

Alexius, Annika; Carlsson, Mikael

Working Paper

Measures of Technology and the Business Cycle

Working Paper, No. 2002:10

Provided in Cooperation with:

Department of Economics, Uppsala University

Suggested Citation: Alexius, Annika; Carlsson, Mikael (2002) : Measures of Technology and the Business Cycle, Working Paper, No. 2002:10, Uppsala University, Department of Economics, Uppsala,
<https://nbn-resolving.de/urn:nbn:se:uu:diva-2230>

This Version is available at:

<https://hdl.handle.net/10419/82841>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Measures of Technology and the Business Cycle*

Annika Alexius[†] and Mikael Carlsson[‡]

May 7, 2002

Abstract

Empirical evidence on the relationship between technology shocks and e.g. hours worked hinges crucially on the identification of the unobservable technological progress. In this paper, we study different measures of technology in order to find out (i) to what extent they capture the same underlying phenomenon and (ii) whether the implications for macroeconomic theory are robust across the approaches. Several versions of the productions function approach and structural VAR models are investigated. Our main finding is that the different technology measures are highly correlated. However, the exact formulation of the identifying restrictions seems to matter for the results. While we replicate the standard finding of a strongly procyclical Solow residual, all other measures of technology are either acyclical or countercyclical.

Keywords: Technology shocks, productions function approach, structural VAR models.

JEL classifications: E32, C32.

*We would like to thank Nils Gottfries and seminar participants at Uppsala University, FIEF and Örebro University for helpful comments and suggestions, and Jon Samuels for providing some of the data.

[†]Department of Economics, Uppsala University, Box 513, SE-751 20 Uppsala, Sweden. Tel: +46 18 4711564. Fax +46 18 4711478. E-mail: annika.alexius@nek.uu.se.

[‡]Department of Economics, Uppsala University, Box 513, SE-751 20 Uppsala, Sweden. Tel: +46 18 4711129. Fax +46 18 4711478. E-mail: mikael.carlsson@nek.uu.se.

1 Introduction

Empirical evidence on the relationship between technology shocks and other variables is important in several areas of macroeconomics. For example, Basu, Fernald and Kimball (1998) and Galí (1999) evaluate the empirical merits of different business cycle models by studying the comovements of technology shocks on one hand and changes in real output, hours worked, and input on the other. They find that technological improvements have contractionary short-run effects on inputs, which is inconsistent with the predictions of real business cycle (RBC) models. Since technology shocks cannot be observed, such evidence is necessarily conditioned on the particular method used to capture technological progress.

A second field where the identification of the unobservable technology shocks plays a crucial role is structural VAR studies of the sources of fluctuations in various variables. Conclusions like "technology shocks cause about 40 percent of the variability of real output at business cycle frequencies" (King, Plosser, Stock and Watson (1991)) or "the bulk of the long-run movements in real exchange rates are due to real demand shocks, whereas the influence of supply shocks is negligible at all horizons" (Clarida and Galí (1994)) have had considerable impact on subsequent research. A relevant question is to what extent the different approaches for identifying technology shocks actually capture the true underlying phenomenon. This issue has frequently been debated in the literature on structural VAR models, but it has not been systematically studied empirically.

Because structural shocks are inherently unobservable, there is no true measure against which the outcome of a VAR can be evaluated. Furthermore, there are no alternative measures of monetary shocks or real demand shocks, other than those identified by structural VARs. What Clarida and Galí (1994) do to check the validity of their identification scheme is to plot the demand shocks captured by their VAR model and discuss whether it is possible to detect the major demand related events of the sample period in the graph. If major policy changes etc. can be seen in the graph, this is interpreted as evidence in favor of

the validity of the identification scheme.

However, technology shocks differ from other structural shocks in this respect since there exist well-established alternative methods for identifying them. Most importantly, measures of technological progress can be constructed as the residual from a production function. This methodology was pioneered by Solow (1957) and subsequently refined by Hall (1988), Hall (1990), Basu and Kimball (1997) and others.

In this paper, we apply the two main techniques for identifying technological change to identical U.S. data in order to (i) compare the measures of technology to each other and (ii) investigate whether they display similar cyclical patterns. To what extent do structural VAR models capture the same unobservable phenomenon as production function residuals? Does the evidence about the relationship between technology shocks and e.g. labor input differ between the method used to capture the unobservable technological progress? If the implications for macroeconomic theory are similar across the measures of technology, potential differences between them are less consequential than if the empirical support in favor of e.g. RBC models varies systematically between the approaches.

Structural VAR models with restrictions on the long-run effects of shocks are used to distinguish technology shocks from other sources of fluctuations in various fields. Examples are Blanchard and Quah (1989) and King et al. (1991) for real output, Dolado and Jimeno (1997) for unemployment, Quah and Vahey (1995) for inflation, and Alexius (2001) and Clarida and Galí (1994) for real exchange rates. King et al. (1991) and Galí (1999) represent two different strategies for how a structural VAR can be used to identify technology shocks. King et al. (1991) estimate a six-variable cointegrated VAR including the levels of real output, consumption, investment, the real money supply, a nominal interest rate and inflation. Technology shocks are identified by the assumption that no other structural shock affects real output in the long-run. Galí (1999) focuses on a small two-variable VAR model with changes in labor productivity and hours worked. He separates technology shocks from non-technology shocks

by assuming that only the former have long-run effects on labor productivity.

The production function approach has little in common with structural VAR models. Solow (1957) measures technological change as the growth of output that remains unexplained once increases in the production factors have been taken into account. Equivalently, the technology shock is the residual from a production function equation. Solow's original method requires perfect competition, constant returns to scale and full factor utilization. Since deviations from these assumptions introduce cyclical non-technology related variation, the classic Solow residual is not likely to be a good measure of technology at business cycle frequencies. Instead, we rely on the refinements of the Solow residual developed by Hall (1988, 1990) and Basu and Kimball (1997) where imperfect competition, non-constant returns to scale, and variable factor utilization are allowed.

We use two versions of the production function approach and the structural VAR methodology to estimate technology growth for the U.S. non-farm private economy: the classic Solow residual, the Basu and Kimball (1997) approach using data on hours per employee to control for varying factor utilization, a large cointegrated VAR model a'la King et al. (1991) and a small two variable VAR in first differences as in Galí (1999).

Although we are not aware of previous systematic comparisons of the different approaches for identifying technology shocks, several authors provide correlations between the technology shocks identified by their VAR models and some other measure of technology. King et al. (1991) report correlations of 0.48 and 0.19 with the classic Solow residual and Hall's (1988) refined measure of technology, respectively. Kiley (1998) calculates 34 correlations between his VAR technology shocks and two refined Solow residuals. More than half of them are insignificant and the cross industry average is 0.22. These two studies compare technology shocks from different approaches for particular sample periods, and industries in the latter case, but they do not investigate the concordance of the methods given that they are actually supplied with identical information. While the data requirements of the production function approach differs considerably

from those of the large cointegrated VARs, we try to construct data sets that are as coherent as possible across the approaches.

Our main findings can be summarized as follows. (i) Structural VAR models produce technology shocks that are highly correlated with the production function residuals. (ii) While we replicate the standard finding of a strongly procyclical Solow residual, all other measures of technology are either acyclical or countercyclical. Thus all alternative measures of technology support the view that the procyclicality of the Solow residual is a consequence of variations in factor utilization or other non-technology related variation rather than a characteristic of the true technology shocks. (iii) The exact formulation of the long run restrictions used to identify technology shocks appear to have important effects on the results in the direction suggested by economic theory.

The paper is organized as follows. Section 2 presents the data. In Section 3, the different approaches for identifying technology shocks are described. Section 4 presents the main results and studies various robustness issues. In Section 5, we analyze the differences between the measures of technology in terms of the theoretical motivations of the approaches. We also present some empirical evidence of what kind of noise the different methods appear to capture. Section 6 concludes.

2 The Data

To avoid the aggregation bias created by heterogenous parameters across industries, the production function approach requires disaggregate data. Industry data on gross output and inputs are only available on annual frequency. On the other hand, large cointegrated VAR models focus on the endogenous interaction between macroeconomic aggregates. Furthermore, the King (1991) specification is preferably estimated using quarterly rather than annual data due to the large number of parameters to be estimated. Therefore, two U.S. data sets are used in this paper: annual disaggregate industry data and quarterly aggregate data. We try to render the comparisons between the VAR technology shocks and pro-

duction function residuals as exact as possible by constructing coherent data and estimating the models for both aggregation levels when feasible.

The disaggregate data set is developed by Dale Jorgenson and consists of a panel of 33 industries (roughly two-digit SIC-level), covering the entire U.S. non-farm private economy. It contains annual observations on quantities and prices of output and inputs for the period 1948 to 1991. This data set has been widely used, e.g. by Basu et al. (1998) and Basu and Fernald (2001). Further details can be found in Jorgenson, Gollop and Fraumeni (1987). For comparability with the former two references, we focus on the sample period 1950-1989.

The aggregate data set contains real output, consumption, investment, real money supply, inflation, nominal interest rates, population, and hours worked for the period 1950:1 to 1989:4. It is collected from the BEA, the BLS and the Federal Reserve Board of Governors, see Appendix A for details.

The methods for estimating technology growth can all be viewed as decompositions of output, or labor productivity (output/hours) in the Galí (1999) model, into a technology driven component and a component driven by other factors. To make the comparison of technology measures across aggregation levels and methods meaningful, we need to use consistent measures of output and hours across the data sets. To this end, we use the same population on both the aggregate and the disaggregate level for output and hours, i.e. the U.S. non-farm private economy. Moreover, the (small) remaining discrepancies are corrected by adjusting the quarterly observation in the aggregate data set so that they sum up to the annual observation in the disaggregate data set in each year.¹

¹The value of these factors are within the range 0.92 to 1.09. Thus, the differences before the correction is made are quite small.

3 Identification of Technology Shocks

There are considerable methodological differences within each of our main approaches for identifying technology shocks. Two baseline VAR specifications are estimated in this paper: the large cointegrated model of King et al. (1991), and the two-variable model of Galí (1999). In addition to the classic Solow (1957) residual, we use the specification of Basu and Kimball (1997) to construct robust technology series on industry data. We also estimate several minor variations of the specifications to study the robustness of the results.

3.1 The VAR Approach

VAR models can be used to produce a measure of technology by imposing restrictions on the long run effects of the unobservable structural shocks. The models of King et al. (1991) and Galí (1999) represent two different empirical strategies. Galí (1999) uses a two-variable VAR with the (stationary) first differences of labor productivity and hours worked. King et al. (1991) estimate a large, cointegrated VAR with four real and two nominal variables.

King et al. (1991), Galí (1999) and others present theoretical models to motivate their identifying restrictions. The formulation of the long run restrictions is remarkably similar across a large number of VAR studies, however. Monetary shocks are identified using the long run neutrality of money, i.e. by assuming that monetary shocks do not affect real variables in the long run. Technology shocks are assumed to be the sole long run driving force of real output in the King et al. (1991) specification and of labor productivity in the Galí (1999) specification. The apparently subtle difference between the identifying assumptions of the King et al. (1991) and Galí (1999) models turns out to be potentially important and we will return to this issue in Section 5.1.

3.1.1 A large VAR-model a'la King et al. (1991)

King et al. (1991) estimate a six variable VAR containing the logs of output per capita, y , consumption per capita, c , investment per capita, i , real money

balances per capita ($m - p$), a nominal interest rate, R , and inflation, Δp , where lower case letters denote the log of the variable, Δ is the first difference operator and the total population is used to derive per capita series. We follow their approach and estimate the following cointegrated VAR:²

$$\Delta z_t = \mu + \Pi z_{t-1} + \sum_{i=1}^p \Gamma_i \Delta z_{t-i} + \xi_t, \quad (1)$$

where $z_t = [y, c, i, (m - p), R, \Delta p]'$, μ is a vector of drift terms, Π is a reduced rank matrix contain the error correction parameters times the cointegrating vectors β , Γ is a coefficient matrix and ξ_t is a vector of white noise disturbances. The cointegrated VAR in (1) can be rewritten as a common trends model (see e.g. Hylleberg and Mizon (1989)):

$$z_t = z_0 + \phi(L) v_t + \Theta \tau_t, \quad (2)$$

where

$$\tau_t = \mu + \tau_{t-1} + \varphi_t. \quad (3)$$

Here, z_0 denotes a vector of initial conditions, v_t is a vector of white noise disturbances and $\phi(L)$ is a matrix lag polynomial. Hence, the term $\phi(L) v_t$ constitutes the transitory component of z_t . Given the dimension n of the VAR, the number of cointegrating vectors, r , in (1) determines the number of independent stochastic trends k in the common trends model (2) as $k = n - r$. The stochastic trends are denoted τ_t , which is a k -dimensional vector of random walks with drift μ and innovations φ_t . Thus, the I(1) component of z_t is captured by the term $\Theta \tau_t$, where the loading matrix Θ determines how the endogenous variables are affected by the permanent shocks φ_t in the long run. The permanent shocks are also included in v_t , which allows them to affect the transitory or cyclical component of z_t . The empirical model is hence consistent with the real business cycle notion that technology shocks can cause business cycle fluctuations.

For exact identification of the k structural shocks in φ_t , we need to impose $k(k - 1)/2$ restrictions on the long run impact matrix Θ (see e.g. Warne

²Note that our data set differ somewhat from what King et al. (1991) use.

(1993)). Restrictions on Θ , the cointegrating rank of the system and/or the parameter values in the cointegrating vectors can frequently be derived from economic theory. For instance, the balanced growth conditions imply that the ratios of consumption and investment to output should be constant in the long run. Consumption and investment should then be cointegrated with output and the parameters in the cointegrating vector should be unity. The cointegrating vectors β imply restrictions on the long run impact matrix Θ through the condition that $\beta'\Theta = 0$. Monetary neutrality can also be formulated in terms of the parameters in the long run impact matrix. If money is neutral in the long run, as is the case in most standard models, the parameters in Θ that capture effects of monetary shocks on real variables should be equal to zero.

We estimate the King et al. (1991) specification for quarterly US aggregate data. As in King et al. (1991), the sample starts in 1954:1 to avoid the effects of price controls, the Korean War, and the Treasury-Fed accord on the nominal variables. The main features of the King et al. (1991) specification, the cointegrating rank and hence the number of stochastic trends, are consistent with their findings. The number of lags p is determined using information criteria (Akaike, Schwarz, Hannan-Quinn) as well as misspecification tests such as residual autocorrelation. We use the LM test for first and fourth order autocorrelation, and the Portmanteau test for higher order autocorrelation. This procedure results in two lags in the baseline specification. Because inflation and the nominal interest rate increase up to 1980 and decrease thereafter, we include a trend shift dummy for μ .

The cointegrating rank is determined using the Johansen (1991) multivariate maximum likelihood approach. Using critical values from Osterwald-Lenum (1992), the test statistics indicate three cointegrating vectors (see Table 1). Following King et al. (1991), the cointegrating vectors are normalized as long run equilibrium relationships between (i) consumption, output, inflation and the nominal interest rate, (ii) investment, output, inflation and the nominal interest rate, and (iii) demand for real balances, output, inflation and the nominal interest rate.

The parameters of the cointegrating vectors have the expected signs and magnitudes (see Table 2). The results imply that the real interest rate are negatively related to consumption and investments. Moreover, the coefficients on real output in the long-run equilibrium relationships for consumption, investment and real balances are $[-0.861, -0.747, -1.271]$. The restriction that the first two of these coefficients equals -1 is not rejected, i.e. it is the ratios of consumption and investment to output that enters into the long run equilibrium relationships. Other restrictions suggested by economic theory are that the real variables are unaffected by inflation and the nominal interest rate in the long run, or that they are affected only by the real interest rate. In the baseline specification we impose the most restrictive restriction that is not rejected by the data, namely that the coefficients on real output in the equilibrium relations for consumption and investment equal -1 and the coefficients on inflation and the nominal interest rate are equal with opposite signs (see Table 2 for details). Hence, the money demand relationship is left unrestricted. These restrictions on the cointegrating space imply that consumption and investment are unaffected by nominal shocks.

Following King et al. (1991), we interpret the three stochastic trends as technology (supply), real interest rate (demand), and a nominal (monetary) trend. Technology shocks are identified by the assumption that no other shocks affect real output in the long run. This implies that Θ_{12} and Θ_{13} in the loading matrix are zero. Long-run monetary neutrality provides the third required restriction by imposing a zero long-run effect of monetary shocks on the real interest rate.

3.1.2 A Small VAR-model a'la Galí (1999)

Galí (1999) separates the influence of technology shocks from that of non-technology shock within a two variable VAR-model containing the first differences of labor productivity, x_t , defined as output per hour, and hours worked, h_t . Following Galí (1999), we estimate the following VAR:

$$\begin{bmatrix} \Delta x_t \\ \Delta h_t \end{bmatrix} = \mu + \sum_{i=1}^p \Gamma_i \begin{bmatrix} \Delta x_{t-i} \\ \Delta h_{t-i} \end{bmatrix} + u_t, \quad (4)$$

where μ is a vector of drift terms, p is the number of lags, Γ are matrices containing estimated parameters of the lag polynomial, and u_t is a vector of reduced form residuals. Denoting the technology shock v_t^t and the non-technology shocks v_t^{nt} , and defining $C(1)$ as the long run impact matrix of the unobservable structural shocks, we arrive at the equation:

$$\begin{bmatrix} \Delta x_t \\ \Delta h_t \end{bmatrix} = \mu + \begin{bmatrix} C^{11}(1) & C^{12}(1) \\ C^{21}(1) & C^{22}(1) \end{bmatrix} \begin{bmatrix} v_t^t \\ v_t^{nt} \end{bmatrix}. \quad (5)$$

The identifying assumption that only technology affects labor productivity in the long run implies that $C^{12}(1) = 0$. To enable as exact comparisons of the different approaches as possible, we estimate the Galí specification on several aggregation levels and frequencies: (i) Annual aggregate data (using one lag). This data set is identical to the one used for the aggregate productions function residuals. (ii) Quarterly aggregate data (using three lags), which is the real output series used in the King et al. (1991) approach. (iii) Disaggregate annual industry data (also with a single lag in the baseline specification). As production function residuals are constructed for each industry before they are aggregated to an economy wide measure, we can compare them to industry specific VAR technology shocks by estimating the Galí (1999) specification for each industry.

3.2 The Production Function Approach

The idea behind the production function approach is that technological change can be measured as the residual from a production function, taking increases in production factors and the intensity with which they are used into account. We start by postulating the following production function for firm i :

$$Y_{it} = F(Z_{it}K_{it}, E_{it}H_{it}, V_{it}, M_{it}, A_{it}), \quad (6)$$

where gross output Y_{it} is produced combining the stock of capital K_{it} , hours worked H_{it} , energy V_{it} and intermediate materials (less energy) M_{it} . The firm

may also adjust the level of utilization of capital, Z_{it} , and labor, E_{it} . Finally, A_{it} is the index of technology which we want to capture.

By differentiating the log of (6) with respect to time and invoking cost minimization (see e.g. Carlsson (2000) for the details) we arrive at:

$$\Delta y_{it} = \eta_i [\Delta x_{it} + \Delta u_{it}] + \Delta a_{it}, \quad (7)$$

where Δ denotes growth rates, η is the overall returns to scale, Δx_{it} is a cost share weighted input index defined as $c_{iK}\Delta k_{it} + c_{iH}\Delta h_{it} + c_{iV}\Delta v_{it} + c_{iM}\Delta m_{it}$, $\Delta u_{it} = c_{iK}\Delta z_{it} + c_{iH}\Delta e_{it}$ and c_{iJ} is the cost share of factor J in total costs.³ Thus, given data on factor compensation, changes in output, input and utilization, and an estimate of the returns to scale η_i , the resulting residual Δa_{it} provides a times series of technology growth for firm i . Notice that Δa_{it} reduces to the Solow residual if $\eta = 1$, $\Delta u_{it} = 0$ and if there are no economic profits.⁴ Hence, Δa_{it} is a Solow residual purged of the effects of increasing returns, imperfect competition and varying factor utilization.

The main empirical problem associated with (7) is that capital and labor utilization are generally unobservable. A solution to this problem is to include proxies for utilization in (7). We follow the approach of Basu and Kimball (1997) and use hours per employee as proxy for both labor and capital utilization.

3.2.1 The Basu and Kimball (1997) Specification

The intuition behind the approach taken by Basu and Kimball (1997) is that a cost-minimizing firm, facing a well behaved cost function with respect to factor adjustment, should be indifferent between different margins of adjustment. In particular, the cost of increasing output by increasing the number of hours worked, enticing more effort from the labor force given the number of hours worked or using capital more intensely should all be equal. Hours worked can

³Here it is assumed that the cost shares are constants. We will return to this assumption below.

⁴The zero economic profit condition imply that the factor cost shares in total costs equal the factor cost shares in total revenues which is used when compiling the Solow residual.

therefore be used as proxy for the intensity with which the firm uses labor as well as capital. Basu and Kimball formalize this idea and use the first order conditions of a dynamic cost-minimization problem to derive a relation between utilization growth, Δu , and the growth rate of hours per employee, Δhpe . Inserting this relationship into (7) yields the empirical specification employed by e.g. Basu et al. (1998), Basu and Fernald (2001) and Basu, Fernald and Shapiro (2001) to estimate technology growth:

$$\Delta y_{it} = \alpha_i + \eta_i \Delta x_{it} + \gamma_i \Delta hpe_{it} + \varepsilon_{it}, \quad (8)$$

where Δx_{it} is defined as in (7) and Δhpe_{it} is the growth rate of hours per employee.⁵

When implementing the Basu and Kimball (1997) specification, we follow the empirical strategy outlined by Basu et al. (2001). First, the specifications are regarded as log-linear approximations around the steady state growth path. Thus the products $\eta_i c_{iJ}$ (i.e. the output elasticities) are treated as constants. Second, the steady state cost shares are estimated as the time average of the empirical cost shares. Third, when compiling the cost shares we assume that firms make zero economic profits in the steady state.⁶ This allows us to estimate the cost share of capital as a residual. Finally, the growth rate of technology, Δa_t , is modeled as a random walk with the drift α and the random shock ϵ_t . This strategy for modeling the technology process is consistent with the assumptions underlying the structural VAR approach.

As a robustness exercise, we also employ an alternative approach to control for factor utilization. Burnside, Eichenbaum and Rebelo (1995) apply the idea of Griliches and Jorgenson (1967), to use energy consumption as a proxy for capital utilization. This procedure can be legitimized by assuming that there is a zero

⁵Basu and Kimball (1997) also generalize their approach by allowing for variation in the rate of capital depreciation (due to varying capital utilization). However, given the statement of Basu et al. (2001), i.e. "...including these terms barely affects estimates of technical change", p. 14, we do not consider this generalization here.

⁶For evidence in favor of this assumption see the discussion in Rotemberg and Woodford (1995).

elasticity of substitution between energy and the flow of capital services, $Z_{it}K_{it}$, which implies that energy and capital services are perfectly correlated. Adding the assumption that labor utilization is constant, we arrive at the empirical specification of Burnside et al. (1995):⁷

$$\Delta y_{it} = \alpha_i + \eta_i \Delta \tilde{x}_{it} + \varepsilon_{it}, \quad (9)$$

where input growth $\Delta \tilde{x}_{it}$ is now defined as $(c_{iK} + c_{iV})\Delta v_{it} + c_{iH}\Delta h_{it} + c_{iM}\Delta m_{it}$. Energy is however only likely to be a good proxy for the utilization of heavy equipment. This specification is therefore less appropriate outside the manufacturing sector. Since the Burnside et al. specifications relies on a different set of assumptions than the Basu and Kimball specification, we estimate both approaches for the manufacturing industry as a robustness test.

3.2.2 Instrumentation and Estimation

Because the firm is highly likely to consider the current state of technology when making its input choices, instrumental variable techniques are required to credibly identify the residuals from the robust production function specifications above as technology growth. The most commonly used instruments in the literature are variations of the so-called Hall-Ramey instruments and Federal Reserve policy shocks. The Hall-Ramey instruments consist of the growth rate of the real price of oil, the growth rate of real defense spending and a dummy variable for the political party of the president. We use the following instrument set: the lagged Federal Reserve policy shock derived from an estimated reaction function of the Federal Reserve and the lagged growth rates of the real oil price and real defense spending.

Following Basu et al. (1998) and Basu and Fernald (2001) we combine industries into groups and restrict the hours per employee parameter, γ , in (8) to be equal across industries. The industries are divided into four groups, i.e. mining

⁷Burnside et al. (1995) used electricity consumption as proxy for capital utilization. We will use the broader measure of energy consumption available in the Jorgenson data set.

(four industries), non-durables manufacturing (10 industries), durables manufacturing (11 industries) and services and others (8 industries). Within each group we allow for fixed industry effect and heterogenous returns to scale. Each group is then estimated with standard 3SLS methods using the instruments discussed above.

The results presented in Table 3 show that the null hypothesis of the Sargan-tests of valid instruments and a correctly specified model can not be rejected on the five-percent level in any of the systems estimated. Table 3 also presents relevance measures of the instrument sets, i.e. R^2 :s and partial R^2 :s (defined as in Shea (1997)) averaged over industries. The relevance of the instrument set is relatively low and the results are somewhat sensitive to the exact specification of the instrument set. These problems are often encountered when estimating production function regressions because it is difficult to find good instruments (see e.g. Burnside (1996) for a discussion). Given that we are interested in comparing different methods for capturing technology growth, it is important that our approaches yield technology shocks that are similar to the typical findings. In Table 4, we compare our results for the Basu and Kimball specification to the corresponding numbers presented by Basu et al. (1998) and Basu and Fernald (2001).

Since there are differences between our approach and the specifications in Basu et al. (1998) or Basu and Fernald (2001), we do not expect the results to coincide.⁸ However, the results for the comovement with other variables are numerically similar to the results presented in Basu et al. (1998) and Basu and Fernald (2001). We find a correlation between the Basu and Kimball technology measure and output growth of 0.08 as compared to 0.04 reported in Basu et al. (1998) and Basu and Fernald (2001). Our estimate of the correlation between the Basu and Kimball technology measure and hours growth (the Solow residual) is -0.38 (0.55) as compared to -0.44 (0.40) reported by Basu et al. (1998) and Basu and Fernald (2001). The mean of our technology shock is also very close

⁸For example, we use a later revision of the Jorgenson data set than Basu et al. (1998) and Basu and Fernald (2001) and we do not estimate the cost of capital directly as they do.

to what Basu et al. (1998) and Basu and Fernald (2001) find, 0.011 as compared to 0.013. We find a somewhat higher standard deviation, 0.013 as compared to 0.019. Overall, our approach appears to yield a typical estimate of technology growth.

In Table 3, we also present the averages of the estimated returns to scale for each group. The average returns to scale are close to one in the durables manufacturing and the mining group and around 0.7 in the non-durables and the services and others groups. Thus, our results are in line with e.g. Basu et al. (2001) who find no evidence for widespread increasing returns to scale. The estimates of the hours per employee parameter, i.e. γ , is positive as expected but the estimated standard errors are large in case of the mining industry and the services and others group.

4 Empirical Results

To study whether the different approaches capture the same unobservable phenomenon we calculate the correlations between the different measures of technology. These results are presented in Section 4.2. A second issue is whether the differences between the approaches matter in the sense that the implications for macroeconomic models are sensitive to the choice of method. This is discussed in Section 4.3, where we report the correlations between our technology shocks and business cycle variables. The effects of minor variations in the specifications of the VAR models and other robustness issues are analyzed in Section 4.4. In section 4.5. we repeat the experiment of Kiley (1998), i.e. apply the approaches for extracting technology shocks to industry-level data. In contrast to Kiley (1998) we use exactly the same data across methods. First, however, we have to construct variables that are comparable between the approaches and aggregation levels.

4.1 Aggregation issues

To compare the VAR technology shocks to the production function residuals, the industry-level technology growth series are aggregated into an economy wide measure. Following Basu et al. (1998) and Basu and Fernald (2001) we define aggregate technology growth, Δa_t^A , as:

$$\Delta a_t^A = \sum_i \omega_{i,t} \frac{\Delta a_{i,t}}{1 - \eta_i(c_{V,i} + c_{M,i})}, \quad (10)$$

where ω_i is industry i 's share of aggregate value added, η_i is the returns to scale, and $c_{V,i}$ and $c_{M,i}$ are the time average of the cost shares of energy and materials, respectively. The denominator in (10) converts gross output technology growth to a value added measure. This conversion allows us to compare the aggregate technology series from the production function approach to the technology series from the structural VAR-models, which are estimated using value added data. To compare technology growth series on different frequencies, we convert quarterly series to annual series by summation.

Other aggregate variables that we will use in the following sections are aggregate real value added growth, Δy_t^A , defined as the log difference of the sum of real value added across industries, and aggregate total hours growth, Δh_t^A , equals the log difference of the sum of total hours across industries. Furthermore, the aggregate primary input index is defined as:

$$\Delta x_t^A = s_H^A \Delta h_t^A + (1 - s_H^A) \Delta k_t^A, \quad (11)$$

where s_H^A is defined as the time average of the share of labor expenditures in aggregate nominal value added and Δk_t^A is the first log difference of the sum of capital across industries. Given the definitions above, the aggregate Solow residual is conveniently defined as:

$$SR_t = \Delta y_t^A - \Delta x_t^A. \quad (12)$$

The aggregation procedure outlined above is applied to the non-farm private economy in Section 4.2 and to the manufacturing sector in Section 4.5.

4.2 Do the methods capture the same phenomenon?

We compare four different measures of technology from the two main approaches: the classic Solow residual, the Basu and Kimball (1997) refined production function residuals with hours worked as proxy for factor utilization, structural technology shocks from the large, cointegrated six variable VAR of King et al. (1991), and from the small two variable VAR in first differences of Galí (1999). Table 5 contains the results for the aggregate US private non-farm economy.

Focusing first on the correlations between the VAR technology shocks and the production function residuals in the columns labelled Solow (SR) and BK (Basu and Kimball) in the second half of Table 5, we see that all four measures of technology are positively related to each other, and generally significantly so. The correlations between the Galí (1999) VAR technology shocks and the classic and refined Solow residuals are 0.39 and 0.68, respectively. The correlations are somewhat lower in case of the King et al. (1991) measure, 0.42 and 0.31 for the Solow and Basu and Kimball (1997) production function residuals. There is thus a reasonably high correspondence between the two main approaches for identifying technology shocks at the economy wide level.

We also document a high degree of coherence within each main approach for identifying technological progress. The correlation between the technology shocks identified by the two structural VAR models is 0.43. These two specifications are very different. They are estimated using different data, hours worked and labor productivity in the Galí (1999) case, and real output, consumption, investment, changes in real money, inflation and a nominal interest rate in case of the King et al. (1991) model. The statistical setup also differs as the King et al. (1991) specification is a large cointegrated VAR in the levels of the data while the Galí (1999) model focuses on the stationary first differences of two variables (cf. equations (1) and (4)). The two VAR models nevertheless produce technology shocks that are fairly similar. The classic and refined Solow residuals are even closer related to each other as they have a correlation of 0.59. Note that the correlation between the Galí (1999) VAR technology shocks and

the refined production function residuals is higher than the correlations between the different measures belonging to the same approach.

A third observation from Table 5 is that there is a tendency towards dichotomy among our four baseline measures of technology. The technology shocks emerging from the Galí (1999) model are highly correlated to the Basu and Kimball (1997) refined production function residuals, while the King et al. (1991) specification produces technology shocks that display a higher correlation with the classic Solow residual than with the Basu and Kimball (1997) measure. We will return to possible reasons for this phenomenon in Section 5.

4.3 Do the resulting technology shocks have the same cyclical pattern?

To study whether the different approaches for identifying technological progress have similar implications for the empirical validity of different classes of business cycle models, we calculate the correlations between the measures of technology and changes in output, input, and hours worked. The results are presented in the first half of Table 5. First, it is clear that we replicate the standard finding of a strongly procyclical Solow residual. It is positively correlated to output growth (0.81) but insignificantly related to hours growth (0.29) and changes in the input index (0.09).

It has been argued that the procyclicality of the Solow residual is due to firms endogenous responses to demand changes in the presence of phenomena such as imperfect competition, increasing returns to scale and variable factor utilization rather than to truly procyclical technological changes (see e.g. Basu and Fernald (2001) and the references therein). When imperfect competition, non-constant returns to scale, and cyclical factor utilization are allowed, the cyclical behavior of the technology measures changes dramatically. The Basu and Kimball measure is uncorrelated with output growth (0.16), while significantly negatively related to both the input index (-0.49) and hours growth (-0.34).

An interesting finding is that the cyclical pattern of the technology measure derived from the Galí (1999) VAR model is very similar to what we observe for the Basu and Kimball measure. It is uncorrelated with output (-0.03), and significantly negatively related to changes in input (-0.54) and hours worked (-0.57). The technology shocks from the King et al. (1991) VAR also display a qualitatively similar but less distinct cyclical behavior as the correlation with output is insignificantly positive and the correlations with changes in input and hours worked are negative but insignificant.

The results in Table 5 hence show that the cyclical behavior of the technology series derived from the structural VARs resembles the refined Solow residuals rather than the classic Solow residual. Technological improvements are associated with periods of contractions in input and hours growth, whereas output growth does not increase significantly, at least not contemporaneously. These results are at odds with the RBC-models' prediction of a positive contemporaneous response of inputs in response to a technology improvement. Moreover, the similarities in the cyclical behavior between the measures of the Basu and Kimball specification, the VAR model of King, and the VAR model of Galí confirm that these measures reflect the same underlying unobservable phenomenon. The classic Solow residual alone leads to a different conclusion about the relationship between technology shocks and the business cycle.

4.4 Robustness

The choice of various details in the empirical specification of a VAR is rarely self evident in the sense that there is only one possibility or even one clearly superior alternative. Different information criteria typically produce different optimal choices of lag length, different tests or significance levels may indicate that different number of lags are required to remove residual autocorrelation, restrictions can be imposed or not imposed on the cointegrating space, and so on. To investigate whether this is important for the results, we study the sensitivity of the technology shocks respect to the minor changes in the empirical

specification.

We have estimated seven structural VAR models for the aggregate US non-farm economy: Four King models using two and four lags, with and without restrictions on the cointegrating space, and three Galí models with one and two lags on annual data and three lags using quarterly data. None of the models display obvious signs of misspecification and they are all optimal choices using at least some combination of criteria for model evaluation. The exception here is the unrestricted King specification with two lags, where the stationary transformations (the cointegrating relations and the transitory components of the time series) do not appear to be entirely stationary. This may be due to imprecisely estimated cointegrating vectors. The model behaves well after theoretical restrictions have been imposed on the long run equilibrium relationships. We nevertheless include the unrestricted two-variable model to preserve the symmetry of the robustness exercise, but put little weight on these results as this would not be a suitable choice as baseline specification.

The results from the robustness analysis are presented in table 6. Neither small variations of the number of lags nor imposing restrictions on the cointegrating vector have major effects on the technology series derived from the King model. Five out of the six relevant correlations are significantly positive on the five-percent level and the average correlation between the four versions of the King et al. (1991) technology shocks is 0.67. The small VAR model of Galí is also robust to small variations in the number of lags. Indeed, the technology shocks emerging from the one lag and the two lag version of the Galí model are perfectly correlated. Thus, both VAR models are quite robust to minor alterations in the empirical specification. Furthermore, the relationship between the cyclical variables and the VAR measures are similar to the baseline results presented above.

We also investigate the robustness of a different type of output from structural VAR models that is frequently used in various fields, namely forecast error variance decompositions. Forecast error variance decompositions show how much of the variance of a variable that stems from a certain structural shock

at a particular horizon. At business cycle frequencies, variance decompositions provide information about how much of the business cycle variations in real output that are caused by technology shocks. Following King et al. (1991), we have chosen the three-year horizon as the business cycle frequency. Table 7 contains the three-year FEVDs of changes in real output for the four large, cointegrated VAR models. It is clear that technology shocks is a minor source of business cycle fluctuations in this data set. Only 6.1 to 22.4 percent of the variations are caused by technology shocks and none of the shares is significant. While the results differ slightly between the specifications, the qualitative conclusion remains the same across the variance decompositions of output growth. This can be interpreted as additional evidence against real business cycle models since it relies on technology shocks as the primary driving force behind business cycle movements. Hence, the different King specifications capture similar technology shocks and the results in terms of the empirical relevance of business cycle models are very robust to various permutations of the VAR.

As a robustness check of the production function approach, we estimate the Burnside et al. (1995) specification, where energy consumption rather than hours per employee is used as proxy for capital utilization. Since energy is only likely to be a good proxy for the service flow of heavy equipment, we focus on manufacturing data. The correlation between the measures from the Basu and Kimball and the Burnside specifications is as high as 0.76. Both the Basu and Kimball residual and the Burnside residual are significantly negatively correlated to the input index (-0.72 and -0.43) and hours growth (-0.68 and -0.34) and insignificantly related to output growth (-0.25 and 0.20). The point estimates of the correlations for the Basu and Kimball measure imply a more countercyclical behavior than what is found for the Burnside residual. A possible explanation for this is that the Burnside et al. specification only controls for capital utilization, whereas it may be argued that the Basu and Kimball specification controls for both capital and labor utilization. The Basu and Kimball and the Burnside residuals are both positively correlated to the Solow residual (0.20, 0.59), although only the Burnside residual is significantly so. The qual-

itative conclusions about the relationship between the technology growth and cyclical variables are however similar between the Basu and Kimball and the Burnside et al. specifications.

4.5 Evidence from industry data

Kiley (1998) estimates the Galí specification for 17 American manufacturing industries and compares the resulting technology shocks to the measures of Basu and Kimball (1997) and Burnside et al. (1995). Here, we replicate the experiment of Kiley (1998) but supply the methods with exactly the same data. Table 9 summarizes the results from this comparison.

Kiley (1998) finds that 7 (9) of the 17 correlations between the VAR technology shocks and the Basu and Kimball (Burnside) measure are significantly positive. The average correlations across the industries are only 0.23 (0.22). We find an average correlations between the Galí technology measure and the Basu and Kimball measure across all industries of 0.56, with 27 out of 33 correlations significantly positive. These results are confirmed when turning to the Burnside measure, using energy consumption to correct for variable factor utilization. The average correlations between the Burnside residual and Galí measure across the manufacturing industries is 0.47, with 17 out of 21 correlations significantly positive. In the second half of Table 9, we show that this results holds also when only the industries that are identically defined are used. Moreover, the coherence between the two refined production function residuals is extremely high. The average correlation between the Basu and Kimball and Burnside et al. series amounts to 0.83, with all 21 underlying correlations significantly positive. Thus, we find much more coherence between the VAR approach and the refined production function residuals when they are supplied with identical data than reported by Kiley (1998), who compare his VAR shocks to production function residuals for the same industries and time period but constructed using a different data set.

5 Interpreting the results

A pattern that is observed in the main results in Section 4.2 and perhaps even more clearly in the VAR robustness exercise in Section 4.4 is that the King technology shocks are more similar to the classic Solow residuals than to the refined production function residual of Basu and Kimball. The Galí technology shocks are characterized by the opposite behavior and display higher correlations with the Basu and Kimball measure than with the Solow residual. Possible reasons for this systematic difference between the technology shocks captured by the two VARs can be extracted by considering the restrictions used to separate technology shocks from other structural shocks. We also present some empirical evidence of what kind of noise the different measures of technology may capture.

In the King et al. (1991) specification, technology shocks are identified by assuming that no other shocks have permanent effects on real output per capita. Galí (1999), on the other hand, uses the assumption that only technological changes have long-run effects on labor productivity (output per hour). The implications of the identifying assumptions of the two baseline VAR models can be analyzed in the context of a dynamic general equilibrium (DGE) model. For instance, Shapiro and Watson (1988) consider a (reduced form) DGE model where long-run movements in output are due both to changes in technology and to permanent shocks to labor supply. The King et al. (1991) specification will fail to isolate technology shocks in this situation because changes in per capita labor supply are included in the measure of technology. However, permanent shifts in labor supply have no long-run effect on output per hour, i.e. labor productivity, in a standard DGE model (see e.g. Shapiro and Watson (1988) or Francis and Ramey (2002)).⁹ Thus, the identifying assumption of Galí (1999), i.e. that only technology shocks have a permanent effect on labor productivity, is robust to the presence of permanent labor supply shocks. Put differently, technology (supply) shocks as defined by King et al. (1991) will include exogenous shocks

⁹This is due to that when labor supply increases capital will be accumulated until factor prices and labor productivity return to their previous value.

to labor supply per capita.

Shapiro and Watson (1988) show empirically that a permanent labor supply shock has a positive effect on output both initially and in the long-run. To see the consequences for our different measures of technology, suppose that the economy is subject to a permanent labor supply shock in period t . The King et al. (1991) approach would mislabel the permanent labor supply shock as a positive technology shock in period t since it hits the economy in period t and has a positive long run effect on real per capita output. As output rises in period t , we also expect the Solow residual to rise, due to e.g. procyclical factor utilization. Thus, the Solow residual misinterprets the permanent labor supply shock in period t as a positive technology shock. Permanent labor supply shocks is thus likely to have a positive effect on the correlation between the classic Solow residual and the technology measure of King et al. (1991) as well as on the correlation between these two measures and output. The Basu and Kimball (1997) approach should be neutral to labor supply shocks since the approach controls for factor utilization as well as factor accumulation. Hence, labor supply shocks are likely to drive a wedge between the technology measures of King et al. (1991) and the Solow residual on one hand and the Galí (1999) and the Basu and Kimball measure on the other, which is what we find.

Empirical evidence about what kind of noise the technology shocks from the two VAR models capture can be obtained from the two production function residuals. The difference between the Solow residual and the Basu and Kimball measure is that the latter is purged from non-technology induced variation. Hence, the component of the Solow residual that is orthogonal to the Basu and Kimball measure consists of non-technology related variation. It can be extracted from the Solow residual by regressing the series on a constant and the Basu and Kimball measure. This non-technology component of the Solow residual (NTC) is included in the final row of Table 6. As expected, it is highly procyclical. The technology shocks from the two structural VARs pick up this non-technology variation to varying extent. All but one of the King measures are significantly positively related to the non-technology component, whereas the

Galí measures are uncorrelated with the non-technology component. The results support the view that the technology measure derived from the King model mix technology shocks with other non-technology phenomena. The Galí model, on the other hand, appears to be not only theoretically but also empirically more robust to such non-technology related events.

Thus far, we have used the information in the production function residuals to discuss the properties of the VAR technology shocks. Because the true technology shocks are unobservable, we can also turn matter around and use the VAR results to analyze the production function residuals. In accordance with previous findings, the results in Section 4 demonstrate that cyclical properties of the production function residuals change drastically as non-constant returns to scale and variable factor utilization are introduced. The classic Solow residual is strongly procyclical, while the refined measures are either acyclical or countercyclical. It is however not self evident that only irrelevant demand related noise is removed in the process of refining the Solow residual. If technology shocks are really procyclical, it could be argued that the instrumental variable estimation may remove also this true procyclicality. This risk is evident because of the difficulties involved in finding good instruments. Nelson and Startz (1990) show that the instrumental variables estimator is biased in the direction of the OLS estimator when the relevance of the instruments is low. Such a bias would imply that the returns to scale are overestimated if technology growth is procyclical and hence, that the true procyclicality of technology shocks will be underestimated.

The VAR approach identified technology shocks by imposing restrictions on their long run effects. Since no instruments are used in the estimation, the technology shocks produced by structural VARs are not affected by potential problems with weak instruments. The VAR technology shocks presented in Section 4 display a cyclical behavior that is much more similar to the pattern found in the refined production function residuals of Basu and Kimball (1997) and Burnside et al. (1995) than to the strongly procyclical classic Solow residual. The King measures have higher correlations with the Solow residual, but

their cyclical properties resemble what we find for the Basu and Kimball (1997) measure. Hence, evidence from the structural VARs clearly support the view that it is appropriate to refine the Solow residual as measure of technology at business cycle frequencies also if good instruments are hard to find.

6 Conclusions

The identification of unobservable structural shocks is important in many areas of applied macroeconomics. For example, VAR models produce conclusions about what factors that have caused business cycle fluctuations in real output or movements in real exchange rates. It is generally difficult to evaluate these findings because alternative measures of monetary shocks or real demand shocks do not exist. Technology shocks constitute a rewarding object for evaluating the structural VAR approach to the identification of structural shocks because other established methods of measuring technology are available. Production function residuals rely on entirely different theoretical foundations and are also constructed using an empirical strategy that has little in common with the VAR methodology.

We have applied two versions of the production function approach and two structural VAR models to identical data in order to investigate whether they capture the same unobservable phenomenon and whether the implications for macroeconomic theory are robust with respect to the choice of method. Our main finding is that structural VAR models identify technology shocks that are highly correlated with the classic as well as refined Solow residuals, thus confirming that the VAR methodology for disentangling structural shocks makes sense. In particular, the small VAR a’la Galí (1999) produces technology shocks that have a correlation of 0.68 with the refined Solow residuals of Basu and Kimball (1997).

We also repeat the experiment of Kiley (1998) by applying the small VAR a’la Galí as well as the refined Solow residuals to industry-level data. We find twice as many significant correlations and they are (on average) more than

twice as high as reported in the previous study by Kiley (1998). Kiley compares technology shocks that are constructed using the same methods but applied to differing data sets. Thus, the coherence between the two approaches increases dramatically when they are supplied with identical data.

Also, technology shocks identified by structural VARs are remarkably robust with respect to minor changes in the empirical specification; changing the number of lags included in the VAR or imposing restrictions on the cointegrating vectors has only minor effects on the results.

The relationship between technological progress and business cycle variables is similar across three of the four measures of technology: the refined versions of the Solow residual and the technology shocks derived from the two structural VARs. Technological improvements are associated with contractions in input and hours, whereas there is no significant increase in output. In contrast, the classic Solow residual is found to be strongly procyclical (as in other studies). The fact that technological progress as identified by the VAR models displays a cyclical behavior that is similar to the refined Solow residuals confirms the impression that the two approaches capture the same unobservable phenomenon. Another interpretation of this result is that the structural VARs confirm that refined production function residuals constitute a more appropriate measure of technology at business cycle frequencies than the classic Solow residual.

A final observations is that the exact formulation of the long-run restrictions used to identify technology shocks in the structural VAR models appears to have important effects on the results in the direction expected from economic theory. The Galí (1999) specification captures technology shocks that are highly correlated with the refined Solow residual of Basu and Kimball (1997), while the technology shocks from the large, cointegrated King et al. (1991) model are more related to the classic Solow residual. Furthermore, the King et al. (1991) technology shocks display significant correlations with a measure of non-technology related variation, while the Galí (1999) technology shocks are unrelated to this measure. This systematic difference between the results from the two structural VAR models could be due to differences in the identifying restrictions. The King

et al. (1991) measure includes changes in per capita labor supply and therefore captures supply shocks in general rather than pure technological progress. The technology shocks produced by the Galí (1999) specification are however robust to the presence of shocks to per capita labor supply.

References

- Alexius, A.: 2001, Sources of real exchange rate fluctuations in the nordic countries, *Scandinavian Journal of Economics* **103**, 317–331.
- Basu, S. and Fernald, J.: 2001, *Why Is Productivity Procyclical? Why Do We Care?*, In C. Hulten, D. Edwin and M. Harper, ed., New Developments in Productivity Analysis, The University of Chicago Press, Chicago, IL.
- Basu, S., Fernald, J. and Kimball, M.: 1998, Are technology improvements contractionary?, *International Finance Discussion Papers No. 625, Board of Governors of the Federal Reserve System*.
- Basu, S., Fernald, J. and Shapiro, M.: 2001, Productivity growth in the 1990s: Technology, utilization, or adjustment?, *NBER Working Paper No 8359*.
- Basu, S. and Kimball, M.: 1997, Cyclical productivity with unobserved input variation, *NBER Working Paper No 5915*.
- Blanchard, O. and Quah, D.: 1989, The dynamic effects of aggregate demand and supply disturbances, *American Economic Review* **79**, 655–673.
- Burnside, C.: 1996, Production function regressions, returns to scale and externalities, *Journal of Monetary Economics* **37**, 177–201.
- Burnside, C., Eichenbaum, M. and Rebelo, S.: 1995, *Capital Utilization and Returns to Scale*, In B. Bernanke and J. Rotemberg, ed., NBER Macroeconomics Annual, MIT Press, Cambridge, MA.

- Carlsson, M.: 2000, Measures of technology and the short-run responses to technology shocks: is the rbc-model consistent with swedish manufacturing data?, *Working Paper 2000:20, Department of Economics, Uppsala University* .
- Clarida, R. and Gali, J.: 1994, Sources of real exchange rate fluctuations: How important are nominal shocks?, *Carnegie-Rochester Conference Series on Public Policy* **41**, 1–56.
- Dolado, J. and Jimeno, J.: 1997, The causes of spanish unemployment: A structural var approach, *European Economic Review* **41**, 1281–1307.
- Francis, N. and Ramey, V.: 2002, Is the technology-driven real business cycle hypothesis dead? shocks and aggregate fluctuations revisited, *NBER Working Paper No 8726* .
- Gali, J.: 1999, Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations?, *American Economic Review* **89**, 249–271.
- Griliches, Z. and Jorgenson, D.: 1967, The explanation of productivity change, *Review of Economic Studies* **34**, 249–283.
- Hall, R. E.: 1990, *Invariance Properties of Solow's Productivity Residual*, In P. Diamond, ed., *Growth/Productivity/Unemployment: essays to celebrate Bob Solow's birthday*, MIT Press, Cambridge, MA.
- Hall, R. E.: 1988, The relation between price and marginal cost in u.s. industry, *Journal of Political Economy* **96**, 921–947.
- Hylleberg, S. and Mizon, G. E.: 1989, Cointegration and error correction mechanisms, *Economic Journal* **99**, 113–125.
- Johansen, S.: 1991, Estimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models, *Econometrica* **59**, 1551–1580.

- Jorgenson, D., Gollop, F. and Fraumeni, B.: 1987, *Productivity and U.S. Economic Growth*, Elsevier Science Publishers, Amsterdam, The Netherlands.
- Kiley, M.: 1998, Labor productivity in u.s. manufacturing: Does sectoral comovement reflect technology shocks?, *Mimeo, Federal Reserve Board*.
- King, R. G., Plosser, C. I., Stock, J. H. and Watson, M. W.: 1991, Stochastic trends and economic fluctuations, *American Economic Review* **81**, 819–840.
- Nelson, C. and Startz, R.: 1990, The distribution of the instrumental variables estimator and its t-ratio when the instrument is a poor one, *Journal of Business* **63**, S125–S140.
- 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**, 461–472.
- Quah, D. and Vahey, S.: 1995, Measuring core inflation, *Economic Journal* **105**, 1130–1144.
- Rotemberg, J. and Woodford, M.: 1995, *Dynamic General Equilibrium Models with Imperfectly Competitive Product Markets*, In T.F. Cooley, ed., *Frontiers of Business Cycle Research*, Princeton University Press, Princeton, NJ.
- Shapiro, M. and Watson, M.: 1988, *Sources of Business Cycle Fluctuations*, In Stanley Fischer, ed., *NBER Macroeconomics Annual*, MIT Press, Cambridge, MA.
- Shea, J.: 1997, Relevance in multivariate linear models: A simple measure, *Review of Economics and Statistics* **79**, 348–352.
- Solow, R. M.: 1957, Technological change and the aggregate production function, *Review of Economics and Statistics* **11**, 145–155.
- Warne, A.: 1993, A common trends model: Identification, estimation and inference, *Seminar Paper No. 555, IIES, Stockholm University*.

7 Data Appendix

The disaggregate US data set is fully described in Jorgenson et al. (1987) and was downloaded from Dale Jorgenson's web site. Total hours worked and employment was kindly provided by Jon Samuels.

The **Output** (value added) volume index and current price series for the non-farm business sector are collected from the NIPA's, downloaded from the BEA web site. These series are then used to construct a chained 1987 dollar series (matching the Jorgenson data using 1987 as base year) and the implicit GDP deflator.

The **Total Hours Worked** index for the non-farm business sector is collected from the BLS web site.

The **Investment** series is defined as gross private fixed investment. The Investment volume index and current price series are collected from the NIPA's, downloaded from the BEA web site. These series are then used to construct a chained 1987 dollar series.

The **Total Population** series is collected from the NIPA's, downloaded from the BEA web site.

The **Consumption** series is defined as personal consumption expenditures. Consumption volume index and current price series are collected from the NIPA's, downloaded from the BEA web site. These series are then used to construct a chained 1987 dollar series.

The **Price level** is measured as the GDP deflator.

The **Nominal interest** rate series is measured as the three-month U.S. Treasury bill rate, and is collected from the Federal Reserve Board of Governors web site. Monthly observations are averaged to quarterly observations.

The **Nominal Money Supply** is measured as M2 and is collected from the Federal Reserve Board of Governors web site. Before 1959:1 we use the same M2 series as King et al. (1991), available at Mark W. Watson's home page. Monthly observations are then averaged to quarterly observations.

The **Real Oil Price** is measured as the PPI for crude petroleum, taken

from the BLS web site, deflated with the GDP deflator.

The **Real Defense Spendings** series is measured as national defense outlays, collected from the NIPA series downloaded from the BEA web site, deflated with the GDP deflator.

The **Federal Reserve Policy Shocks** are measured as the residuals from an estimated reaction function of the Federal Reserve. Following Burnside (1996) we assume that the three month T-bill rate is the policy variable, determined by lagged values of real GDP, the GDP deflator, the PPI for industrial commodities, M2 and the three month T-bill rate, as well as current values of real GDP, the GDP deflator and PPI for industrial commodities. All included variables, except the three month T-bill rate, are in logs. We use quarterly data and estimate the reaction function with four lags over the sample 1949:1-1989:4. The sum of the four residuals in $t-1$ is then used as an instrument. The PPI for industrial commodities is collected from the BLS web site. We use the average of monthly data to convert the series to quarterly data.

Table 1: The Johansen (1991) Trace Test for Cointegrating Rank

H_0	King (2)	King (4)
$n - r = 0$	135.32	148.03
$n - r = 1$	83.01	93.02
$n - r = 2$	47.43	58.25
$n - r = 3$	24.35	27.21
$n - r = 4$	9.63	6.51
$n - r = 5$	0.51	2.53

Bold type denote significance on the 5-percent level using critical values from Osterwald-Lenum (1992).

Table 2: Estimates of the Cointegrating Vectors in the King Specifications

	y	c	i	$m - p$	R	π
King (2)	-0.861	1.0	0.0	0.0	0.051	-0.063
	-0.747	0.0	1.0	0.0	0.116	-0.167
	-1.271	0.0	0.0	1.0	-0.025	0.022
King (4)	-1.275	1.0	0.0	0.0	0.022	0.025
	-1.470	0.0	1.0	0.0	0.058	-0.041
	-1.496	0.0	0.0	1.0	0.020	-0.031
King (2) R	-1.0	1.0	0.0	0.0	0.049	-0.049
	-1.0	0.0	1.0	0.0	0.117	-0.117
	-1.626	0.0	0.0	1.0	-0.024	0.011
King (4) R	-1.0	1.0	0.0	0.0	0.051	-0.051
	-1.0	0.0	1.0	0.0	0.143	-0.143
	-1.742	0.0	0.0	1.0	-0.051	0.035

Bold type denotes significance at the 5-percent level.

Table 3: U.S. Industry Production Function Regressions

Groups	Hours correction			Electricity correction	
	ARTS	γ	Sargan	ARTS	Sargan
Mining	0.94	0.59 (0.61)	0.42	—	—
Non Durables	0.69	1.69 (0.48)	0.50	0.76	0.08
Durables	1.05	0.76 (0.36)	0.93	1.02	0.90
Services and Others	0.70	0.70 (0.73)	0.07	—	—
Relevance Measures					
	Δx	Δhpe	$\Delta \tilde{x}$		
Average R2	0.16	0.14	0.17		
Average Partial R2	0.09	0.08	0.17		

Sample 1950-1989. The ARTS column presents the average returns to scale by group. The gamma column gives point estimates of the hours per employee coefficient (heteroscedasticity robust s.e. in parenthesis). The Sargan column presents the p-value of the Sargan-test of overidentifying restrictions. Average R2 and Average Partial R2 corresponds to averages of R2 and Partial R2:s (defined as in Shea (1997)) across all industries.

Table 4: Comparison of the Basu and Kimball Measure With Previous Studies

	Descriptive Statistics		Correlations		
	Mean	Std. Dev.	Δy^A	Δh^A	SR
BFK (1998) / BF (2001)	0.013	0.013	0.04	-0.44	0.40
BK	0.011	0.019	0.08	-0.38	0.55

Sample 1950-1989. Bold type denotes correlation significant from zero on the five-percent level. BFK (1998) / BF (2001) row corresponds to the results for the Basu and Kimball specification presented in Basu et al. (1998) and Basu and Fernald (2001). The BK row corresponds to the results from the Basu and Kimball specification applied in this paper

Table 5: Measures of Technology and the Business Cycle - U.S. Private Economy

	Δy^A	Δx^A	Δh^A	SR	BK	K2R	G1
Output Growth	1						
Input Growth	0.66 (0.00)	1					
Hours Growth	0.77 (0.00)	0.94 (0.00)	1				
Solow Residual	0.81 (0.00)	0.09 (0.60)	0.29 (0.09)	1			
BK	0.16 (0.37)	-0.49 (0.00)	-0.34 (0.05)	0.59 (0.00)	1		
King (2) R	0.17 (0.34)	-0.25 (0.15)	-0.21 (0.22)	0.42 (0.01)	0.31 (0.07)	1	
Galí (1)	-0.03 (0.88)	-0.54 (0.00)	-0.57 (0.00)	0.39 (0.02)	0.68 (0.00)	0.43 (0.01)	1

Sample 1955-1989. Bold type denotes correlation significantly different from zero on the five-percent level. P-values in parenthesis

Table 6: Robustness

	Δy^A	Δh^A	SR	BK	K2R	K4R	K2	K4	G1	G2	G3Q
K(2)R	0.25 (0.15)	-0.18 (0.31)	0.52 (0.00)	0.31 (0.07)	1						
K(4)R	0.27 (0.12)	-0.08 (0.67)	0.46 (0.01)	0.19 (0.28)	0.88 (0.00)	1					
K(2)	-0.11 (0.52)	-0.29 (0.09)	0.07 (0.69)	0.18 (0.30)	0.57 (0.00)	0.21 (0.24)	1				
K(4)	0.17 (0.34)	-0.12 (0.49)	0.34 (0.05)	0.12 (0.50)	0.92 (0.00)	0.84 (0.00)	0.57 (0.00)	1			
G(1)	-0.01 (0.95)	-0.57 (0.00)	0.43 (0.01)	0.68 (0.00)	0.43 (0.01)	0.34 (0.05)	0.35 (0.04)	0.30 (0.09)	1		
G(2)	0.02 (0.92)	-0.56 (0.00)	0.47 (0.01)	0.70 (0.00)	0.45 (0.01)	0.35 (0.04)	0.34 (0.05)	0.30 (0.09)	1.00 (0.00)	1	
G(3)Q	0.31 (0.07)	-0.21 (0.23)	0.57 (0.00)	0.57 (0.00)	0.44 (0.01)	0.33 (0.06)	0.24 (0.16)	0.31 (0.07)	0.70 (0.00)	0.71 (0.00)	1
NTC	0.88 (0.00)	0.60 (0.00)	0.77 (0.00)	0.00 (1.00)	0.42 (0.01)	0.44 (0.01)	-0.06 (0.75)	0.34 (0.05)	-0.00 (0.99)	0.03 (0.88)	0.27 (0.12)

Sample 1956-1989. Bold type denotes correlation significantly different from zero on the five-percent level. P-values in parenthesis. K denotes the King model and G is the Galí model (G3Q is estimated on quarterly data). Number of lags in parenthesis. The R marker denotes models with restrictions imposed on the cointegrating vectors. NTC is the non-technology component of the Solow residual derived by regressing the Solow residual on a constant and the BK measure.

Table 7: The Share of the Three-year FEVD of Aggregate Output growth Due to Technology Shocks.

	King (2) R	King (4) R	King (2)	King (4)
Δy^A	22.4 (0.17)	17.7 (0.23)	6.1 (0.65)	21.7 (0.15)

P-values within parenthesis.

Table 8: Robustness of Correlations Basu and Kimball / Burnside et al. Measures - Manufacturing Industry Only

	Δy^M	Δx^M	Δh^M	SR	BK	BER
BK	-0.25 (0.15)	-0.72 (0.00)	-0.68 (0.00)	0.20 (0.25)	1	
BER	0.20 (0.26)	-0.43 (0.01)	-0.34 (0.05)	0.59 (0.00)	0.76 (0.00)	1

Sample 1955-1989. Bold type denotes correlation significantly different from zero on the five-percent level. P-values in parenthesis

Table 9: Average Correlations Across Industries and Comparison with Kiley (1998)

	BK	BER
BK	1	
BER	0.83 (21/21)	1
Galí	0.56 (27/33)	0.47 (17/21)
Comparison With Kiley (1998)		
Galí	0.50 (12/16)	0.42 (12/16)
Galí (Kiley)	0.21 (6/16)	0.19 (8/16)

Sample 1953-1989. Number of significantly positive correlations on the five-percent level / Number of industries in parenthesis. The comparison with Kiley (1998) in the bottom panel is across identically defined industries. The statistics in the two bottom rows are compiled from the results presented in Kiley (1998).