Regress and Progress! An Econometric Characterization of the Short-Run Relationship between Productivity and Labor Input in Brazil*

Matheus Albergaria de Magalhães**
Paulo Picchetti***

Abstract

What do technology shocks do? This is a hard question to answer. Real-Business-Cycle (RBC) models have provided a better understanding of the effects of technology shocks over business-cycle frequencies. Still, some problems remain. This paper addresses the empirical adequacy of first-generation RBC models through the use of structural vector autoregressions (SVAR) models. We employ an identification condition that imposes few *a priori* restrictions upon the data and is consistent with a broad class of macroeconomic models. Based on those conditions, we are able to obtain conditional correlation coefficients and impulse response functions that may be confronted with the theoretical implications of RBC models. We also report evidence related to short-run increasing returns to labor (SRIRL) in the Brazilian industry. Our results cast doubt on some RBC models' main predictions. In particular, the estimated conditional correlations between labor input and productivity measures are negative for technology shocks and positive for non-technology shocks, with the labor input displaying a negative response to technology shocks over business-cycle horizons. These results are robust to several specification issues, such as sample instability and the consideration of higher-order systems during estimation.

Keywords: SVAR Models, RBC Models, Technology Shocks, Productivity, SRIRL.

JEL Codes: C32, C52, E32.

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**Department of Economics, University of São Paulo. Address for correspondence: Rua Iquiririm, 125/102-B - Vila Indiana São Paulo - SP - 05586-000. E-mail: matt@usp.br

***Department of Economics, University of São Paulo, Rua Luciano Gualberto, 908 - Cidade Universitária, São Paulo - SP - 05586-080. E-mail: picchetti@usp.br

"Progress, don't regress."
Edward C. Prescott

1. Introduction

Real-Business-Cycle (RBC) models have been widespread all over the world. Such models are currently used to help documenting stylized facts for several countries and to explain the main differences between artificial and real economies. Brazil has been no exception to that. In the last years, we have seen an increasing amount of research that is based on the RBC paradigm when explaining fluctuations in the Brazilian economy (Kanczuk and Faria, 2000, Val and Ferreira, 2001, Ellery et al., 2002). We probably have learned a lot from those research efforts, not only in terms of the quantitative aspects of Brazilian business cycles, but also in terms of the adequacy of such simplified models to our economic environment.

Calibration methods have been the metric used in RBC models to check their empirical adequacy. Following these methods, the researcher, based on available microdata and long-run observations, chooses values for the model's parameters, which work as a benchmark for comparisons between real and artificial economies (in terms of second-moment statistics). Although calibration methods are now widely used in several branches of Economics, there is not a clear consensus over its superiority when compared to traditional estimation methods.[1]

Coincidentally, in Brazil, little has been done in terms of checking the empirical adequacy of RBC models through the use of conventional statistical/econometric techniques.[2] The present paper tries to fill this gap in the literature. We go in a different direction when checking the empirical adequacy of RBC models. It is important to stress that the empirical criticisms contained here are related to first-generation RBC models only (one-shock models, basically).[3] We do not see our results as definitive evidence against such models. Still, we think that these results may draw attention to unresolved issues in models of the kind.

Actually, we hope to provide two basic motivations for future research. First, from the results reported, we hope to stimulate the construction of new theoretical models that aim at solving some of the inconsistencies described here. Second, we also hope to stimulate the elaboration of additional empirical work that employs

[1] About calibration methods, see Kydland and Prescott (1991a, 1996). On the debate about calibration and estimation methods, see the symposiums contained in the 1994 final issue of the *Journal of Applied Econometrics*, the 1995 November issue of the *Economic Journal* and the 1996 winter issue of the *Journal of Economic Perspectives*. See, in particular, Gregory and Smith (1995), who contrast the main advantages and disadvantages of both empirical approaches.

[2] In the United States, however, this kind of approach has grown since the mid-eighties. Examples of seminal works in this line are the papers by Eichenbaum and Singleton (1986), Altug (1989), Eichenbaum (1991) and Canova et al. (1994). In the Brazilian case, see the the works by Pessôa (1999) and Sousa (2001).

[3] For further developments in that literature, see Cooley and Prescott (1995), King and Rebelo (2000) and Rebelo (2005).

alternative datasets and sample periods, in order to confirm (or not) our results.

The paper is divided as follows: in the second section, we make a brief review of some of the papers related to the problems of RBC models when trying to explain labor market phenomena. In the third section, we describe the data and variables employed in our analysis. The fourth section presents the econometric model employed, while the fifth section contains the main results obtained. In the sixth section, we perform several tests, trying to check the robustness of our results. Finally, in the seventh section, we present our conclusions and point to some possible routes for future research.

2. Empirical Puzzles in the Labor Market

One of the most problematic areas related to RBC models has been the labor market. The first-generation models (Kydland and Prescott, 1982, Long and Plosser, 1983) were based on a high degree of intertemporal substitution of labor, a hypothesis that contrasts with most of the available empirical evidence. From Kydland and Prescott's original results, we may have a better understanding of some of the related problems. Table 1 contains their results:

Table 1
Kydland and Prescott's (1982) results for the American economy

	American economy		Artificial economy	
Variable	Std. dev.	Corr(i, y)	Std. dev.	Corr(i, y)
Real output	1.8	1.00	1.8 (.23)	1.00
Consumption	1.3	.74	.63 (.09)	.94 (.01)
Investment	5.1	.71	6.45 (.62)	.80 (.04)
Inventories	1.7	.51	2.00 (.20)	.39 (.06)
Capital	.7	-.24	.63 (.08)	-.07 (.06)
Hours	2.0	.85	1.05 (.13)	.93 (.01)
Productivity	1.0	.10	.90 (.10)	.90 (.02)

Source: Kydland and Prescott (1982).
Notes:
(a) The data used in the calculations above are quarterly and related to the 1950:1/1979:2 period. All the data are expressed in logarithms and have been smoothed by the Hodrick-Prescott filter (Hodrick and Prescott (1997)).
(b) The second and fourth columns of the table exhibit standard-deviation values (expressed in percentage terms), while the third and fifth columns exhibit correlation values between each variable and real output.
(c) In the case of the artificial economy, values in parenthesis are equivalent to each statistic's standard errors.

Although the results contained in the table above show a good adjustment of Kydland and Prescott's model to the data (given the simplicity of the model), there are still some problems. First, the artificial economy predicts a much lower volatility for labor input than the one usually observed in reality (about 50% less).

Second, if technology shocks are the main factor behind aggregate fluctuations – as implied by the model – then the employment and productivity variables should be highly and positively correlated. Still, the empirical evidence points to a low positive value or even a negative value for the correlation between these variables (not reported in the table). Also, according to the logic of the model, there should be a high correlation between productivity and output. However, this correlation tends to be lower than that predicted by first-generation models (for the United States, the reported correlations are around .1, while Kydland and Prescott provide a point estimate around .9 for their artificial economy).

The first two problems have been labeled by some authors as the "employment-variability" and "productivity" puzzles, respectively (see Stadler (1994), for instance). These puzzles have resulted in the elaboration of additional models that try to solve such inconsistencies.

For instance, Hansen's indivisible labor model (Hansen, 1985) is aimed at solving the employment-variability puzzle. In order to do this, the author considers an environment where agents have a non-convex set of production possibilities (they either work a full-time period or they are unemployed, which is usually called "extensive margin" in the related literature). His main result is now well-known: the labor-leisure elasticity derived from his model is infinite for the aggregate economy, even though individual agents may exhibit low values for such an elasticity. Kydland and Prescott (1991b) extended Hansen's model by allowing variations in both margins ("extensive" and "intensive"). These authors get a result where more than 70% of the fluctuations that occurred in the U.S. over the 1954/1988 period can be ascribed to technology shocks.

One way to circumvent the productivity puzzle is to incorporate additional features into the benchmark model. For instance, Christiano and Eichenbaum (1992), by employing a modified version of the generalized method of moments (GMM), and based on the productivity puzzle, construct a model with two types of shocks: technology shocks and government spending shocks. In this case, government spending shocks act as potential shifters of the labor-supply schedule, which compensates labor-demand schedule movements (and this raises the magnitude of the correlation between labor input and productivity).

Hansen and Wright (1992) summarize some of the available evidence for the American economy until the early nineties. By using two different measures for labor input (the hours series containted in the *Household* and *Establishment* surveys), they consider four different versions of RBC models (non-separable preferences, indivisible-labor, government spending shocks and household production) and calibrate these models in order to see their empirical adequacy to the data. Their main results are reported in table 2 below.

Table 2
Hansen and Wright's (1992) results for the American labor market

American economy	σ_y	σ_h/σ_v	σ_w/σ_v	σ_h/σ_w	$corr(h,w)$
	1.92				
HSHOURS		.78	.57	1.37	.07
ESTHOURS		.96	.45	2.15	-.14
Models					
Standard	1.30	.49	.53	.94	.93
Non-separable preferences	1.51	.65	.40	1.63	.80
Indivisible labor	1.73	.76	.29	2.63	.76
Government spending	1.24	.55	.61	.90	.49
Household production	1.71	.75	.39	1.92	.49

Source: Hansen and Wright (1992, table 3).
Notes:
(a) The data used in the calculations above are quarterly and related to the 1947:1/1991:3 period. All the data are expressed in logarithms and have been smoothed by the Hodrick-Prescott filter. Here, $\sigma_i (i = y, h, w)$ represents variable i's standard deviation, while $corr(h, w)$ represents the correlation between h and w. The terms y, h and w denote output, hours worked and productivity, respectively.
(b) The HSHOURS and ESTHOURS terms denote the hours measures from the *Household Survey* and the *Establishment Survey*, respectively.

The first third and fourth lines in the table show the statistics derived from the use of the hours measures employed. The remaining lines exhibit the performance of each model. As we can see from the results contained in the table, some models are able to account well for the employment-variability puzzle (see, in the third column of the table, the adequacy of the indivisible-labor and household production models). On the other hand, none of the models can account for the productivity puzzle (see the last column in the table).

Departing from the productivity puzzle, Galí (1999) uses the structural vector autoregressions (SVAR) technique (Blanchard and Quah, 1989) to ask about the empirical adequacy of RBC models.[4] For the author, the main focus when analyzing the performance of these models should be on *conditional* correlations (instead of unconditional ones). Following this reasoning, he states that the conditional correlations based on technology and non-technology shocks may be quite different and this could work as an empirical test for the adequacy of different models. In this sense, RBC models tend to predict a positive "technology" (conditional) correlation between labor and productivity measures, at the same time that they predict a negative correlation in the case of "non-technology" shocks. Galí also constructs a theoretical model (based mainly on New Keynesian features) where the predictions in terms of correlations are totally reversed: "technology" shocks in his model generate a negative conditional correlation between labor and productivity while "non-technology" shocks generate a positive value for that statistic.

Using quarterly data for the American economy and for the G-7 countries, Galí imposes an alternative identification condition in his model that allows him to estimate conditional correlations between labor input and productivity measures.

[4] More details on the SVAR technique below. Interested readers may check, besides the original reference, Hamilton (1994, chap.11), and Enders: (1995, chap.5). Examples of other applied works involving this technique are Galí (1992) and Shapiro and Watson (1988). Critiques to the technique are found in Cooley and Dwyer (1998), Chari et al. (2004) and Erceg et al. (2004).

His model's identification condition is the following: technology shocks have a permanent effect on both variables in the estimated system (labor input and productivity), while non-technology shocks (that can be broadly seen as "demand" shocks)[5] have a permanent effect on labor input only (that is, non-technology shocks cannot affect productivity in the long run).

Galí's main results are the following:

- The estimated conditional correlations between labor input and productivity measures have a negative sign for technology shocks and a positive sign for non-technology shocks.
- The estimated impulse-response functions show a persistent decline for the labor input measures in response to technology shocks.
- The productivity measures employed exhibit a pattern of temporary increase due to positive non-technology ("demand") shocks.

These results are robust to specification issues, as well as to the use of different labor input measures (hours worked or employment) and detrending methods (data in first differences or filtered through Hodrick and Prescott's method (Hodrick and Prescott, 1997).[6]

In an older version of that paper (Galí, 1996), the author also tests the existence of "short-run increasing returns to labor" (SRIRL), an important phenomenon, widely reported in the empirical literature on productivity (see Gordon (1992), for instance). Also, SRIRL might be the main factor behind the procyclical behavior of productivity measures and it may explain why the measures employed in RBC models as proxies for technology shocks (the rate of growth of TFP, that is, the Solow residual) are not adequate for such a task.

In the Brazilian case, Sousa (2001) applied Galí's methodology to Brazilian industrial data. The author deals with monthly data and her results tend to confirm some of Galí's main findings. The present paper tries to enrich Sousa's analysis by employing quarterly data (the usual frequency of business cycles) and by performing several robustness tests to confirm the main results obtained.

3. Data and Variables Employed

Our dataset is the same as that used by Kanczuk and Faria (2000) and it covers the 1985:01/1999:03 period.[7] Basically, it corresponds to data from the Brazilian

[5] Galí (1999:250) states that "non-technology" shocks in his model may be seen as monetary policy shocks, for instance.

[6] By employing different methodologies, Basu et al. (1998) and Shea (1998) obtain results that are similar to Galí's original findings. For examples of applications of Galí's approach to other countries, see Galí (2004), Sousa (2001) and Weder (2003).

[7] We thank Fábio Kanczuk for kindly providing his original data. In the robustness tests section, we expand Kanczuk and Faria's original dataset to check whether the main results hold. More details below.

Institute of Geography and Statistics (IBGE). We employ an output measure constructed by those authors to match the main characteristics of a closed-economy RBC model. We also employ an aggregate output measure: IBGE's quarterly estimates of real GDP. Since we are interested in constructing labor productivity measures, we employ two measures that represent labor input: IBGE's indexes of hours paid and employment. The productivity measures correspond to the difference between the natural logarithms of production and labor input measures, basically.

When checking the robustness of our main results, we also employ additional macroeconomic variables in the estimations. These are the following: a monetary aggregate measure (M2 and M3 money concepts) as well as an interest rate measure (SELIC). Since Brazil is a country that has undergone severe inflationary episodes over the sample period, we also use two price indexes: the general price index (IGP-DI) and the broad consumer price index (IPCA). We hope that the inclusion of these indexes help us capture inflationary effects upon our variables in the sample period considered, although we are aware of the problems related to this period (actually, a common problem related to all applied works concerning the Brazilian economy over time spans that are similar to ours). In Appendix A, we describe the variables employed in the analysis. All these variables are available online at the Applied Economic Research Institute (IPEA) of the Brazilian government (*www.ipeadata.gov.br*).[8]

4. Empirical Framework

We follow Galí's econometric model. Our empirical strategy is the following:

- To estimate a reduced-form VAR model, considering related specification issues (lag-length criteria and diagnostic tests of the estimated residuals).

- To estimate a SVAR from the VAR form obtained above, after imposing long-run restrictions that grant identification. In doing so, we will be able to obtain conditional correlation coefficients and perform impulse-response analysis.

Before implementing this empirical strategy, a word about identification conditions is necessary. That is what we do next.

4.1 Identification

We consider a production function of the form:

$$Y_t = AZ_tN_t^{\varphi} \tag{1}$$

[8]The extended dataset is available from the authors upon request.

where Y represents output, while Z and N represent an aggregate technology index and labor input, respectively. A and φ are parameters. In particular, φ represents the labor elasticity of output.

Departing from a model with monopolistic competition, sticky prices and variable labor effort, Galí (1999) derives the following expressions, related to the covariances between the model's main variables:

$$\begin{aligned} \operatorname{cov}(\triangle y_t, \triangle n_t) &= \frac{2s_m^2 + (1-\gamma)(1-2\gamma)s_z^2}{\varphi} \\ \operatorname{cov}(\triangle y_t, \triangle x_t) &= \frac{2(\varphi-1)s_m^2 + (\gamma+\varphi-1)s_z^2}{\varphi} \\ \operatorname{cov}(\triangle n_t, \triangle x_t) &= \frac{2(\varphi-1)s_m^2}{\varphi^2} - \frac{(1-\gamma)[(2-\varphi)+2\gamma(\varphi-1)]s_z^2}{\varphi^2} \end{aligned} \tag{2}$$

In the expressions above, the s_m^2 and s_z^2 terms represent the non-technology and technology shock variances respectively, while γ and φ are the model's parameters. The former represents the central bank's degree of monetary accommodation while the latter is the elasticity of output to labor input. The symbols $\triangle y$, $\triangle n$ and $\triangle x$ represent growth rates (first differences of natural logarithms) of output, labor and productivity, respectively.

As we can notice, these covariance signs depend on the magnitude of the model's parameters (γ and φ). If $\gamma \in [0, 1/2)$, the model predicts a positive covariance between output and labor input; that is, a procyclical pattern for labor input, which is a basic business cycle stylized fact. If $\varphi > 1$, productivity will also be procyclical, another stylized fact.[9] In terms of the covariance between labor and productivity, its sign will depend on the magnitude of the parameters, as well as on the relative importance of different shocks (captured by the variances s_m^2 and s_z^2). We can have a better understanding of the latter point by dividing the above expression in terms of *conditional* covariances as follows:

$$\begin{aligned} \operatorname{cov}(\triangle n_t, \triangle x_t/z) &= -\frac{(1-\gamma)[(2-\varphi)+2\gamma(\varphi-1)]s_z^2}{\varphi^2} \\ \operatorname{cov}(\triangle_t, \triangle x_t/m) &= \frac{2(\varphi-1)s_m^2}{\varphi^2} \end{aligned}$$

The above expressions denote the conditional covariances between labor and productivity based on "technology" and "non-technology" shocks, respectively. These expressions represent the covariances of the variables in a situation where only one type of shock is considered at a time. If $\gamma \in [0, 1)$ and $\varphi \in (1, 2)$, we have that $cov(\triangle n_{t,}, \triangle x_t/z) < 0$ and $cov(\triangle n_t, \triangle x_t/m) > 0$. The methodology employed in

[9] This last condition ($\varphi > 1$) is equivalent to the SRIRL condition, which is empirically testable in the current setting (see below).

this paper allows testing these predictions, as well as the magnitude of one of the model's parameters (φ), related to SRIRL phenomena. We have three hypotheses related to the identification of the SVAR model (Gali 1999:255–256). These are the following:

- The economy's aggregate output is determined by a homogeneous, first-degree and strictly concave production function:

$$Y_t = F\left(K_t, Z_t L_t\right) \tag{3}$$

  where Y represents output, while K and L represent the effective capital and labor input services employed (thus allowing for unobservable variations in the utilization rate of both inputs). Z represents an exogenous technology parameter that follows a stochastic process with a unit root.

- The capital-labor ratio (measured in effective units) $K_t/Z_t L_t$ follows a stationary stochastic process.

- The (effective) labor input (L) is determined by a first-degree homogeneous function that depends on hours worked (N) and effort (U).

$$L_t = g\left(N_t, U_t\right) \tag{4}$$

with effort per hour (U_t/N_t) following a stationary stochastic process. From the latter hypothesis we can derive the expression:

$$x_t = z_t + \zeta_t \tag{5}$$

where $\zeta_t \equiv \log F(K_t/Z_t L_t, 1) g(1, U_t/N_t)$ is stationary under the above assumptions.

The latter expression means that only permanent shifts in technology's stochastic component can be the source of a unit root process in productivity. That is, only technology shocks may have a permanent effect on the productivity level (even though other shocks may have a temporary effect).

This identification condition is different from the one originally contained in Blanchard and Quah (1989). These authors use a condition where demand shocks do not have a permanent effect on output, with this variable being affected only by supply shocks. Here, we can see our technology shocks as "supply" shocks in the sense proposed by Blanchard and Quah. The same is true for non-technology shocks, which can be seen, broadly speaking, as "demand" shocks. In this way, the model employed here says nothing about the effects of both shocks on output. When constructing (labor) productivity measures, we employ alternative output measures (industrial production or GDP) and we are also able to estimate impulse-response functions for the latter (see below). The important thing to notice here is that our identification condition is broader than Blanchard and Quah's, in the sense that it allows for permanent long-run effects of both shocks ("supply" and "demand") over output during estimation.[10]

4.2 Econometric model[11]

Here we describe the SVAR technique employed in the subsequent analysis. First, suppose that the vector $\{(x_t, n_t)\} = \{q_t\}$ is a bivariate $I(1)$ process with a stationary VAR representation in first differences. The observed variations in the variables contained in $\{q_t\}$ can be interpreted as originating from two types of disturbances, namely "technology" and "non-technology" shocks, assumed to be orthogonal to each other. The latter idea may be represented by the following formulas:

$$\begin{aligned}
\triangle x_t &= \sum_{k=0}^{\infty} c_{11}(k)\varepsilon^z_{t-k} + \sum_{k=0}^{\infty} c_{12}(k)\varepsilon^m_{t-k} \\
\triangle n_t &= \sum_{k=0}^{\infty} c_{21}(k)\varepsilon^z_{t-k} + \sum_{k=0}^{\infty} c_{22}(k)\varepsilon^m_{t-k}
\end{aligned}$$

Representing the above formulas in a more compact notation, we have:

$$\triangle q_t = \begin{bmatrix} \triangle x_t \\ \triangle n_t \end{bmatrix} = \begin{bmatrix} C^{11}(L) & C^{12}(L) \\ C^{21}(L) & C^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon^z_t \\ \varepsilon^m_t \end{bmatrix} \equiv C(L)\,\varepsilon_t \tag{6}$$

where $\varepsilon_t = [\varepsilon^z_t, \varepsilon^m_t]'$ represents a vector whose elements are period t's technology (ε^z_t) and non-technology (ε^m_t) shocks. Since these shocks are assumed to be orthogonal to each other, we have that $E\varepsilon_t\varepsilon'_t = I$ (after performing a scale normalization). The $C^{ij}(L)$ terms represent polynomials in the lag operator L, while $\mathbf{C}(L)$ is a matrix containing long-run multipliers.

Since the sequence of shocks $\{\varepsilon^z_t, \varepsilon^m_t\}$ is not observed, the problem is to recover them from a reduced-form VAR estimation. Given that the first differences of the variables in $\{q_t\}$ are stationary, there exists a VAR representation of the form:

$$\begin{bmatrix} \triangle x_t \\ \triangle n_t \end{bmatrix} = \begin{bmatrix} A^{11}(L) & A^{12}(L) \\ A^{21}(L) & A^{22}(L) \end{bmatrix} \begin{bmatrix} \triangle x_{t-1} \\ \triangle n_{t-1} \end{bmatrix} + \begin{bmatrix} e^1_t \\ e^2_t \end{bmatrix} \tag{7}$$

or

$$q_t = A(L)q_{t-1} + e_t$$

[10] For alternative identification conditions employed in the literature see, for instance, Shapiro and Watson (1988), Christiano et al. (2003a,b) and Uhlig (2003).

[11] This section is based on Enders (1995), and Galí (1996). There are some differences between the working paper (Galí, 1996) and the final version (Galí, 1999) of Galí's work. We choose to follow mainly Galí (1996), since it allows for testing the presence of SRIRL phenomena in our dataset.

In the equation above, e_t represents a column vector containing the error terms of the reduced-form VAR, while $A(L)$ is a 2×2 matrix whose elements are the lag polynomials $A^{ij}(L)$, for $i, j = 1, 2$.

Based on the equivalence between the one-step ahead forecast error of the variables in $\{q_t\}$ and the bivariate moving average representation of (7), we have the following relationships between errors and shocks:

$$\begin{aligned} e_{1t} &= c^{11}(0)\varepsilon_t^z + c^{12}(0)\varepsilon_t^m \\ e_{2t} &= c^{21}(0)\varepsilon_t^z + c^{22}(0)\varepsilon_t^m \end{aligned}$$

or, more compactly

$$e_t = \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} = \begin{bmatrix} c^{11}(0) & c^{12}(0) \\ c^{21}(0) & c^{22}(0) \end{bmatrix} \begin{bmatrix} \varepsilon_t^z \\ \varepsilon_t^m \end{bmatrix}$$

The relationships described above plus the identification condition provide four restrictions that can be used to identify the four unknowns $c^{11}(0)$, $c^{12}(0)$, $c^{21}(0)$ and $c^{22}(0)$; that is, to recover the shocks $(\varepsilon_t^z,\ \varepsilon_t^m)$ from the reduced-form VAR residuals $(e_{1t},\ e_{2t})$. The four restrictions are the following:

Restriction 1:

$$Var\,(e_{1t}) = c^{11}(0)^2 + c^{12}(0)^2$$

Restriction 2:

$$Var\,(e_{2t}) = c^{21}(0)^2 + c^{22}(0)^2$$

Restriction 3:

$$Ee_{1t}e_{2t} = c^{11}(0)c^{21}(0) + c^{12}(0)c^{22}(0)$$

Restriction 4:

$$\left[1 - \sum_{k=0}^{\infty} a^{12}(k)\right] c^{11}(0) + \sum_{k=0}^{\infty} a^{22}(k)c^{12}(0) = 0$$

The latter restriction means that non-technology shocks cannot have a permanent effect on productivity. In terms of the specification represented by (6), this means that $C_{12}(l) = 0$, with the long-run multiplier matrix, $\mathbf{C}(l)$ being lower-triangular. Based on the coefficients of $\mathbf{C}(L)$, we are able to obtain impulse-response functions and conditional correlation coefficients. Given a time series for each component of $\{q_t\}$, it is possible to obtain consistent estimates of the conditional correlations ($\rho_z(\triangle x_t, \triangle n_t)$ and $\rho_m(\triangle x_t, \triangle n_t)$) based on their sample correlations, $\hat{\rho}(\triangle x_t^z, \triangle n_t^z) \equiv \hat{\rho}_z$ and $\hat{\rho}(\triangle x_t^m, \triangle n_t^m) \equiv \hat{\rho}_m$. These correlation coefficients come from the formula:

$$\rho\,(\triangle x_t, \triangle n_t/i) = \frac{\sum_{j=0}^{\infty} C_j^{1i} C_j^{2i}}{\sqrt{var\,(\triangle x_t/i)\,var\,(\triangle n_t/i)}} \tag{8}$$

where $i = z, m$, and $var(\triangle x_t/i) = \sum_{j=0}^{\infty}(C_j^{1i})^2$ and $var(\triangle n_t/i) = \sum_{j=0}^{\infty}(C_j^{2i})^2$ represent the conditional variances for the productivity and labor input measures, respectively.

5. Results

5.1 VAR estimation

Before turning to the results obtained from the SVAR estimation, we report some results related to the reduced-form VAR that we employ in the first step of our strategy.

First, we pretested all the variables involved in the estimation for the presence of unit roots. We performed several unit-root tests: the usual ADF (Dickey and Fuller, 1981) and Phillips-Perron (Phillips and Perron, 1988) tests as well as the tests proposed by Dickey and Pantula (1987) (for checking the presence of two unit roots in each series). All the results of unit-root tests are reported in Appendix B. To check the robustness of these results, we also report results based on the KPSS test (Kwiatkowski et al., 1992) for alternative number of lags, where the null hypothesis corresponds to the stationarity of the series. The results based on such a test (reported in table B.5) show that even in the case of variables where the ADF and Phillips-Perron test results point towards stationarity in levels – such as the labor input measures – we end up rejecting the null hypothesis of the KPSS test. Because of these results, we conclude that most of the variables in our dataset may be characterized as I(1) processes. The monetary policy and inflation measures, however, may be considered as I(2) processes (see tables B.1 and B.4). We make use of these results when estimating reduced-form VAR specifications below.[12]

Next, we tested for the existence of a long-run relationship between the variables employed in the VAR estimations (namely, labor input and productivity measures). In doing so, we employ two distinct approaches for testing cointegration: Engle-Granger's (Engle and Granger, 1987) and Johansen's (Johansen, 1988). We use both approaches in order to provide robust results. These results are reported in Appendix C. From the results obtained, we can conclude that labor input and productivity measures do not cointegrate.[13]

Before estimating a VAR involving labor input and productivity measures, we check some additional specification criteria. First, we checked for lag-length choice, by employing five different selection criteria: Akaike (AIC), Schwarz (BIC) and Hannan-Quinn (H-Q) information criteria as well as the Final Prediction Error (FPE) and the Likelihood Ratio Test statistic with correction of degrees of freedom for small samples (LR). All the criteria point to parsimonious specifications, with

[12]Results are also confirmed by the visual inspection of the series figures (log-levels, first and second differences), as reported in Appendix A.

[13]For examples of works that use cointegration techniques to evaluate the empirical adequacy of RBC models, see King et al. (1991) and Canova et al. (1994), for instance.

two lags in general. However, when checking the adequacy criteria for the VAR estimated, results are considerably better for specifications with four lags. In the case of specifications where we employ an alternative measure for the industrial production index (IBGE's original measure), results are better when we use a dummy variable for the second quarter of 1990 (this dummy variable captures the anomalous effects of the Collor Plan on the economy in that period). Since we are dealing with quarterly data, we decide to report results for specifications involving four lags of each variable employed in the reduced-form VAR only (see Apendix D for results related to VAR adequacy criteria).[14]

From these results, we are able to see that we have a good statistical fit for the VAR estimated, no matter what labor input measure is employed (hours or employment) or the sample period considered. Next, we show the results for the estimated conditional correlations as well as the impulse-response functions derived from the SVAR specification.

5.2 SVAR results

Table 3 contains the results for the correlation coefficients estimated from the SVAR specification using the Kanczuk-Faria dataset (1985:01/1999:03 period). The table also reports standard errors for these coefficients, as well as Galí's original results for comparative purposes.[15]

Table 3
Estimated correlations between productivity and labor input measures for the Brazilian industry, 1985:01/1999:03

	Unconditional	Conditional	
Hours		Technology	Non-technology
First-Differences	.29*	-.72	.62***
	(.18)	(.49)	(.13)
Corr(y, n)	.79	-.71	.84
Employment		Technology	Non-technology
First-Differences	.25*	-.16	.55***
	(.15)	(.44)	(.16)
Corr(y, n)	.77	-.39	.82
Galí (1999)		Technology	Non-technology
First-Differences	-.26**	-.82***	.26***
	(.08)	(.12)	(.12)

Source: authors' calculations.
Notes:
(a) Sample Period: 1985:01/1999:03.
(b) Correlations were estimated from a SVAR model involving productivity and labor input measures, for specifications with four lags of each variable and a constant term.
(c) The term "$corr(y, n)$" denotes estimated correlations among output and labor input measures (more details below).
(d) Standard errors were obtained from a Monte Carlo procedure with 500 draws (see details in text). The (*), (**) and (***) terms denote statistical significance at the 10%, 5% and 1% levels, respectively.

[14] The main qualitative results reported here do not change when we employ specifications with two lags.

[15] The standard errors for the estimated coefficients and impulse-response functions were computed through a Monte Carlo method that creates samples from the estimated asymptotic distribution of the VAR coefficients and the covariance matrix of the innovations. The reported standard errors correspond to the standard deviation of each statistic across 500 draws.

From the above results, we can notice that the main qualitative results obtained by Galí for the American economy are also confirmed in the case of Brazilian industrial data. However, some differences remain. First, in terms of unconditional correlations, the Brazilian data show positive values, around .3, (however, these values are marginally significant). Second, although the non-technology coefficients are quite robust across different labor input measures (around .6), the same is not true for the technology coefficients. In the case of such coefficients, the reported magnitudes vary considerably, depending on which labor input measure one considers, where neither of them is statistically different from zero. At first, this might reflect the unimportance of such a component in the performed estimations. However, some additional tests present a different picture, as shown below.

Figures 1 and 2 confirm the signs of the conditional coefficients, by showing scatterplots between labor input (hours or employment, respectively) and productivity measures. We consider unconditional correlations (first line of the figures) as well as each conditional correlation (technology and non-technology components; second and third lines of the figures, respectively). The first column contains results for first-differenced data while the second column shows results for series smoothed through the Hodrick-Prescott filter. We employ this filter in order to show that our results are robust to detrending methods.

Figures 3 and 4 show the estimated impulse-response functions for cases where we employ hours or employment as a labor input measure, respectively (lines with dots represent the responses while lines with triangles represent the associated standard errors). The first column of each graph shows the effect of a positive technology shock (a one standard deviation increase in the model's technology component, actually), while the second column shows the effect of a positive non-technology shock. We consider a twelve-quarter horizon (three years). Besides being the same horizon considered by Galí, it is also consistent with usual definitions of business-cycle frequencies (see Cooley (1995), for instance).

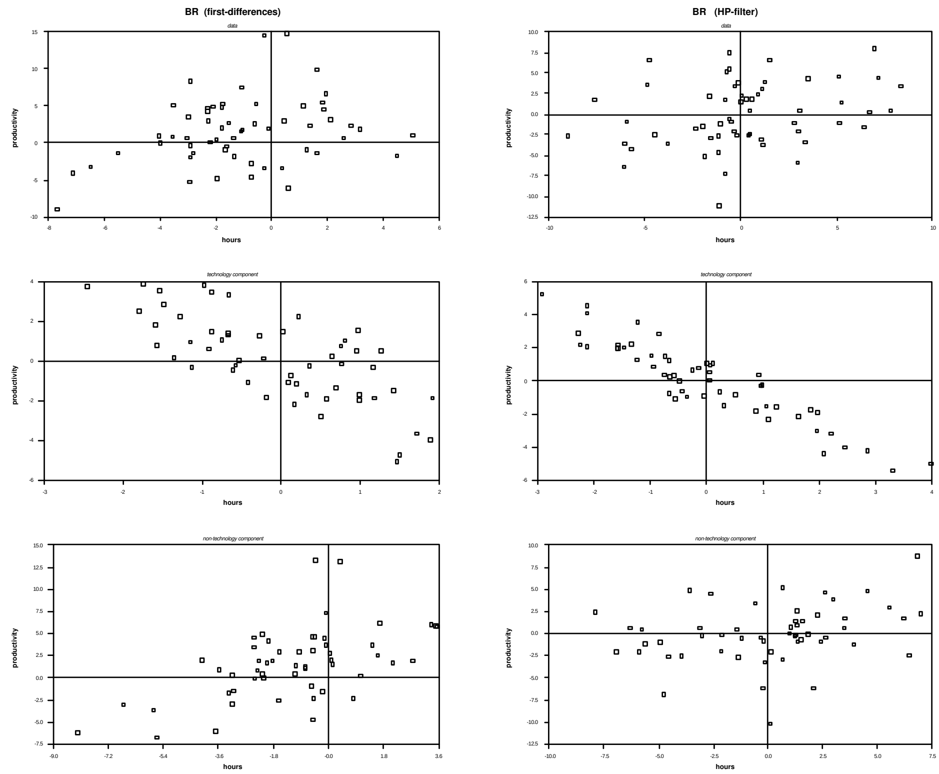

Figure 1
Scatterplots (hours vs. productivity)

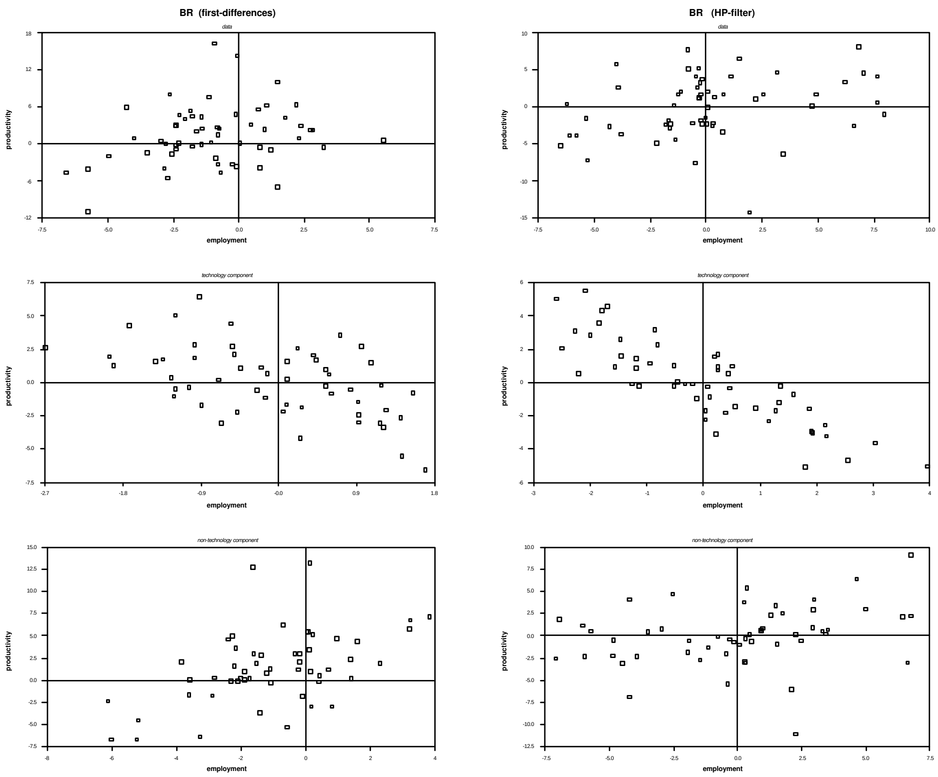

Figure 2
Scatterplots (employment vs. productivity)

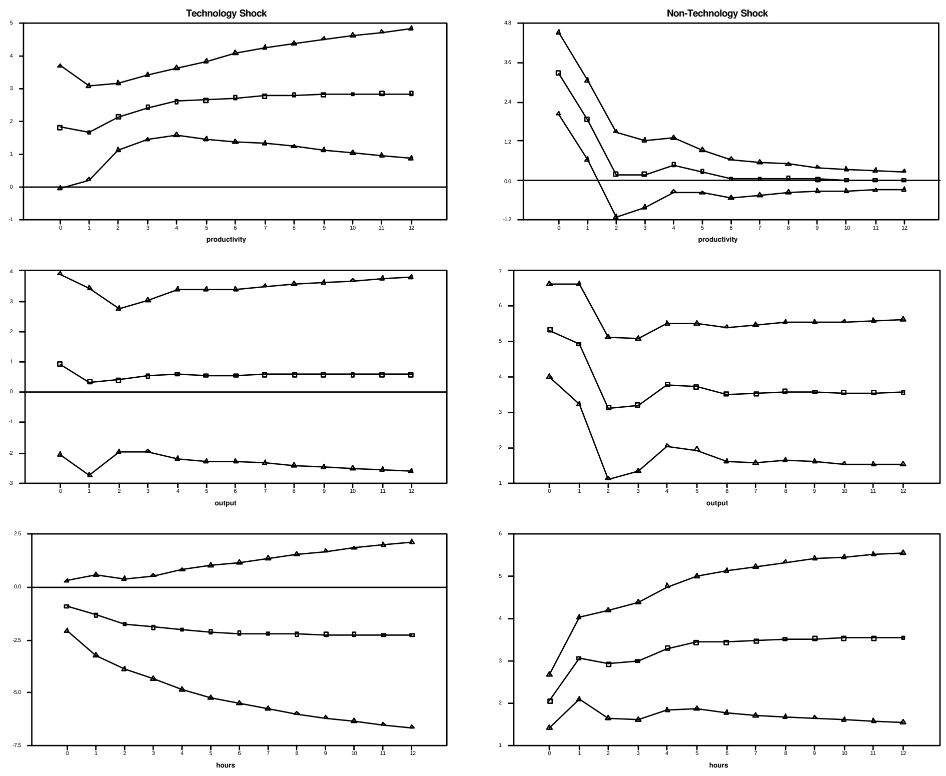

Figure 3
Impulse-response functions (hours)

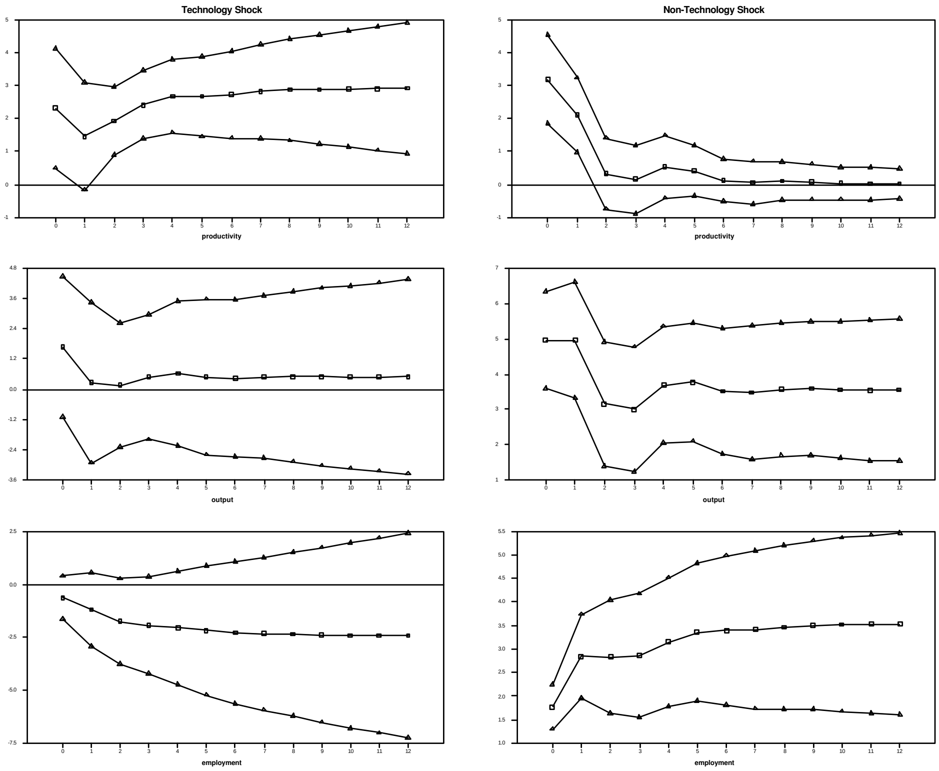

Figure 4
Impulse-response functions (employment)

Some general patterns emerge from the figures above. In the case of a positive technology shock, productivity is permanently affected, reaching a higher equilibrium level after a few quarters. This pattern can be explained by the responses exhibited by output and labor input measures, since the former slightly rises while the latter shows a persistent decline.[16] In the American case, Galí reports a result where there is an initial negative response of hours to technology shocks which tend to be reverted after a few quarters (see Galí (1999), figures 2 and 3). In the Brazilian case, such a reversion does not happen, even if we consider a 20-quarter horizon (not shown). This specific result contrasts sharply with the predictions of first-generation RBC models and it has spawned a growing literature that has

[16]It is important to notice that in the case of technology shocks, the dynamic response of output is estimated with very low accuracy. This result was also reported for the American economy (see below).

been trying to check its robustness.[17]

When we consider the effects of a positive non-technology shock, we notice that productivity converges to zero after some quarters (by construction). However, it still shows dampening oscillations, a result that could point to the importance of "demand" shocks over productivity measures in the short run. Output and labor input measures respond positively to this shock, with both variables reaching permanently higher equilibrium levels after five or six quarters.

We still have another possibility in the present context: testing the occurrence of SRIRL phenomena in our dataset. Considering the production function represented by (1), we can obtain the following expression, written in terms of (log) first differences:

$$\triangle y_t = \delta + \varphi \triangle n_t + u_t \tag{9}$$

where $u_t \equiv \triangle z_t - \delta$ and $\delta \equiv E(\triangle z_t)$. In this specification, φ captures the effect of (non-measurable) effort variations associated with labor input movements in equilibrium, besides the elasticity of output with respect to labor input. A basic problem with such a specification, however, is that when performing estimations, there might be a correlation between the error term $\triangle z_t$ and the regressor $\triangle n_t$, as well as the possibility of occurrence of serial correlation in $\triangle z_t$.

If we estimate the above specification through ordinary least squares (OLS), the estimates might be biased upwards, since the error term and the regressor may exhibit a positive correlation between each other. If such a correlation is negative, our estimates will be biased downwards. A possible solution to these problems would be the use of instrumental variables estimation methods. A well-known problem with the use of instrumental variables is the obvious choice of good instruments (see Angrist and Krueger (2001), for instance). However, Galí (1996:25) states that an appropriate instrument for this estimation can be extracted from the SVAR estimation. If the SVAR's identification condition remains valid, then the non-technology component of labor input variations ($\triangle n_t^m$) is orthogonal to $\triangle z_t$ at all horizons. This way, we are able to estimate φ consistently by applying OLS to the following specification:

$$\triangle y_t = \delta + \varphi \triangle n_t^m + u_t^*, \tag{9'}$$

where $u_t^* \equiv \varphi \triangle n_t^z + \triangle z_t - \delta$ and $\{\triangle n_t^m\}$ is a sequence representing the non-technology component of labor input variations.[18]

We estimated both specifications. The results are contained in table 4.

[17] See Francis and Ramey (2001), Christiano et al. (2003a,b), Uhlig (2003), Fernald (2004) and Galí (2004). Galí and Rabanal (2004) provide a survey of this empirical debate.

[18] Since the sequence $\{\triangle n_t^m\}$ is not observed directly, there is the possibility of occurrence of small sample bias in the estimates reported. Although we are aware of this possibility, we hope to stimulate future research aimed at solving such a problem.

Table 4
SRIRL estimates for the Brazilian industry, 1985:01/1999:03

Hours	OLS	SVAR
φ	1.51***	1.97***
s.e.	(.29)	(.20)
Employment	**OLS**	**SVAR**
φ	1.50***	1.84***
s.e.	(.29)	(.28)
Galí (1996)	**OLS**	**SVAR**
φ	.79***	1.16***
s.e.	(.05)	(.05)

Source: authors' calculations.
Notes:
(a) Sample Period: 1985:01/1999:03
(b) SRIRL coefficients were estimated from specifications involving a constant term and one of the following regressors: growth rates of labor input measures (OLS) or the non-technology component obtained from SVAR estimation.
(c) Robust standard errors reported in parenthesis. The (*), (**) and (***) terms denote statistical significance at the 10%, 5% and 1% levels, respectively.

From the reported results, we notice the occurrence of SRIRL phenomena in our dataset. This might represent a potential explanation for productivity's procyclical pattern, although the estimated coefficients for the Brazilian industry are significantly larger than Galí's. There are two possible reasons for that: first, it reflects the higher volatility of the Brazilian economy; second, it reflects the (considerably) higher volatility of industrial data, as recognized by Kanczuk and Faria (2000) in their original study. Still, the values reported are in accordance with Galí's results for other G-7 countries, such as Germany and France, for instance (see Galí (1996), table 6).[19]

A final test that we could perform here is the following: if RBC models can explain business-cycle phenomena, then they should be able to replicate most of the related stylized facts. When we consider calibration exercises, we notice that these models replicate those facts in quite an accurate manner. Still, Galí (1999), showed that this is not necessarily true if one considers his approach. By plotting technology and non-technology components of output and labor input measures, he shows that technology components do not exhibit a close pattern, a contrary evidence to the main predictions of RBC models. Also, in the case of non-technology components, labor input is clearly procyclical, exhibiting downturns that closely match NBER's business-cycle chronology.

[19] Sousa (2001) reports results for estimated SRIRL coefficients ranging from 1.3 to 2.73. These magnitudes are greater than the ones reported here.

We also performed a similar exercise using Brazilian data. One initial problem, however, is related to the fact that there is not a Brazilian institute that elaborates a business-cycle chronology. In the last few years, Chauvet (2002) elaborated a chronology for business cycles in Brazil (in both annual and quarterly frequencies). The author constructs such a chronology through the use of two different methodologies: a "smoothed probabilities" method and through a rule-of-thumb where two consecutive periods of output decline are considered a recession. Her results are reported in table 5.

Table 5
Chauvet's (2002) quarterly chronology for business cycles in Brazil

Methodology			
"Smoothed probabilities"		Two consecutive declines	
"Peak"	"Trough"	"Peak"	"Trough"
1981:01	1981:04	1981:01	1981:04
1982:04	1983:01	1982:03	1983:01
1987:02	1987:03	1987:02	1987:03
1988:02	1988:04	1988:02	1988:04
1990:01	1991:01	1989:04	1991:01
1991:04	1992:02	1991:04	1992:03
1995:02	1995:03	1995:02	1995:03
1998:01	1998:04	1998:01	1998:04

Source: Chauvet (2002, table 5).

Since the chronologies obtained from different methods are quite similar, we decided to report only results related to the "rule-of-thumb" method.[20] Figures 5 and 6 contain results for the hours and employment measures, respectively. All the variables considered were smoothed through the Hodrick-Prescott filter in order to emphasize their cyclical components.[21]

[20]Results do not change when we consider the smoothed probabilities method, though.

[21]A word of caution is needed here. Although we employ the Hodrick-Prescott filter in some parts of the text, we are aware of the problems related to it, especially with the possibility that the filter generates cyclical patterns in series that originally contained none (see Cogley and Nason (1995)). Still, our intention here is to provide some robustness checks for the results obtained from first-differenced data.

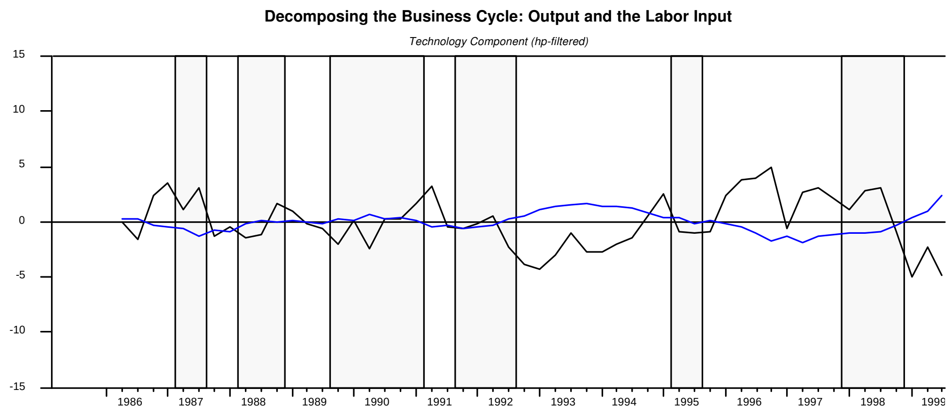

Figure 5
Output and hours over business-cycle horizons

Although there is not a perfect correlation between the non-technology components of output and labor input, we can notice a stronger association in this case, when compared to the case of technology components. Table 3 reports results for the estimated correlations: the unconditional correlation between output and hours is around .79, while the conditional correlations based on technology and non-technology components are -.71 and .84, respectively (results are similar for the case where employment is used as a labor input measure). Also, in the case of non-technology components, both variables tend to show short-run declines that match quite well Chauvet's chronology. However, the same is not true for technology components. While this can be seen as an informal test regarding the empirical adequacy of RBC models, our results could be flawed for many reasons, such as instability of the sample period or for being the result of very parsimonious systems (in terms of the number of variables involved in estimation). These are issues that we consider next, in the robustness tests section.

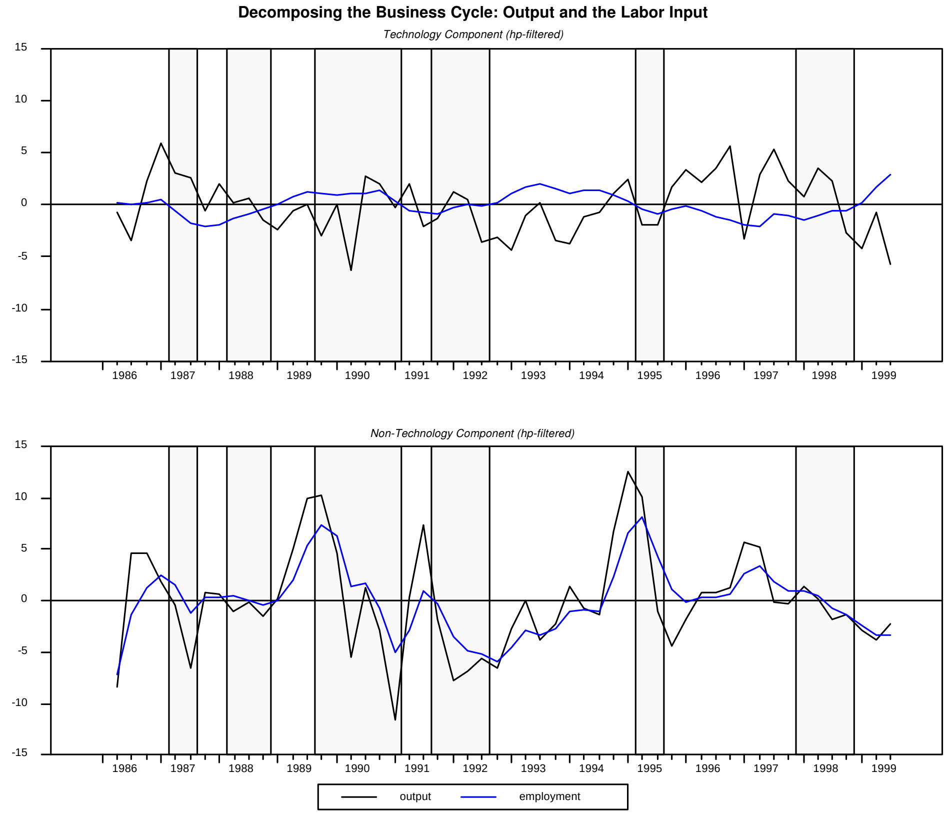

Figure 6
Output and employment over business-cycle horizons

6. Robustness

In this section, we describe the results of several tests carried out in order to check the robustness of the main results reported above.

Since Kanczuk and Faria's original dataset covers the 1985:01/1999:03 period only, we decided to extend it to a more recent period. Using data from IBGE, we are able to expand our sample until the first quarter of 2001, since IBGE's Monthly Industrial Survey (PIM) – our original source for labor input measures – was interrupted at that time and replaced by the Monthly Industrial Employment and Wage Survey (PIMES), which is based on a different methodology.[22] The same is true for the monetary aggregates (M2 and M3) employed in the estimation of

[22]We still constructed labor input measures based on both surveys. Although we are aware

larger-order systems (see below), which went through a methodological change in the year of 2001. Because of these data constraints, we decided to report most results for the 1985:01/2001:01 period only.

When comparing the extended database to Kanczuk and Faria's, we noticed that the labor input measures are basically the same for the common sample period (correlation coefficient of .99), although the same is not true for the industrial production measures (correlation coefficient of .9). Those differences may arise because of the different methods employed by Kanczuk and Faria, since these authors consider a closed-economy model in their calculations ($Y = C + I$, where C and I stand for consumption and investment, respectively). Because Kanczuk and Faria had access to some information regarding the construction of IBGE's industrial production index that we do not have, we are not able to obtain the same measure they do. Anyway, we see the use of IBGE's original industrial production index as an additional robustness check for our results.

We also carried out estimations considering alternative measures of output and/or labor input. First, we considered quarterly measures of aggregate output (real GDP) from IBGE, which were combined with the original labor input measures employed in order to proxy for aggregate (labor) productivity.[23] This can be seen as an effort to check whether our main results hold for the economy as a whole. Tables 6 and 7 contain results for all alternatives considered during estimations.

of the methodological problems related to such a procedure, we noticed that the main results do not change once we consider this extended sample period (1985:01/2004:01).

[23] We are also aware of the methodological problems of such a procedure, but we still see it as a valid robustness check for our results. For related problems with measuring productivity using Brazilian industrial data, see, for instance, Bonelli and Fonseca (1998).

Table 6
Estimated correlations between productivity and labor input measures for the Brazilian industry, several sample periods

Sample Period:1985:01/2001:01	Output Measure: Ind. Production		Dummy: no
	Unconditional	Conditional	
Hours		Technology	Non-Technology
First-Differences	.1	-.52*	.5***
	(.2)	(.29)	(.15)
Corr(y, n)	.79	.63	.79
Employment		Technology	Non-Technology
First-Differences	.08	-.65***	.45***
	(.17)	(.25)	(.12)
Corr(y, n)	.75	.24	.78
Sample Period:1985:01/2001:01	Output Measure: Ind. Production		Dummy: yes
	Unconditional	Conditional	
Hours		Technology	Non-Technology
First-Differences	.1	-.5*	.51***
	(.2)	(.29)	(.13)
Corr(y, n)	.79	.69	.79
Employment		Technology	Non-Technology
First-Differences	.08	-.71***	.44***
	(.17)	(.25)	(.12)
Corr(y, n)	.75	.7	.78
Sample Period:1985:01/2004:01	Output Measure: Ind. Production		Dummy: yes
	Unconditional	Conditional	
Hours		Technology	Non-Technology
First-Differences	.18	-.79***	.56***
	(.18)	(.29)	(.09)
Corr(y, n)	.76	.48	.78
Employment		Technology	Non-Technology
First-Differences	.13	-.66***	.47***
	(.15)	(.25)	(.09)
Corr(y, n)	.71	.38	.73
Sample Period:1985:01/2001:01	Output Measure: GDP		Dummy: no
	Unconditional	Conditional	
Hours		Technology	Non-Technology
First-Differences	-.11	-.5**	.5**
	(.13)	(.24)	(.22)
Corr(y, n)	.27	-.54	.83
Employment		Technology	Non-Technology
First-Differences	-.12	-.47**	.33*
	(.12)	(.23)	(.2)
Corr(y, n)	.25	-.53	.28
Mean	.06	-.6	.47

Source: authors' calculations.
Notes: see table 3 above.

Table 7
SRIRL estimates for the Brazilian industry, several sample periods

Sample Period: 1985:01/2001:01	Output Measure: Ind. Production	Dummy: no
Hours	OLS	SVAR
φ	1.15***	1.98***
s.e.	(.29)	(.26)
Employment	OLS	SVAR
φ	1.13***	1.92***
s.e.	(.29)	(.27)
Sample Period: 1985:01/2001:01	Output Measure: Ind. Production	Dummy: yes
Hours	OLS	SVAR
φ	1.51***	2.03***
s.e.	(.29)	(.18)
Employment	OLS	SVAR
φ	1.51***	1.95***
s.e.	(.29)	(.29)
Sample Period: 1985:01/2004:01	Output Measure: Ind. Production	Dummy: yes
Hours	OLS	SVAR
φ	1.28***	2.25***
s.e.	(.28)	(.29)
Employment	OLS	SVAR
φ	1.25***	2.22***
s.e.	(.29)	(.41)
Sample Period: 1985:01/2001:01	Output Measure: GDP	Dummy: no
Hours	OLS	SVAR
φ	.75**	1.95***
s.e.	(.31)	(.57)
Employment	OLS	SVAR
φ	.67**	1.8***
s.e.	(.31)	(.6)
Mean	1.16	2.01

Source: authors' calculations.
Notes: see table 4 above.

The results contained in the tables above show that the main results obtained in terms of the estimated conditional correlations are robust to differences in sample periods or variables employed in the analysis. In particular, the unconditional correlation between productivity and labor input measures is not statistically different from zero, while the conditional correlations based on technology components are around -.6 and the conditional correlations based on non-technology components are around .5 (all estimated coefficients for conditional correlations – including those based on technology components – are statistically significant at the 10% level, at least).

The results in terms of SRIRL are also confirmed across different specifications, although magnitudes are lower in the case of specifications where GDP is employed. Still, all the estimated coefficients are significant at the 5% level.[24]

Another problem with our estimations is related to the size of the estimated systems. Although much can be learned from small-dimensional systems, we may be making a specification error by considering only two variables (productivity

[24]Another possibility here would be to use a larger span of labor input data. In that case, the only available measure of this kind in Brazil is the Federation of Industries of the State of São Paulo (FIESP) database, which has produced labor input measures since 1975. However, the main problem with these series is that they are related to São Paulo's industry only. The results of such an experiment (not reported) confirm our main findings.

and labor input) in our analysis. A possible solution to this problem would be to consider higher-order systems. We follow this empirical strategy by estimating a VAR that employs other macroeconomic variables, besides the productivity and labor input measures originally employed in the SVAR estimation. Although we do not intend to consider such a multivariate system as the best possible explanation for the Brazilian macroeconomic environment, it may be useful as a robustness check for our initial estimates. It is worth noting that in this case there is not a clear interpretation for the long-run restrictions imposed upon this system's estimation. The only restriction which has a clearer interpretation is that productivity is still permanently affected by technology shocks.

The additional macroeconomic variables that we consider are real balances (M/P), the real interest rate ($r = i - \pi$) and the inflation rate (π). In constructing the former two measures, we take advantage of the fact that the (nominal) money concepts (M2 and M3) and the price index measures (IGP-DI or IPCA) may be considered as $I(2)$ processes (see Appendix B for results on unit root tests).[25] The same kind of reasoning can be applied to interest and inflation rates, which may be considered as $I(1)$ processes.[26] However, since such assumptions are about the existence of cointegration relationships between the money and price measures employed, we also estimate multivariate systems that consider all variables expressed in differences (first or second differences, depending on the order of integration of each variable).[27] Tables 8 and 9 contain results for the estimated correlation and SRIRL coefficients, respectively.

[25]The results obtained with specifications involving alternative measures of money (M2 or M3) or price indexes (IGP-DI or IPCA) are basically the same. Due to space constraints, we decided to report only those results where M2 and the IGP-DI index were used.

[26]There is an important consequence of modeling the real interest rate as an $I(1)$ process, since this means that there is not an equilibrium value to which this variable converges in the long run. Because of this fact, we decided to test for the presence of structural breaks in the original series, using Perron's (1989) procedure. The results obtained (not reported) show that the series can be characterized by a structural break, regardless of the time period where the break is imposed. Because of that result, we also considered estimations where the interest rate enters the estimated VAR(5) in levels. The main results (not shown) are not affected by such a possibility. See Campbell and Perron (1991), for the near-observational equivalence between trend stationary (TS) and difference-stationary (DS) processes. We thank an anonymous referee for pointing this out.

[27]When testing for the existence of long-run relationships between each pair of these variables, we ended up rejecting the cointegration hypothesis.

Table 8
Estimated correlations between productivity and labor input measures for the Brazilian industry, VAR(5)

Sample Period: 1985:01/1999:03					
	Unconditional	Conditional (VAR(5))		Conditional (VAR(5))(diffs)	
Hours		Technology	Non-Technology	Technology	Non-Technology
First-Differences	.29*	-.21	.41***	-.72***	.44***
	(.18)	(.28)	(.07)	(.18)	(.07)
Employment	Technology	Non-Technology	Technology	Non-Technology	
First-Differences	.25*	-.2	.4***	-.66***	.4***
	(.15)	(.18)	(.12)	(.16)	(.08)
Sample Period: 1985:01/2001:01					
	Unconditional	Conditional (VAR(5))		Conditional (VAR(5))(diffs)	
Hours		Technology	Non-Technology	Technology	Non-Technology
First-Differences	.1	-.41***	.27***	-.63***	.29***
	(.2)	(.13)	(.07)	(.11)	(.06)
Employment	Technology	Non-Technology	Technology	Non-Technology	
First-Differences	.08	-.49***	.26***	-.71***	.29***
	(.17)	(.12)	(.08)	(.06)	(.07)
Mean	.18	-.28	.31	-.63	.36

Source: authors' calculations.
Notes:
(a) Correlations were estimated from a VAR(5) model involving productivity and labor input measures, as well as other macroeconomic variables (real balances, real interest rate and the inflation rate).
(b) The third and fourth columns of the table contain results for the model that ranges on cointegration relations among the variables in the system, while the fifth and sixth columns contain results where variables are in first or second differences (depending on their order of integration).
(c) Standard errors were obtained from a Monte Carlo procedure with 500 draws (see details in text). The (*), (**) and (***) terms denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 9
SRIRL estimates: VAR(5)

Sample Period: 1985:01/1999:03			
Hours	OLS	VAR(5)	VAR(5)(diffs)
φ	1.51***	1.89***	1.88***
s.e.	(.29)	(.28)	(.25)
Employment	OLS	SVAR	SVAR
φ	1.51***	1.68***	1.92***
s.e.	(.29)	(.24)	(.28)
Sample Period: 1985:01/2001:01			
Hours	OLS	SVAR	SVAR
φ	1.15***	1.56***	1.61***
s.e.	(.29)	(.28)	(.31)
Employment	OLS	SVAR	SVAR
φ	1.13***	1.67***	1.65***
s.e.	(.29)	(.37)	(.34)
Mean	1.33	1.66	1.77

Source: authors' calculations.
Notes:
(a) SRIRL coefficients were estimated from specifications involving a constant term and one of the following regressors: labor input measures' growth rates (OLS) or the non-technology component obtained from VAR(5) estimation.
(b) Standard errors were obtained from a Monte Carlo procedure with 500 draws (see details in text). The (*), (**) and (***) terms denote statistical significance at the 10%, 5% and 1% levels, respectively.

In terms of the results contained in table 8, we observe an initial disparity between the estimated coefficients when looking at the results of the VAR(5) concerned with cointegration relationships among the variables in the system. However, when looking at the results for the VAR estimated with all variables expressed in differences, we get a more robust result. On the other hand, the results contained in table 9, related to SRIRL coefficients, provide substantial robustness to the findings reported before, regardless of the specification considered.

Figures 7 and 8 contain the estimated dynamic responses to a positive technology shock for all the variables in the system (the first graph uses hours as a labor input measure while the second graph uses employment).

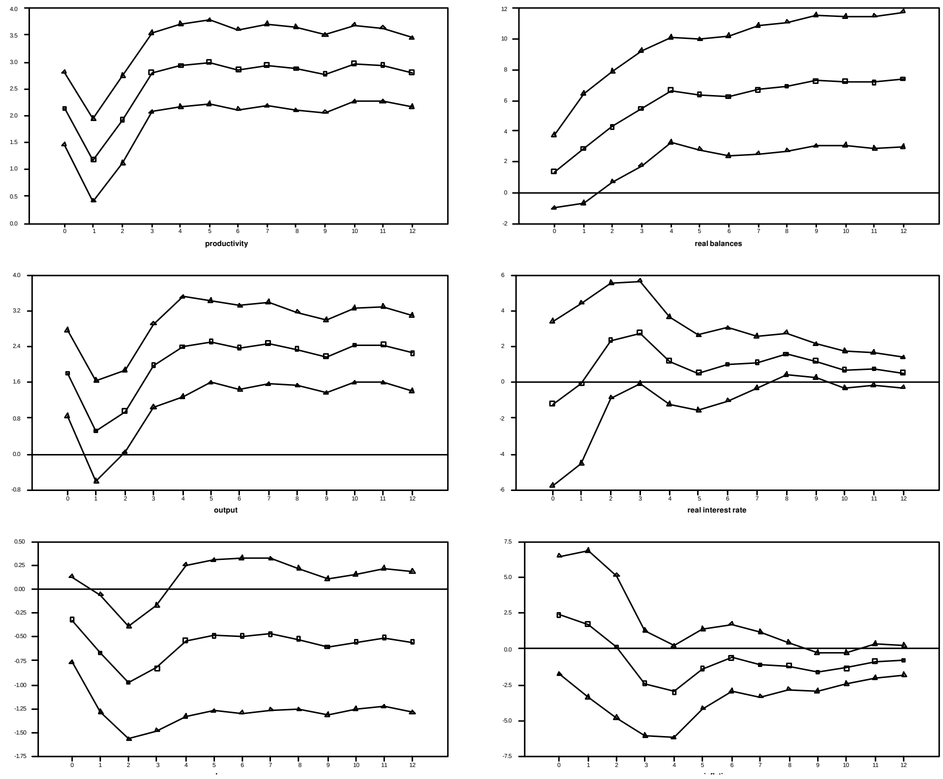

Figure 7
VAR(5): Impulse-response functions (hours)

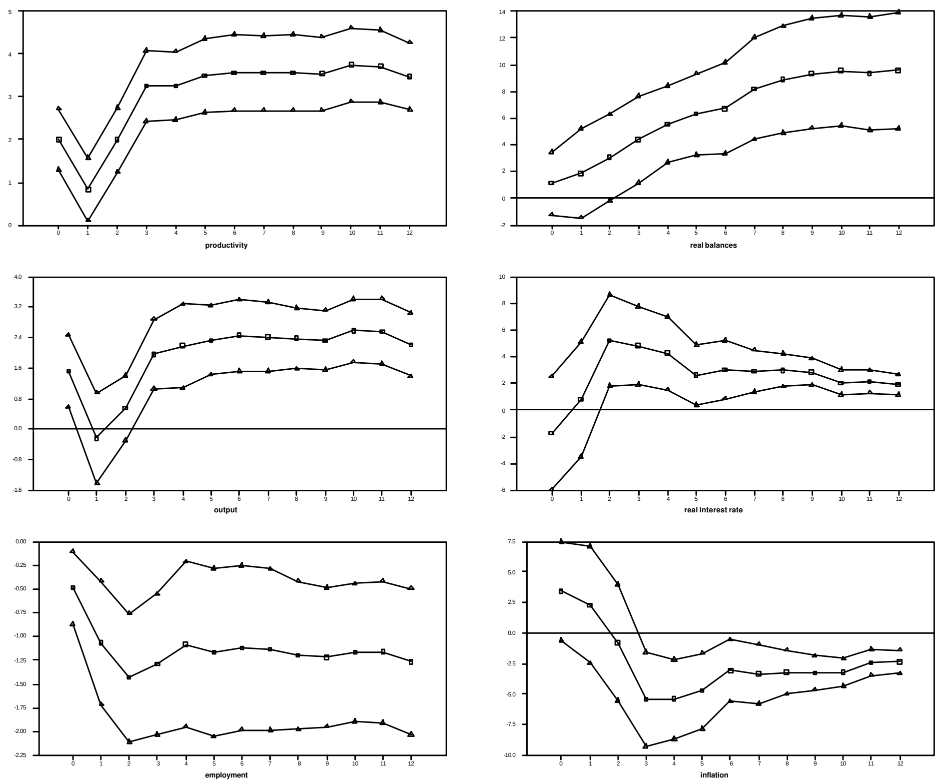

Figure 8
VAR(5): Impulse-response functions (employment)

Acording to the dynamic responses contained in both Figures, we can have a picture of the general patterns followed by all variables as they respond to a positive technology shock. First, the productivity and output measures still exhibit a positive response to a technology shock, although both variables present dampening oscillations toward equilibrium in this situation. Both labor input measures (hours and employment) still exhibit a contractionary pattern in response to a positive technology shock.

Nevertheless, the other variables in the system present a different pattern. Real balances, for instance, present a steady rise towards its equilibrium level. The same is true for the real interest rate, although this variable tends to converge asymptotically to zero after twelve quarters. On the other hand, inflation presents an initial rise due to a positive technology shock, but after that, this variable exhibits a contractionary pattern for several quarters, also tending asymptotically to zero.

While the explanation for the other variables in the system could generate some aditional research in the future, the basic point here is that the results obtained with bivariate systems employing productivity and labor input measures remain robust to the inclusion of other variables during estimation. This result demonstrates that we were not making a specification error when performing estimations with the simpler systems above. Moreover, the contractionary response of labor input to technology shocks is confirmed, an important result also uncovered by other authors for the American economy (see Basu et al. (1998), for instance). However, we tend to see the results of both specifications with some caution, since our sample size is relatively small. It is a well-known result in time series econometrics that a higher-order VAR tends to rapidly consume degrees of freedom.

As we said above, we are dealing with a problematic sample period, related to the eighties and the nineties in Brazil. Over this period, the country went through various inflationary episodes and stabilization plans (most of which failed, except for the Real Plan, implemented in 1994). All these episodes may cause a substantial amount of instability in our estimations.

Recently, Galí et al. (2003) have drawn attention to the importance of structural instability in SVAR analyses of the type performed here. When performing their estimations, these authors divide their original sample to check for such an instability.

Still, there is another possibility in this direction. For instance, we can retrieve a "problematic" period from our original sample, a period in which we cannot have a purely economic explanation for the events that occurred, and then redo our estimations. Although the best way to proceed would be to perform an analysis of influence, we decide to draw selected periods from the sample and re-estimate our SVAR specifications in order to verify whether we could get more robust results. Tables 10 and 11 contain the results for the estimated correlation and SRIRL coefficients, respectively.[28]

[28] See Davidson and MacKinnon (1993) about analysis of influence. Galí et al. (2003), follow the same procedure when dealing with American data. When performing Chow stability tests for the variables entering the reduced-form VAR, we cannot reject the null hypothesis of no structural change for the period before or after 1990:02 in our sample. The same is true in the case of alternative time spans (such as the periods before and after 1994:02). Results are not shown due to space constraints.

Table 10
Estimated correlations between productivity and labor input measures for the Brazilian industry, without selected periods

	Unconditional		Conditional
Sample Period: 1985:01/1999:03 (w/o 1990)	Output Measure: Ind. Production		Dummy: no
Hours		Technology	Non-Technology
First-Differences	.14	-.6***	.58***
	(.1)	(.28)	(.1)
Employment		Technology	Non-Technology
First-Differences	.16	-.61***	.59***
	(.11)	(.32)	(.11)
Sample Period: 1985:01/2001:01 (w/o 1990)	Output Measure: Ind. Production		Dummy: no
Hours		Technology	Non-Technology
First-Differences	-.02	-.56***	.56***
	(.13)	(.2)	(.2)
Employment		Technology	Non-Technology
First-Differences	.02	-.67***	.56***
	(.14)	(.23)	(.15)
Sample Period: 1985:01/2001:01 (w/o 1990:02)	Output Measure: Ind. Production		Dummy: no
Hours		Technology	Non-Technology
First differences	-.11	-.9***	.28**
	(.12)	(.2)	(.13)
Employment		Technology	Non-Technology
First-Differences	-.08	-.75***	.32***
	(.12)	(.21)	(.12)
Sample Period: 1985:01/2001:01 (w/o 1990:02)	Output Measure: GDP		Dummy: no
Hours		Technology	Non-Technology
First-Differences	-.11	-.5**	.36**
	(.12)	(.22)	(.17)
Employment		Technology	Non-Technology
First-Differences	-.1	-.39*	.25
	(.13)	(.23)	(.2)
Mean	-.01	-.62	.44

Source: authors' calculations.
Notes: see table 3 above.

Table 11
SRIRL estimates, without selected periods

Sample Period: 1985:01/1999:03 (w/o 1990)	Output Measure: Ind. Production	Dummy: no
Hours	OLS	SVAR
φ	1.16***	1.55***
s.e.	(.1)	(.11)
Employment	OLS	SVAR
φ	1.19***	1.59***
s.e.	(.1)	(.12)
Sample Period: 1985:01/2001:01 (w/o 1990)	Output Measure: Ind. Production	Dummy: no
Hours	OLS	SVAR
φ	.98***	1.54***
s.e.	(.12)	(.23)
Employment	OLS	SVAR
φ	1.02***	1.5***
s.e.	(.13)	(.17)
Sample Period: 1985:01/2001:01 (w/o 1990:02)	Output Measure: Ind. Production	Dummy: no
Hours	OLS	SVAR
φ	.87***	1.34***
s.e.	(.14)	(.1)
Employment	OLS	SVAR
φ	.89***	1.38***
s.e.	(.16)	(.13)
Sample Period: 1985:01/2001:01 (w/o 1990:02)	Output Measure: GDP	Dummy: no
Hours	OLS	SVAR
φ	.74**	1.49***
s.e.	(.3)	(.44)
Employment	OLS	SVAR
φ	.74**	1.37***
s.e.	(.35)	(.49)
Mean	.95	1.47

Source: authors' calculations.
Notes: see table 4 above.

The results obtained are robust to the withdrawal of different time periods from the sample. Specifically, in terms of conditional correlations, we have results where both correlations have opposite signs, no matter what labor input measure we consider. In terms of SRIRL results, the OLS estimates are around .95 on average, while the SVAR estimates are higher, being around 1.47. The above results seem to confirm our initial findings, going in the same direction as Galí's original results.[29]

There were, however, two results of our original analysis that were not confirmed when performing the robustness checks. First, the reported correlation between cyclical components of output and labor input change considerably once we use different variables (see table 6, where those correlations are reported). The only robust result in this case is that we find high correlations for the non-technology components. The importance of technology components over business-cycle horizons is, at best, mixed. Second, the dynamic responses of output are not robust

[29]We also performed a robustness check where we changed the order of the variables entering the reduced-form VAR while maintaining our identification hypothesis (that non-technology shocks do not affect productivity in the long run). Results (not shown) remain the same in the case of such an experiment. We thank an anonymous referee for this suggestion.

to the use of different measures for this variable (not reported). In some cases, output rises to a one-standard deviation shock in productivity, while in others it presents a contractionary response. As pointed above, the important thing to notice here is that the response of output to technology shocks is estimated with very low accuracy. Actually, this was a point also noticed by Christiano et al. (2003b) for the American case.[30]

7. Conclusions and Future Research

In this paper, we asked about the empirical adequacy of RBC models from an unusual point of view. We did not make any use of calibration or simulation methods. Instead, we employed a technique that puts few *a priori* restrictions upon the data. By proceeding this way, we wanted to check whether the predictions derived from such models are compatible with business-cycle phenomena. Also, we wanted to check the occurrence of SRIRL phenomena in Brazil.

Three main results emerge from the estimations reported here. First, although the unconditional correlation between productivity and labor input is not statistically different from zero, the conditional correlations – based on technology and non-technology components – have opposite signs and similar magnitudes. Second, the dynamic response of labor input to technology shocks exhibits a contractionary pattern in the short run, a stronger result than that originally reported by Galí (1999) for the American economy. In particular, this result casts serious doubts on the performance of first-generation RBC models. Third, we report the existence of SRIRL phenomena in the datasets employed.

Most of the results obtained are robust to specification issues, such as sample instability or higher-order dimensional systems. Still, some caution is needed when looking at it. Our sample period is a problematic one, since it contains a wide variety of socio-economic phenomena in it. Also, research related to SRIRL phenomena (in the lines suggested by Gordon (1992)) and to the evaluation of alternative monetary policy schemes (Galí et al., 2003) may be helpful in qualifying the results reported here. Another interesting possibility would be to perform counterfactual exercises for the Brazilian economy in the lines suggested by Christiano et al. (2003b) and McGrattan (2004).

Future research should concentrate on checking these results for alternative datasets and time spans. In particular, we see the result of a contractionary response of labor input to technology shocks as a promising area for future research, although we consider this sole result as a narrow standard for judging the adequacy of RBC models. We find that research that follows alternative strands in checking

[30]By employing a different methodology, Basu et al. (1998) report a result where technology shocks may have contractionary effects on output. Collard and Dellas (2004) argue that negative responses of employment and output to technology shocks may arise in a multisector RBC model or in an open-economy model where domestic and foreign intermediate goods are seen as gross complements.

the empirical adequacy of RBC models may represent a very promising area, since calibration exercises seem to involve quite subjective impressions that might affect the predictions derived from them. Research strategies that can combine the recent approaches suggested by Chari et al. (2004) and Galí and Rabanal (2004) may provide a more complete account for the problem at hand.

Since its beginning, the RBC research agenda never meant to represent the only (or best) possible explanation for business-cycle phenomena. Models of this kind have always been refined in order to incorporate new hypotheses that would provide a better description of reality. Although we follow a different direction in this paper, we hope to contribute to this research agenda by providing alternative empirical evidence related to some of the main predictions of RBC models.

References

Altug, S. (1989). Time-to-build and aggregate fluctuations: Some new evidence. *International Economic Review*, 30(4):889–920.

Angrist, J. D. & Krueger, A. B. (2001). Instrumental variables and the search for identification: From supply and demand to natural experiments. NBER Working Paper no. 8456, 31p.

Basu, S., Fernald, J. G., & Kimball, M. (1998). Are technology improvements contractionary? Board of Governors of the Federal Reserve System, International Finance Discussion Paper Series no. 625, 56p.

Blanchard, O. J. & Quah, D. T. (1989). The dynamic effects of aggregate demand and supply disturbances. *American Economic Review*, 79(4):655–673.

Bonelli, R. & Fonseca, R. (1998). Ganhos de produtividade e de eficiência: Novos resultados para a economia brasileira. *Pesquisa e Planejamento Econômico*, 28(2):273–314.

Campbell, J. & Perron, P. (1991). Pitfalls and opportunities: What macroeconomists should know about union roots. NBER Technical Working Paper no. 100, 69p.

Canova, F., Finn, M. G., & Pagan, A. (1994). Evaluating a real business cycle model. In Hargreaves, C., editor, *Non-Stationary Time Series Analysis and Cointegration*, pages 225–255. Oxford, London.

Chari, V. V., Kehoe, P. J., & McGrattan, E. (2004). Are structural VARs useful guides for developing business cycle theories? Federal Reserve Bank of Minneapolis Working Paper no. 631, 45p.

Chauvet, M. (2002). The Brazilian business cycle and growth cycle. *Revista Brasileira de Economia*, 56(1):75–106.

Christiano, L. J. & Eichenbaum, M. (1992). Current real-business-cycle theories and aggregate labor market fluctuations. *American economic Review*, 82(3):430–450.

Christiano, L. J., Eichenbaum, M., & Vigfusson, R. (2003a). The response of hours to a technology shock: Evidence based on direct measures of technology. Northwestern University, 12p, mimeo.

Christiano, L. J., Eichenbaum, M., & Vigfusson, R. (2003b). What happens after a technology shock? Northwestern University, 52p, mimeo.

Cogley, T. & Nason, J. M. (1995). Effects of the Hodrick-Prescott filter on trend and difference stationary time series: Implications for business cycle research. *Journal of Economic Dynamics and Control*, 19(2):253–278.

Collard, F. & Dellas, H. (2004). Supply shocks and employment in an open economy. *Economics Letters*, 82:231–237.

Cooley, T. F. (1995). *Frontiers of Business Cycle Research*. Princeton University, New Jersey.

Cooley, T. F. & Dwyer, M. (1998). Business cycle analysis without much theory: A look at structural VARs. *Journal of Econometrics*, 83(1):57–88.

Cooley, T. F. & Prescott, E. C. (1995). Economic growth and business cycles. In Cooley, T. F., editor, *Frontiers of Business Cycle Research*, pages 1–38. Princeton University Press, New Jersey.

Davidson, R. & MacKinnon, J. G. (1993). *Estimation and Inference in Econometrics*. Oxford University Press, New York.

Dickey, D. A. & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, 49(4):1057–1073.

Dickey, D. A. & Pantula, S. (1987). Determining the order of differencing in autoregressive processes. *Journal of Business and Economic Statistics*, 15(4):455–461.

Eichenbaum, M. (1991). Real business-cycle theory: Wisdom or whimsy? *Journal of Economic Dynamics and Control*, 15(4):607–626.

Eichenbaum, M. & Singleton, K. J. (1986). Do equilibrium real business cycle theories explain postwar U.S. business cycles? In Fisher, S., editor, *NBER Macroeconomics Annual*, pages 91–134,63–130. NBER.

Ellery, R. G., J., Gomes, V., & Sachshida, A. (2002). Business cycle fluctuations in Brazil. *Revista Brasileira de Economia*, 56(2):269–308.

Enders, W. (1995). *Applied Econometric Time Series*. John Wiley and Sons.

Engle, R. F. & Granger, C. W. J. (1987). Cointegration and error-correction: Representation, estimation and testing. *Econometrica*, 55:251–276.

Engle, R. F. & Yoo, B. S. (1987). Forecasting and testing in cointegrated systems. *Journal of Econometrics*, 35(1):143–159.

Erceg, C. J., Guerrieri, L., & Gust, C. (2004). Can lon-run restrictions identify technology shocks? Board of the Federal Reserve System, International Finance Discussion Paper Series no. 792, 53p.

Fernald, J. (2004). Trend breaks, long run restrictions and the contractionary effects of technology shocks. Federal Reserve Bank of Chicago, 31p, mimeo.

Francis, N. & Ramey, V. A. (2001). Is the technology-driven real business cycle hypothesis dead? Shocks and aggregate fluctuations revisited. UCSD Working Paper, 38p.

Galí, J. (1992). How well does the IS-LM model fit postwar U.S. data? *Quarterly Journal of Economics*, 107(2):709–738.

Galí, J. (1996). Technology, employment and the business cycle: Do technology shocks explain aggregate fluctuations? NBER Working Paper no. 5721, 48p.

Galí, J. (1999). Technology, employment and the business cycle: Do technology shocks explain aggregate fluctuations? *American Economic Review*, 89(1):249–271.

Galí, J. (2004). On the role of technology shocks as a source of business cycles: Some new evidence. *Journal of the European Economic Association*, 2(2-3):372–380. Papers and Proceedings.

Galí, J., López-Salido, J. D., & Vallés, J. (2003). Technology shocks and monetary policy: Assessing the Fed's performance. *Journal of Monetary Economics*, 50(3):723–743.

Galí, J. & Rabanal, P. (2004). Technology shocks and aggregate fluctuations: How well does the RBC model fit postwar U.S. data? NBER Macroeconomics Annual.

Gordon, R. J. (1992). Are procyclical productivity fluctuations a figment of measurement error? Northwestern University, 34p, mimeo.

Gregory, A. W. & Smith, G. W. (1995). Business cycle theory and econometrics. *Economic Journal*, 105:1597–1608.

Hamilton, J. D. (1994). *Time Series Analysis*. Princeton University, Princeton.

Hansen, G. D. (1985). Indivisible labor and the business cycle. *Journal of Monetary Economics*, 16(3):309–327.

Hansen, G. D. & Wright, R. (1992). The labor market in real business cycle theory. *Federal Reserve Bank of Minneapolis Quarterly Review*, Spring:2–12.

Hodrick, R. & Prescott, E. C. (1997). Post-war U.S. business cycles: A descriptive empirical investigation. *Journal of Money, Credit and Banking*, 29(1):1–16.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12:231–254.

Johansen, S. (1992). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, 59(4):1551–1580.

Kanczuk, F. & Faria, F. J. (2000). Ciclos reais para a indústria brasileira? *Estudos Econômicos*, 47(4):335–350.

King, R. G., Plosser, C. I., Stock, J. H., & Watson, M. W. (1991). Stochastic trends and economic fluctuations. *American Economic Review*, 81(4):819–940.

King, R. G. & Rebelo, S. (2000). Ressuscitating real business cycles. In Taylor, J. & Woodford, M., editors, *Handbook of Macroeconomics*, pages 927–1007. North-Holland.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of unit root. *Journal of Econometrics*, 54(1):159–178.

Kydland, F. & Prescott, E. C. (1982). Time to build and aggregate fluctuations. *Econometrica*, 50(6):1345–1370.

Kydland, F. & Prescott, E. C. (1991a). The econometrics of the general equilibrium approach to business cycles. *Scandinavian Journal of Economics*, 93(2):161–178.

Kydland, F. & Prescott, E. C. (1991b). Hours and employment variation in business cycle theory. *Economic Theory*, 1(1):63–81.

Kydland, F. & Prescott, E. C. (1996). The computational experiment: An econometric tool. *Journal of Economic Perspectives*, 10(1):69–85.

Long, J. B. & Plosser, C. I. (1983). Real business cycles. *Journal of Political Economy*, 9(1):39–69.

Mackinnon, J. G. (1991). Critical values for cointegration tests. In Engle, R. F. & Granger, C. W. J., editors, *Long-Run Economic Relationship: Readings in Cointegration*. Oxford University.

McGrattan, E. (2004). Comment on Galí and Rabanal's "Technology shocks and aggregate fluctuations: How well does the RBC model fit postwar U.S. data?". Federal Reserve Bank of Minneapolis Staff Report 338, 20p.

Osterwald-Lenum, M. (1992). A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics. *Oxford Bulletin of Economics and Statistics*, 54(4):461–472.

Perron, P. (1989). The Great Crash, the oil price shock and the unit root hypothesis. *Econometrica*, 57(3):1361–1401.

Pessôa, S. M. M. (1999). Métodos de estimação de modelos de ciclos reais: Um estudo para as economias brasileira e americana. Rio de Janeiro: EPGE/FGV-RJ. Dissertação de Mestrado, 250p.

Phillips, P. C. B. & Perron, P. (1988). Testing for unit roots in time series regression. *Biometrika*, 75(3):335–346.

Rebelo, S. (2005). Real business cycle models: Past, present and future. Northwestern University, 25p, mimeo.

Shapiro, M. & Watson, M. W. (1988). Sources of business cycle fluctuations. In *NBER Macroeconomics Annual*, pages 111–148. NBER.

Shea, J. (1998). What do technology shocks do? In *NBER Macroeconomics Annual*. NBER.

Sousa, I. R. (2001). Ciclos reais de negócios e a realidade brasileira. Rio de Janeiro: EPGE/FGV-RJ. Dissertação de Mestrado.

Stadler, G. W. (1994). Real business cycles. *Journal of Economic Literature*, 32(4):1750–1783.

Uhlig, H. (2003). Do technology shocks lead to a fall in total hours worked? Humboldt University, 13p, mimeo.

Val, P. R. C. & Ferreira, P. C. G. (2001). Modelos de ciclos reais de negócios aplicados à economia brasileira. *Pesquisa e Planejamento Econômico*, 31(2):213–248.

Weder, M. (2003). Are aggregate fluctuations in Germany due to technology shocks? Humboldt University, 20p, mimeo.

Appendix A

Descriptive Statistics and Figures

Table A.1
Data descriptive statistics (levels)

Variable	Source	Mnemonic	Units	Mean	Std. Deviation	Minimum	Maximum
Ind. Production	PIM-PF	PIMPF12_QIIG12	Index no.	4.43	.08	4.25	4.6
GDP	IBGE	PIBPMV4	R$ MM	13.01	.09	12.73	13.17
Hours	PIM-DG	PIMDG12_HPIND12	Index no.	4.4	.26	3.96	4.78
Employ-ment	PIM-DG	PIMDG12_POIND12	Index no.	4.99	.23	4.59	5.32
M2	BCB	Bm12_M2N12	R$ MM	4.1	8.3	-10.11	13.03
M3	BCB	Bm12_M3N12	R$ MM	4.49	8.27	-9.58	13.24
Interest Rate	BCB	Bm12_TJOVER12	%month	13.65	14	1.16	54.36
IGP-DI	FGV	Igp12_IGFPF12	R$ MM	-2.73	8.14	-16.67	5.27
IPCA	IBGE	Prices12_IPCA12	R$ MM	-.41	8.1	-14.31	7.44

Notes:
(a) Sample Period: 1985:01/2001:01 (65 observations of each variable). Results are basically the same for the 1985:01/1999:03 period (not shown).
(b) All variables were seasonally adjusted and are expressed in natural logarithms, except for the interest rate.

Table A.2
Productivity measures descriptive statistics (levels)

Variable	Units	Mean	Std. deviation	Minimum	Maximum
X_h	Index number	4.84	.23	4.53	5.24
X_n	Index number	4.81	.22	4.47	5.2
Y_h	Index number	4.81	.24	4.5	5.19
Y_n	Index number	4.78	.23	4.48	5.15

Notes:
(a) Sample Period: 1985:01/2001:01 (65 observations of each variable).
(b) All variables are expressed in natural logarithms.
(c) Productivity measures were constructed by subtracting the natural logarithm of labor input measures from output measures. Here, the terms X_h and X_n denote productivity measures where the output measure used is the industrial production index, while Y_h and Y_n denote productivity measures where the output measure used is GDP. The subscripts h and n denote hours and employment, respectively.

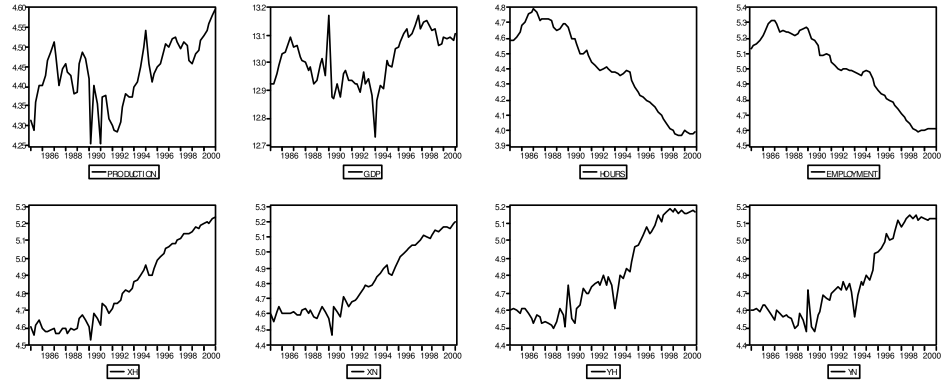

Figure A.1
Main variables (log-levels)

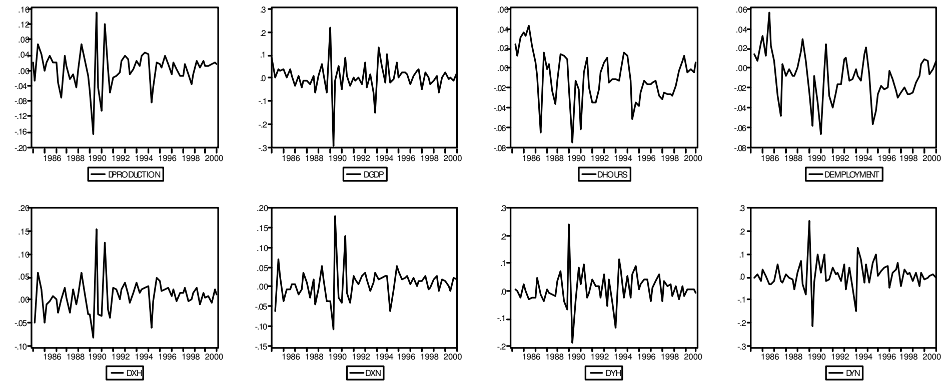

Figure A.2
Main variables (first differences)

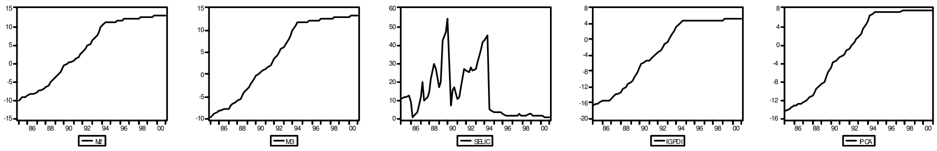

Figure A.3
Money and price variables (log-levels)

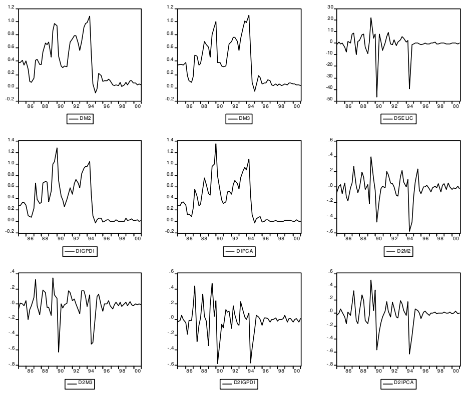

Figure A.4
Money and price variables (first and second differences)

Appendix B

Unit Root Tests

Table B.1
Unit-root tests (Dickey-Pantula): First step (two unit roots)

Variable	$\tau_{\beta 1}$	Lags
Industrial Production	-8.84***	0
GDP	-7.86***	1
Hours	-4.93***	0
Employment	-4.4***	0
M2	-2.71	1
M3	-2.51	1
SELIC	-8.66***	0
IGP-DI	-2.45	1
IPCA	-2.34	1
X_h	-9.18***	1
X_n	-9.24***	1
Y_h	-11.00***	0
Y_n	-11.2***	0

Source: authors' calculations.
Notes:
(a) Sample Period: 1985:01/2001:01. Results do not change when we consider the 1985:01/1999:03 period (not shown).
(b) Critical values for this test are reported in Dickey and Pantula (1987).
(c) The number of lags employed in the tests were chosen in order to obtain white-noise residuals for the regression of each test.
(d) The terms (*), (**) and (***) denote rejection of the test's null hypothesis at the 10%, 5% and 1% significance levels, respectively.

Table B.2
Unit-root tests (Dickey-Pantula): Second step (one unit-root)

Variable	$\tau_{\beta 1}$	$\tau_{\beta 2}$	Lags
Industrial Production	-7.92***	-2.15	0
GDP	-10.56***	-1.95	1
Hours	-4.76***	.03	0
Employment	-4.21***	-.1	0
M2	-3.13***	-1.62	1
M3	-2.92***	-1.61	1
SELIC	-7.65***	-2.52	1
IGP-DI	-2.87***	-1.68	1
IPCA	-2.79***	-1.71	1
X_h	-9.21***	1.16	1
X_n	-9.23***	1.06	1
Y_h	-10.72***	-.09	0
Y_n	-10.87***	-.17	0

Source: authors' calculations.
Notes: see table B.1 above.

Table B.3
Unit-Root tests (ADF and PP)

Variable	ADF test	PP test
Industrial Production	-2.73	-2.66
	(0)	(3)
△ (Industrial Production)	-7.9***	-8.78***
	(1)	(1)
GDP	-2.18	-3.16
	(1)	(5)
$\triangle(GDP)$	-11.58***	-12.01***
	(0)	(2)
Hours	-4.09**	-3.72**
	(1)	(1)
△(Hours)	-4.95***	-4.91***
	(1)	(3)
Employment	-3.56**	-3.45*
	(3)	(1)
△(Employment)	-4.75***	-4.37***
	(1)	(3)
X_h	-3.22*	-3.14
	(0)	(1)
$\triangle(X_h)$	-9.55***	-12.93***
	(0)	(7)
X_n	-2.05	-2.57
	(2)	(2)
$\triangle(X_n)$	-9.57***	-12.84***
	(1)	(7)
Y_h	-3.22*	-3.00
	(0)	(4)
$\triangle(Y_h)$	-8.87***	-11.26***
	(1)	(1)
Y_n	-3.02	-2.78
	(0)	(4)
$\triangle(Y_n)$	-8.92***	-11.47***
	(1)	(1)

Source: authors' calculations.
Notes:
(a) Sample Period: 1985:01/2001:01. Results do not change when we consider the 1985:01/1999:03 period (not shown).
(b) Critical values for this test are reported in Dickey and Fuller (1981) and Mackinnon (1991).
c) The number of lags for each test (reported in parenthesis) was chosen based on the Schwarz Information Criterium.
(d) The terms (*), (**) and (***) denote rejection of the test's null hypothesis at the 10%, 5% and 1% significance levels, respectively.

Table B.4
Unit root tests (ADF and PP)

Variable	ADF test	PP test
M2	-.22	.22
	(2)	(5)
$\triangle$(M2)	-3.18*	-2.31
	(1)	(5)
$\triangle^2$(M2)	-5.86***	-6.11***
	(0)	(18)
M3	-.37	.24
	(2)	(5)
$\triangle$(M3)	-2.97	-2.28
	(1)	(6)
$\triangle^2$(M3)	-6.39***	-7.29***
	(2)	(26)
SELIC	-2.99	-2.92
	(0)	(5)
$\triangle$(SELIC)	-8.6***	-11.87***
	(0)	(18)
IGP-DI	-1.04	.22
	(1)	(5)
$\triangle$(IGP-DI)	-2.43	-2.41
	(0)	(6)
$\triangle^2$(IGP-DI)	-6.8***	-7.98***
	(0)	(16)
IPCA	-1.02	.3
	(1)	(5)
$\triangle$(IPCA)	-2.39	-2.37
	(0)	(6)
$\triangle^2$(IPCA)	-6.84***	-7.67***
	(0)	(19)

Source: authors' calculations.
Notes: see table B.3 above.

Table B.5
Unit root tests (KPSS)

Variable	KPSS test (4 lags)	KPSS test (8 lags)
Industrial production	.2**	.14*
GDP	.22***	.15**
Hours	.19**	.14*
Employment	.22***	.16**
M2	.29***	.18**
M3	.29***	.18**
SELIC	.2**	.15**
IGP-DI	.3***	.19**
IPCA	.31***	.19**
X_h	.28***	.18**
X_n	.3***	.19**
Y_h	.24***	.16**
Y_n	.26***	.17**

Source: authors' calculations.
(a) Sample Period: 1985:01/2001:01. Results do not change when we consider the 1985:01/1999:03 period (not shown).
(b) Critical values for this test are reported in Kwiatkowski et al. (1992).
(c) The terms (*), (**) and (***) denote rejection of the test's null hypothesis at the 10%, 5% and 1% significance levels, respectively.

Appendix C

Cointegration Tests

Table C.1
Engle-Granger cointegration tests (hours and productivity)

Cointegration Regression	CRADF Statistic	Crit. Value (95%)	Lags
$H_t = 188.37 - .82X_{ht}$	-3.09	-3.37	0
$X_{ht} = 223.34 - 1.15H_t$	-3.07	-3.37	0

Source: authors' calculations.
Notes:
(a) Sample Period: 1985:01/2001:01. Results do not change when we consider the 1985:01/1999:03 period (not shown).
(b) Critical values for this test are reported in Engle and Yoo (1987).
(c) The terms H_t and X_{ht} denote measures representing the labor input (hours, in this case) and productivity (output-hours ratio).
(d) The terms (*), (**) and (***) denote rejection of the test's null hypothesis at the 10%, 5% and 1% significance levels, respectively.

Table C.2
Engle-Granger cointegration tests (employment and productivity)

Cointegration regression	CRADF statistic	Crit. value (95%)	Lags
$N_t = 185.77 - .8X_{nt}$	-3.13	-3.37	0
$X_{nt} = 225.97 - 1.17N_t$	-3.13	-3.37	0

Source: authors' calculations.
Notes: see table C1 above. The terms N_t and X_{nt} denote measures representing labor input (employment, in this case) and productivity (output-employment ratio).

Table C.3
Johansen's cointegration tests (hours and productivity)

Null Hypot.	Eigenvalues	λ_{trace}	Crit. Value (95%)	λ_{max}	Crit. Value (95%)	VAR Order
Specification with unrestricted constant						
$r = 0$	.123	8.817	15.41	7.874	14.07	4
$r \leq 1$	.0156	.9423	3.76	.9423	3.76	4
Specification with unrestricted constant and a trend inside the cointegration vector						
$r = 0$	0.2216	22.905	25.32	15.034	18.96	4
$r \leq 1$	0.1229	7.871	12.25	7.871	12.25	4

Source: authors' calculations.
Notes:
(a) Sample Period: 1985:01/2001:01. Results do not change when we consider the 1985:01/1999:03 period (not shown).
(b) Critical values are reported in Osterwald-Lenum (1992).
(c) The terms (*), (**) and (***) denote rejection of the test's null hypothesis at the 10%, 5% and 1% significance levels, respectively.

Table C.4
Johansen's cointegration tests (employment and productivity)

Null Hypot.	Eigenvalues	λ_{trace}	Crit. Value (95%)	λ_{max}	Crit. Value (95%)	VAR Order
Specification with unrestricted constant						
$r = 0$	.1476	10.917	15.41	9.584	14.07	4
$r \leq 1$	.022	1.333	3.76	1.333	3.76	4
Specification with unrestricted constant and a trend inside the cointegration vector						
$r = 0$	0.217	23.933	25.32	14.679	18.96	4
$r \leq 1$	0.1429	9.254	12.25	9.2541	12.25	4

Source: authors' calculations.
Notes: see table C.3 above.

Appendix D

VAR Adequacy Criteria

Table D.1
Diagnostic tests for VAR residuals (hours and productivity)

Sample Period	1985:01/1999:03		1985:01/2001:01	
	Statistic	Prob.	Statistic	Prob.
Autocorrelation (Portmanteau)	43.98	.31	32.21	.46
Autocorrelation (LM Test)	5.36	.25	2.57	.63
Heteroskedasticity (White)	28.74	.23	71.26	.03
Heteroskedasticity (White with cross-terms)	50.68	.17	150.65	.17
Normality (Multivariate Jarque-Bera)	3.81	.43	7.45	.11

Source: authors' calculations.
Notes:
(a) We estimated VAR specifications containing a constant and four lagged values of each variable in the system.
In the case of the extended sample period (1985:01/2001:01) a dummy for the 1990:02 quarter was included as an exogenous variable in the estimations.
(b) The reported values contained in the table correspond to each test statistics and the corresponding probabilities associated.

Table D.2
Diagnostic tests for VAR residuals (employment and productivity)

Sample Period	1985:01/1999:03		1985:01/2001:01	
	Statistic	Prob.	Statistic	Prob.
Autocorrelation (Portmanteau)	44.44	.29	41.63	.12
Autocorrelation (LM Test)	4.68	.32	2.4	.66
Heteroskedasticity (White)	27.59	.28	62.42	.13
Heteroskedasticity (White with cross-terms)	40.91	.52	147.79	.21
Normality (Multivariate Jarque-Bera)	2.22	.7	6.69	.15

Source: authors' calculations.
Notes: see table D.1 above.