{\pi/16}^{\pi/3} F_z(\omega) d\omega}{\int_{\pi/16}^{\pi/3} F(\omega) d\omega} \tag{13}$$

where

$$F_z(\omega) = \frac{1}{2\pi} C_y'(e^{-i\omega})(1, 0)(1, 0)' C_y(e^{i\omega})$$

Table 6: Estimates and confidence intervals of measures of business cycle effects of technology and non-technology shocks

Shock	Sample: 1947:1–1967:1	Sample: 1969:3–2004:4
z	0.282 [0.045,0.653]	0.026 [0.017,0.200]
m	0.718 [0.347,0.955]	0.974 [0.800,0.983]

is the spectrum of Δy_t at frequency ω conditional to technology shocks being the only source of fluctuations.

The statistic (13) measures the proportion of the variability of output at the business cycle frequency band, namely $[\pi/16, \pi/3]$, which is explained by technology shocks. Since ε_t are i.i.d. $N_2(0, I_2)$, it follows that the analogous measure of the business cycle effects of non-technology shocks is obtained as

$$R_m(\pi/16, \pi/3) = 1 - R_z(\pi/16, \pi/3) \tag{14}$$

Evidently, when the data are generated by the sub-sample models (3)-(4), it is required to use the polynomial matrices $A^-(L)$ and $A^+(L)$ in place of $A(L)$.

Table 6 reports the point and interval estimates of these measures. We notice that there is evidence of a sharp decrease in the role of technology shocks as a source of the US business cycle. Indeed, the measure (13) shrank from about 28% to 3%, and this change is clearly statistically significant.

Interestingly, Galì and Gambetti (2006) reached a different conclusion in their empirical analysis of The Great Moderation. After fixing the break date at 1984, they show that the contribution of non-technology shocks to the variance of output sharply fell after the break. However, the results in Table 1 indicate that, conditionally to the presence of a break in the late sixties, a second change of the VAR mean parameters in the middle eighties is insignificant with our data.

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