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Measures of Technology and the Business Cycle: Evidence from Sweden and the U.S.*

by

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Abstract

Empirical evidence on the cyclical behavior of technology shocks, or the relative importance of technology shocks versus other structural shocks as sources of fluctuations, hinges crucially on the identification of technological changes. 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 vary between the approaches. Several variations of the production function approach and structural VAR models are investigated: the classic Solow residual, the refined Solow residuals of Burnside et al (1995) and Basu and Kimball (1997), large cointegrated VAR models as in King et al (1991) and a small VAR in first differences á la Galí (1999). It turns out that the different measures of technological change are reasonably coherent when applied to US data. However, they are often insignificantly related in the case of Sweden. Furthermore, our results do not support the hypothesis that business cycle fluctuations are primarily driven by changes in technology.

Keywords: Technology shocks; Production function approach; Structural VAR models

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1 Introduction

The identification of technological change is a crucial element of several areas of macroeconomics. For example, evidence on the relationship between technology shocks and business cycle variables may be used to evaluate the empirical relevance of different classes of business cycle models. RBC models predict that hours worked should be positively related to technology shocks, whereas models emphasizing e.g. price rigidities generally predict a negative contemporaneous relationship (see e.g. Basu, Fernald and Kimball (1998) and Galí (2000)). In recent empirical studies, the contemporaneous response of hours worked to technology improvements is found to be negative.[1]

The empirical relevance of different classes of business cycle models can also be evaluated using structural VAR models. Variance decompositions provide information about what shocks that have caused the fluctuations in real output at business cycle frequencies. A finding that technology shocks dominate the cyclical fluctuations of real output can be interpreted as empirical support for RBC models, while a finding that monetary shocks are more important constitutes evidence against them.

As all structural shocks, technology shocks are inherently unobservable. Evidence on the relationship between technology shocks and business cycle variables, or the relative importance of supply versus demand shocks, is therefore conditioned on the particular method used to identify the technology shocks. In this paper, we study different measures of technological change in order to answer two questions: To what extent are the different methods for identifying technology shocks capturing the same phenomenon? Do the resulting technology shocks have similar relationships to business cycle variables such as real output growth and hours worked, or is the empirical support for e.g. RBC models a function of the approach used to identify technological change?

The two main techniques used for identifying technology shocks are structural VAR models and the production function approach. There are consid-

[1] See e.g. Galí (1999), Kiley (1998), Basu et al. (1998) and Carlsson (2000).

erable methodological differences within each category. King, Plosser, Stock and Watson (1991), Galí (1999) and others impose restrictions on the long-run effects of shocks within structural VAR models to distinguish technology shocks from other sources of fluctuations. King et al. (1991) estimate a six-variable VAR including real output, consumption, investment, the real money supply, nominal interest rates and inflation. Technology shocks are identified using the assumption that no other structural shock affects real output in the long-run. Galí (1999) focuses on a small two-variable VAR model of 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.

Long-run restrictions on VAR models have been used to identify structural shocks within various fields. Examples are Blanchard and Quah (1989) and King et al. (1991) for real output, Dolado and Jimeno (1997) for unemployment, Wehinger (2000) for inflation, and Clarida and Galí (1994) for real exchange rates. These studies produce conclusions like "technology shocks cause about 40 percent of the variability of real output at business cycle frequencies" or "the bulk of the long-run movements in real exchange rates are due to real demand shocks".

Conclusions from VAR studies about the sources of fluctuations in various variables has had considerable effects on the direction taken by subsequent theoretical research. A relevant question is then to what extent structural VAR models actually capture e.g. true technology shocks. This issue has frequently been debated but not systematically studied empirically. Stockman (1994) and Kiley (1998) question the clear-cut distinction between supply shocks and demand shocks, according to which demand shocks do not affect real output in the long run. They argue that demand shocks can affect real output in the long run, for instance by inducing a larger capital stock. The use of long-run restrictions to identify structural shocks has also been questioned by e.g. Faust and Leeper (1997). Among all, they argue that different types of "true" shocks can only be aggregated into a single structural category if they have the same effect on the endogenous variables. King et al. (1991) and Rogers (1999) demonstrate that the number of variables included in the VAR has a major effect on the conclusions in terms of variance decompositions. In King et al, the share of technology shocks on the three-year forecast error variance of output falls from 70 to 40 percent when two nominal variables are added to the VAR. Similarly, Rogers shows that real demand shocks appear less important to movements in real exchange rate when more variables are included in the model.

An obvious problem when discussing the VAR approach to identifying different types of shocks is that since structural shocks are unobservable, there exists no true measure against which the outcome of the VARs can be evaluated. Clarida and Galí (1994) use what they call "a duck test" to check the validity of their identification scheme. They plot the demand shocks identified by their VAR model and discuss whether it is possible to detect the major demand related events of the sample period in the graph. In the words of Clarida and Galí (1994), "if it walks like a duck and quacks like a duck, it must be a duck". However, technology shocks differ from other structural shocks in the sense that there exist well-established alternative methods for identifying them. The most popular approach is variations of the Solow (1957) residual.

Solow (1957) identifies technological change as the residual from a production function, taking increases in production factors into account. His 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 Solow residual is not likely to be a good measure of technology at the business cycle frequency. Instead, we rely on the refinements of Solow's original method developed in Hall (1988, 1999), Burnside, Eichenbaum and Rebelo (1995) and Basu and Kimball (1997) which allows for these assumptions to be relaxed.

A few authors provide correlations between the technology shocks identified by their VAR models and some other measure of technology. For instance, King et al. (1991) report a correlation of 0.48 between their measure and the Solow residual of Prescott (1986). However, the procedure used by Prescott (1986) is not likely to provide robust estimates of technology movements at business cycle frequencies since it does not take the phenomena listed above into consideration. The correlation with the refined Solow residual of Hall (1988), who corrects for increasing returns to scale and imperfect competition but not for variable factor utilization, is only 0.19. Furthermore, Kiley (1998) calculate correlations between his VAR technology shocks and the extended Solow residuals of Basu and Kimball (1997) and Burnside et al. (1995) for 17 American industries. About half of the correlations are significantly positive and the cross industry average is 0.22. These studies compare technology shocks from different approaches for particular sample periods, and industries in the case of Kiley, but they do not investigate the concordance of the methods given that they are actually supplied with identical information.

In this paper, several different methods for identifying technology shocks are applied to the same data sets. We use the classic Solow residual, the Burnside et al. (1995) and the Basu and Kimball (1997) approaches using data on energy and hours per employee, respectively, to correct for factor utilization, large structural VAR models a'la King et al. (1991) and a small structural VAR as in Galí (1999). The production function approach requires disaggregate data (see e.g. Basu and Fernald (1997)), whereas large VAR models are estimated using aggregate data where variables like the money supply can be assumed to be endogenous. We study four different data sets consisting of disaggregate industry observations and aggregate macrodata for the United States and Sweden. The purpose of the exercise is two-fold. First, we want to compare the different measures of technology with each other to investigate whether they capture the same unobservable phenomenon. Do long-run restrictions on VAR models produce technology shocks resembling those identified by the production function approach? Moreover, it is interesting to compare U.S. results to the results from an small open economy, such as the Swedish. For example, when applying the production function approach on data for a small open economy we can use instruments that are not likely to be neither valid nor relevant for the U.S. economy. Second, because the empirical relationship between technology on one hand and e.g. labor input on the other can be used to distinguish between business cycle models, we investigate whether the technology shocks captured by these different approaches have similar relationships to these other variables. If the implications for macroeconomic theory are similar across different measures of technology, the differences between them are less consequential than if, for instance, the empirical support for RBC models is a function of the method used to capture technology shocks.

The paper is organized as follows. Section 2 discusses the data. Section 3 outlines the different approaches to identifying technology shocks, method-specific estimation considerations and aggregation issues. Section 4 compares the results for the different approaches. Section 5 discusses the robustness of the results and section 6 concludes.

2 The Data

We use four different data sets in this paper: quarterly observations on aggregate data and an disaggregate industry data set on annual frequency for both the U.S. and Sweden. The reason for using two aggregation levels is that the production function approach requires disaggregate data (see e.g. Basu and Fernald (1997)), whereas the large VARs model focus on the endogenous interaction between macroeconomic aggregates.

The disaggregate U.S. data set is compiled by Dale Jorgenson and Barbara Fraumeni and consists of a panel of 33 U.S. industries covering the entire U.S. non-farm private economy for the period 1948 to 1991. Various versions of this data set has been widely used, e.g. by Basu et al. (1998) and Basu and Fernald (2001) and is described in detail in Jorgenson, Gollop and Fraumeni (1987). For comparability with the former two references we focus on the sample period 1950-1989. The Swedish disaggregate data set covers the Swedish non-farm private economy and is divided into 15 industries (see the data appendix for all details).[2] For the disaggregated Swedish data we use the sample 1968-1993.

[2] In a closely related paper Carlsson (2000) analyze a subset of this data set, i.e. the

The aggregate U.S. data set covers the period 1948:1-1989:4 and are collected from the BEA, the BLS and the Federal Reserve Board of Governors. The aggregate Swedish data set is collected from Statistics Sweden and covers the period 1970:1-1993:4.

The methods used in this paper to estimate 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. Thus, 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 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.[3]

3 Identification of Technology Shocks

The two main methods for identifying technology shocks studied here are the production function approach and structural VAR models. Three baseline VAR models are used, the six-variable model of King et al. (1991), a Scandinavian version of the King et al. model and the two-variable model of Galí (1999).

Technology growth can also be estimated as the residuals from a reduced form production function. This methodology was pioneered by Solow (1957). Subsequent research has extended Solow's approach to allow for a variety of phenomena that are likely to introduce non-technology related cyclical variation into the technology measure. In addition to the Solow residual, we use the specifications of Burnside et al. (1995) and Basu et al. (1998), which differ from

manufacturing industries.

[3] The value of these constants is close to one, i.e. within the range 0.96 to 1.02 in the Swedish data and 0.92 to 1.09 in the U.S. data. Thus, the remaining differences before the correction are small.

each other in how cyclical factor utilization is handled.

3.1 The VAR Approach

A measure of technological change can be extracted from structural VAR models by imposing restrictions on the long-run effects of the structural shocks. The models of King et al. (1991) and Galí (1999) represent two different empirical strategies. Galí (1999) focuses on the (stationary) first differences of labor productivity and hours worked within a two-variable VAR. King et al. (1991) estimate a large, cointegrated VAR with six I(1) variables (real output, consumption, investment, real money balances, the nominal interest rate and inflation). We also consider a Scandinavian version of the large VAR model which treats inflation and money growth as stationary variables.

The idea to use restrictions on the long run effects to identify structural shocks is due to Blanchard and Quah (1989). King et al. (1991) and Galí (1999) present theoretical models to motivate their identifying restrictions. However, the formulation of the long run restrictions is remarkably similar across VAR studies. Monetary shocks are identified using the long-run neutrality of money, i.e. by assuming that they have no long-run effect on real variables. Technology shocks are assumed to be the sole driving force of real output (labor productivity in the Galí specification) in the long run. In our large VAR models with unrestricted estimates of the cointegrating vectors, monetary shocks are actually allowed to affect investment and consumption, but not output, in the long run. The parameters capturing the effects of monetary shocks on consumption and investment are however small and often insignificant. In most cases, the restriction that they are either zero or equal with opposite signs for the two nominal variables is not rejected. All restrictions on the cointegrating space hence imply that the monetary shocks do not affect investment and consumption in the long run. The exact formulation of the identifying restrictions differs between the two VAR specifications.

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

King et al. (1991) estimate a six variable VAR containing output, y, consumption, c, investment, i, real money balances $(m-p)$, a nominal interest rate, R, and inflation, Δp, where lower case letters denote the log of the variable and Δ is the first difference operator. We follow their six variable approach both for the U.S. and the Swedish aggregate data sets.[4]

We start with the following n-variable cointegrated VAR:

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

where $z_t = [y, c, i, (m-p), R, \Delta p]'$, μ is a vector of drift terms, Π and Γ are coefficient matrices and ξ_t is a vector of white noise disturbances. The existence of long-run equilibrium relationships (cointegration) among the variables implies that the system is driven by a reduced number of common stochastic trends. Common trends models can be analyzed using the framework developed by King et al. (1991) and refined by Warne (1993) and others. The cointegrated VAR in (1) can be rewritten as a common trends model (see e.g. Hylleberg and Mizon (1989)):

$$z_t = z_0 + \phi(L) v_t + \Theta \tau_t, \tag{2}$$

where

$$\tau_t = \mu + \tau_{t-1} + \varphi_t. \tag{3}$$

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. The term $\phi(L) v_t$ constitutes the transitory component of z_t. The number of cointegrated 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 described by the term $\Theta \tau_t$, where the loading matrix Θ

[4] Note that our U.S. data set differ somewhat from what King et al. (1991) use.

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 component of z_t.

For exact identification of the k structural shocks in φ_t, we need to impose $k(k-1)/2$ restrictions (see e.g. Warne (1993)). Economic theory frequently has implications that can be translated into restrictions on the loading matrix Θ, the cointegrating rank of the system and/or the parameter values in the cointegrating vectors. For instance, the balanced growth conditions imply that the ratios of consumption to output 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 $[1, -1]$. Another example is monetary neutrality. If money is neutral in the long run, monetary shocks only affect nominal variables. The parameters in Θ that capture effects of monetary shocks on real variables should than be zero.

We estimate the King et al. (1991) specification for Swedish and US aggregate quarterly data. The number of lags p is determined using information criteria (Akaike, Schwarz, Hannan-Quinn), but chosen sufficiently high to remove residual autocorrelation as indicated by the LM test for first and fourth order autocorrelation, and the multivariate Portmanteau test. We use four lags in our baseline model for Sweden and two lags for the United States. As up to six lags can be included in the former case, and up to four lags in the latter, we also estimate these alternative models to study the robustness of the results.

The main features of the King et al. (1991) specifications, the cointegrating rank and hence the number of stochastic trends are consistent with their findings. The cointegrating rank is investigated using the Johansen (1991) multivariate maximum likelihood approach (see Table 1). There are three cointegrating vectors, 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.

Most of the parameters of the cointegrating vectors have the expected signs and magnitudes (see Table 2). For instance, the coefficients on real output in the long-run equilibrium relationships for consumption, investment and real money are [-0.86, -0.61, -1.19] for the United States, and [-0.65, -2.91, -0.05] in the case of Sweden. The restriction that these coefficients all equal unity is rejected for Sweden but not for the United States. Other conceivable restrictions are that the real variables are not affected by inflation and the interest rate at all in the long run, or that they are affected only by the real interest rate. The most restrictive restriction that is not rejected by the data for the King specification on US data is that the coefficients on real output all equal unity and the coefficients on inflation and the nominal interest rate are equal with opposite signs in the two long run equilibrium relationships for consumption and investment. The latter restriction is imposed on our U.S. baseline version of the King model.

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 equal 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 Large Scandinavian VAR Model

The inflation rate is assumed to contain a unit root in the King et al. (1991) specification, as are the real money supply and the nominal interest rate. For the United States, inflation is typically considered to be I(1). However, the Swedish inflation rate is more appropriately modelled as stationary with a shift in the mean as the Riksbank decided to reduce inflation in the beginning of the 1990s. Similarly, Swedish real money balances as well as the nominal interest rates is borderline stationary (the ADF test statistics are –2.01 and -2.45, respectively). With a mean shift dummy for the 1990s, all three series are clearly stationary, as is money growth. Hence, a better specification of a large, cointegrated VAR in the case of Sweden is to include the price level and the level of the nominal money supply as I(1) variables.

Four to six lags can be included in the VAR depending on which information criterion and what autocorrelation test and significance level one prefers to rely on. We use four lags in the baseline model. The five-variable VAR model with real output, real consumption, real investment, the nominal price level and the level of the nominal money supply contains three cointegrating vectors (see Table 1). We normalize the cointegrating vectors to get three long run equilibrium relationships between (i) consumption, real output, money, and prices (ii) investment, real output, money, and prices (iii) the nominal money supply, the price level and real output. Economic theory implies that the consumption output ratio, the investment/output ratio and the real money balances to output ratio should be stationary. This full set of restrictions is not rejected by the data.

The two stochastic trends are interpreted as a real technology trend and a nominal demand trend. Only one identifying restriction is required for exact identification. Again, we assume that only technology affects real output in the long run, i.e. that Θ_{12} is zero (given $z_t = [y_t,\, c_t,\, i_t,\, m_t,\, p_t]$).

In the US case, ADF tests indicates that inflation is stationary for the full sample 1947-1989. King et al. (1991) start their sample in 1954, removing the Korean war and price control period around 1950, which yields the standard I(1) inflation rate. Real money balances and the nominal interest rate are clearly I(1). Hence, the King et al. (1991) specification is more appropriate for the United States than for Sweden. However, since the log difference of M2 is also borderline stationary, the Scandinavian model can be applied to US data as well. Two lags are required to remove residual autocorrelation at the ten-percent level according to the multivariate Portmanteau test. The Johansen (1991) trace test statistics for cointegrating rank appear in Table 1. Again, there are three cointegrating vectors which are normalized as above.[5] Here, however,

[5] The cointegrating rank tests are inconclusive in case of the four lag Scandinavian model

even the least restrictive theoretical restrictions on the cointegrating space are rejected by the data in the US case. Hence, we estimate four Scandinavian models for Sweden (given four and six lags, with and without restrictions on the cointegrating space) and two for the US (with two and four lags, without restrictions on the cointegrating space).

3.1.3 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 hours worked and labor productivity. The identifying assumption is that only technology shocks affect labor productivity in the long run. The number of parameters that has to be estimated in the Galí specification is small, which allows us to estimate the model also on annual industry data.

We estimate a large number of Galí specifications on three different levels of aggregation for Sweden and the United States: The non-farm private economy, the manufacturing sector and on each industry. The middle level is added because it can be argued that the production function approach is more appropriate for the manufacturing sector than e.g. for the service sector. In particular, we estimate the Burnside et al. (1995) version of the Solow residual on the manufacturing industries only because energy consumption is a less appropriate measure of capital utilization outside the manufacturing sector.

Since the log differences of hours and labor productivity are stationary, there is no cointegration in the Galí model. The preferred number of lags is determined using information criteria and the binding condition that the residuals should not be autocorrelated. Because different information criteria indicate different lag structures, and there is some degree of freedom in terms of what autocorrelation test and significance level to rely on, we estimate two alternative specifications on each data set. In order to obtain comparable results,

for the US. The trace tests indicate $r = 4$, while the λ-max test indicates no cointegration ($r = 0$). Since this model is only used to study the robustness of the results, we nevertheless rely on the existence of three cointegrating vectors in this case as well.

however, the choices of lag length are not re-optimized for each industry. For the disaggregate industry data, the Galí model is estimated using one and four lags. Aggregate manufacturing is a rare case of unanimous choice of lag length as all information criteria indicate that one lag should be used and there is no significant autocorrelation in the VAR(1) residuals. The aggregate Swedish Galí specification requires four or five lags to remove residual autocorrelation depending on the preferred significance level. Two lags can be used in the aggregate Galí specification for the United States as there is no significant autocorrelation in the residuals. However, the Akaike information criterion indicates five lags and we estimate a four lag model to study the robustness of the results with respect to variations in the choice of lag length.

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 into account. We start by assuming the following firm-level production function:

$$Y_{i,t} = F(Z_{i,t}K_{i,t}, E_{i,t}H_{i,t}, V_{i,t}, M_{i,t}, A_{i,t}), \tag{4}$$

where gross output Y is produced combining the stock of capital K, hours H, energy V and intermediate materials (less energy) M. The firm may also adjust the level of utilization of capital, Z, and labor, E. Finally, A is an index of technology.

Differentiating the log of (4) with respect to time and invoking cost minimization yields a gross output version of the standard Hall (1988, 1990) specification generalized to allow for variable factor utilization. That is:

$$\Delta y_{i,t} = \eta_i[\Delta x_{i,t} + \Delta u_{i,t}] + \Delta a_{i,t}, \tag{5}$$

where η denotes the overall returns to scale and Δx and Δu are cost-share-weighted growth rates (first log differences) of observable inputs (K, H, V, M) and utilization (Z, E), respectively. Thus, given measures of Δy_i, Δx_i, Δu_i and an estimate of η_i, the resulting residual Δa_i provides a times series of technology growth for firm i. That is, the standard Solow residual purged of the effects of increasing returns, imperfect competition and varying factor utilization.

The main empirical problem associated with (5) is that capital and labor utilization are generally unobservable. A solution to this problem is then to include proxies of utilization in (5). We follow the approaches of Basu and Kimball (1997) and Burnside et al. (1995) who include hours per employee and energy, respectively, to control for cyclical factor utilization. Although these two specifications differ in how variation in factor utilization are handled, they both share the basic structure of (5). Thus, the two specifications derived below yield measures of technology that are robust to imperfect competition and non-constant returns to scale and, under various conditions, varying factor utilization.

3.2.1 The Basu and Kimball (1997) Specification

The first approach we consider is to use the restrictions that follow from firms' optimal behavior to derive a relation between factor utilization and observable variables. This is the route taken by Basu and Kimball (1997) who derives a relationship between the growth rate of hours per employee, Δhpe, and utilization growth, Δu, from the first order conditions of a dynamic cost-minimization problem. This 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:

$$\Delta y_{i,t} = \alpha_i + \eta_i \Delta \widehat{x}_{i,t} + \gamma_i \Delta hpe_{i,t} + \varepsilon_{i,t}, \tag{6}$$

where Δ denotes first log difference, c_J is the cost share of factor J in total costs, $\Delta \widehat{x}_t$ is defined as $c_K \Delta k_t + c_H \Delta h_t + c_V \Delta v_t + c_M \Delta m$ and Δhpe is the growth rate of hours per employee.[6]

[6] Expression (6) corresponds to an assumption of (4) being a Cobb-Douglas function. Basu and Kimball (1997) also generalize their approach by including regressors to control for variation in the rate of capital depreciation (due to varying capital utilization). However, as stated in Basu et al. (2001), "...including these terms barely affects estimates of technical change".

When implementing the Basu and Kimball (1997) specification, and the Burnside et al. (1995) specification below, 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, i.e. the output elasticities, ηc_J, are treated as constants. Second, the steady state cost shares are estimated as the time average of the cost shares. Third, when compiling the cost shares we assume that firms make zero economic profits in the steady state.[7] This allows us to estimate the cost share of capital as a residual. Finally, the growth rate of technology, Δa, is modeled as a random walk with the drift α and the random shock ϵ. This strategy for modeling the technology process is consistent with the assumptions underlying the structural VAR approach.

3.2.2 The Burnside et al. (1995) Specification

An alternative approach to identify factor utilization proxies is to make additional assumptions directly about the production technology. The approach employed by e.g. Burnside et al. (1995) employs 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 elasticity of substitution between energy and the flow of capital services, ZK, 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):[8]

$$\Delta y_{i,t} = \alpha_i + \eta_i \Delta \widetilde{x}_{i,t} + \varepsilon_{i,t}, \tag{7}$$

where input growth $\Delta \widetilde{x}_t$ is defined as $(c_K + c_V)\Delta v_t + c_H \Delta h_t + c_M \Delta m_t$.[9] Energy is however only likely to be a good proxy for the utilization of heavy equipment.

[7] For U.S. evidence in favor of this assumption see the discussion in Rotemberg and Woodford (1995). For the industries 1 to 9 in the disaggregate Swedish data set we have data to estimate economic profits. Our data implies a time average (1968-1993) for the share of economic profits in the aggregate revenues for these industries of -0.001.

[8] Note that the term energy is used in a broad sense in this section. In fact, Burnside et al. (1995) used electricity consumption as proxy for capital utilization. We will return to the exact definition of energy that we use in the empirical work when we discuss the data.

[9] In Burnside et al. (1995) time varying cost shares are used. Equation (7) rests, however, on the assumption that $F(ZK, EH, V, M, A) = \{AS^{\alpha_1}(\overline{E}L)^{\alpha_2}M^{\alpha_3},\ S = \min[ZK, V]\}$, where

This specification is therefore less appropriate outside the manufacturing sector. Since the Burnside et al specification relies on a different set of assumptions than the Basu and Kimball specification we estimate both approaches as a robustness test. However, we only use data from the manufacturing sector for the Burnside et al. specification.

3.2.3 Instrumentation and Estimation

Because the firm is highly likely to consider the current state of technology when making its input choices, instrumental variable technique are required to credibly identify the residuals from the robust production function specifications as technology growth. Appropriate instruments to avoid this endogeniety are variables that are exogenous relative to variation in technology while correlated with economic activity. The most commonly used instruments in the literature are variations of the so-called Hall-Ramey instruments and Federal Reserve policy shocks derived from an identified VAR. 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. For the U.S. disaggregate data set 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. This instrument set yields results that are close to the results presented by Basu et al. (1998), Basu and Fernald (2001) and Basu et al. (2001).

Because the relevance of real defense spendings and the political dummy variable in U.S. data has been questioned (see e.g. Wilson (2000) and references therein), it is interesting to compare baseline U.S. result to the results obtained from a different economic environment, allowing for other, potentially highly relevant, instruments. The main point of studying the Swedish economy in addition to the United States is that we can reasonably treat it as a small

$\overline{E}$ denotes the fixed level of effort. Carlsson (2000) experiment with using industrial accidents as a proxy for effort on Swedish data. This approach does not work well and is not considered in this paper.

open economy. This characteristic legitimize the use of other instruments, such as foreign demand, as well as strengthen the validity argument for the real oil price. Moreover, Sweden has maintained a fixed exchange rate regime, with a small number of discrete devaluations, throughout the sampling period. Thus, the nominal exchange rate should be a valid instrument. For the Swedish disaggregate data, we use the same instrument set as in Carlsson (2000), i.e. the current and once lagged growth rate of a foreign demand index, the first and second lag of the growth rate of a nominal exchange rate index, the current value of the growth rate of the real oil price and a political dummy variable (see the data appendix for details).

Following Basu et al. (1998) and Basu and Fernald (2001) we combine industries into groups. Within each group we allow for fixed industry effect and heterogenous returns to scale. When estimating (6) we restrict the hours per employee parameter, γ, to be equal across industries. Each group is then estimated with standard 3SLS methods using the instruments discussed above.

Both the U.S. and the Swedish industries are divided into four groups, i.e. mining (four industries in the U. S. data/one industry in the Swedish data), nondurables manufacturing (10/4 industries), durables manufacturing (11/4 industries) and services and others (8/6 industries). Since the U.S. input data is divided into capital, labor, energy and other intermediate inputs we use this broad energy measure when estimating the Burnside et al. specification on U.S. data.

When estimating the Basu and Kimball specification on Swedish data, we drop the hours per employee proxy for all groups except for mining and petroleum extraction. This is done since the hours per employee parameter is estimated with the wrong sign (negative, but insignificantly so) for these groups. In fact, hours per employee is generally acyclical in the Swedish data set, whereas the same variable is generally strongly procyclical in our U.S. data set.[10] Since

[10] The correlation between the growth rate of aggregate hours per employee and aggregate output growth is -0.07 in the dissagregate Swedish data set, whereas the corresponding correlation for the dissagregate U.S. data set is 0.70. One explanation of the difference in cyclical behavior of hours per employee in the U.S. and Sweden is differences in labor institutions.

the inputs are divided into capital, labor, electricity and other intermediate inputs we use electricity consumption as the energy measure when estimating the Burnside et al. specification on Swedish data.[11]

In Tables 3 and 4, we present a summary of the results from the production function regressions. The null hypothesis of the Sargan-test of valid instruments and a correctly specified model can not be rejected on the five-percent level in any of the systems. Tables 3 and 4 also present relevance measures of the instrument sets, i.e. R2:s and partial R2:s (defined as in Shea (1997)) averaged over industries. In the U.S. case the relevance of the instruments is low and the results are somewhat sensitive to the exact specification of the instrument set. This problem is often encountered when estimating production functions since it is difficult to find good instruments (see e.g. Burnside (1996) for a discussion). The procedure outlined above yields however results that are close to previous U.S. studies (see below). In the Swedish case the instrument set have a quite high explanatory power for the weighted input indices and the results are more robust to variations in the specification of the instrument set. The lower relevance for the Swedish instrument set for hours per employee is due to the fact that the hours per employee variable is generally acyclical in Sweden, whereas the instrument set is designed to be relevant for the level of economic activity.

Tables 3 and 4 presents the average of the estimated returns to scale for each group in the U.S. and Sweden, respectively. For nondurables manufacturing, durables manufacturing and services and others we can compare our findings

For example, the overtime premium, i.e. the markup on the base wage, was 62 percent in the Swedish manufacturing sector as compared to 43 percent in the U.S. manufacturing sector in 1985. Overtime constituted 2.6 percent of total hours worked in Swedish manufacturing during 1981-1992, whereas the same fraction for the U.S. manufacturing sector (calculated from BLS data) was 8.3 percent during the same time period. The Swedish estimates are taken from (or compiled using the data underlying) Nordström-Skans (2001). The US overtime premium is calculated using the estimate of the share of overtime workers receiving a premium (0.865) in the U.S. manufacturing sector presented by Trejo (1993) and by assuming that those workers that did receive a premium received the time-and-a-half premium as mandated by the Fair Labor Standards Act. In the total sample used by Trejo (1993), 95 percent of those who received any type of overtime premium did in fact get the time-and-a-half premium.

[11] Since electricity expenditure are unavailable for industries outside mining and manufacturing, inputs are divided into capital, labor and intermediate inputs in these industries.

for the Basu and Kimball specification with the findings of Basu et al. (2001), although they use a somewhat different time period and methodology. The results for both the returns to scale and the hours per employee parameter are quite similar. For the nondurables manufacturing (durables manufacturing) [services and others], we arrive at an average point estimate of the returns to scale of 0.69 (1.05) [0.70] and an estimate of the hours per employee parameter of 1.69 (0.76) [0.70] as compared to 0.78 (1.03) [1.00] and 1.21 (0.74) [1.33] in Basu et al. (2001). The Swedish manufacturing results are very similar to the results of Carlsson (2000), who estimate both the Basu and Kimball and the Burnside et al. specification using a slightly different empirical strategy. For the Basu and Kimball specification we find an average of the returns to scale point estimates for nondurables (durables) of 1.26 (1.24) as compared to 1.26 (1.30). For the Burnside et al. specification we find an average of the returns to scale point estimates for nondurables (durables) of 1.18 (1.17) as compared to 1.19 (1.18). Thus, overall, our estimation results are in line with previous studies.

3.3 Aggregation

To compare the results of the different approaches to identify technology growth we need to aggregate industry-level technology growth series from the production function approach to aggregate technology growth. Following Basu et al. (1998) and Basu and Fernald (2001) we define aggregate technology growth, Δa^A, as:

$$\Delta a_t^A = \sum_i \omega_{i,t} \frac{\Delta a_{i,t}}{1 - \eta_i(c_{V,i} + c_{M,i})}, \tag{8}$$

where ω_i is the industry's share in aggregate nominal value added. The denominator in (8) 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.

To analyze the cyclical patterns implied by the different technology measures, we calculate correlations between the technology measures and the growth rates of aggregate real value added, aggregate total hours worked and an aggregate primary input index. We define aggregate real value added growth, Δy_t^A, as the first log difference of the sum of real value added across industries.[12] Aggregate total hours growth, Δh_t^A, is defined as the first log difference of the sum of total hours across industries. The aggregate primary input index is defined as:

$$\Delta x_t^A = c_H^A \Delta h_t^A + (1 - c_H^A)\Delta k_t^A, \tag{9}$$

where c_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:

$$SR_t = \Delta y_t^A - \Delta x_t^A. \tag{10}$$

The aggregation procedure outlined above is then applied to two levels: the non-farm private economy and the manufacturing sector.

4 Empirical Results

Although we are not aware of previous systematic studies of whether structural VAR models capture the same technology shocks as the production function approach, several authors calculate correlations between different measures of technological progress. King et al. (1991) report a correlation of 0.48 between their VAR technology shocks and the Solow residual of Prescott (1986), which is constructed assuming constant returns to scale, perfect competition and constant factor utilization. Because deviations from these assumptions introduce

[12] This definition of aggregate value added growth yields an almost identical measure as the divisia definition discussed in Basu and Fernald (1995) on annual basis. Since we lack data to construct the divisia measure on quarterly frequency we use the definition above.

demand related procyclical noise, refined measures are preferable when analyzing the behavior of technology shocks at business cycle frequencies. The correlation between the VAR technology shocks of King et al. (1991) and the Solow residual of Hall (1988), which allows for increasing returns to scale but not variable factor utilization, is only 0.19.

Kiley (1998) compares his VAR technology shocks for 17 American manufacturing industries to the technology measures of Basu and Kimball (1997) and Burnside et al. (1995), i.e. the approaches for taking variable factor utilization into account that we use. 7 of the 17 correlations are significantly positive in the former case and 9 of 17 in the latter. The correlations are however not very high, 0.22 on average and in no case above 0.70. A problem when interpreting these findings is that it is difficult to know just how high the correlations should be in order to justify the conclusion that the VAR models do capture the same underlying phenomenon as the alternative approaches. Kiley (1998) finds his results reassuring even though about half of the correlations are insignificant and King et al. (1991) also consider their correlations of 0.48 and 0.19 between the VAR technology shocks and two Solow residuals sufficiently high. King et al. (1991) and Kiley (1998) compare technology shocks derived from different methods for the same sample periods, and also the same industries in the latter case. We apply the different techniques for identifying technology shocks to identical data sets, which allows a more exact comparison of the methods.

To study whether the different methods capture the same unobservable phenomenon, and whether the differences matter in the sense that different approaches lead to different conclusions about the driving forces of business cycles, we calculate the correlations (i) between the different technology measures, and (ii) between the technology shocks and business cycle variables. The results for Sweden are presented in section 4.1, the results for the United States appear in section 4.2 and industry-level evidence is presented in section 4.4. The effects of minor variations in the specification of the VAR models and other robustness issues are discussed in Section 5.

4.1 Swedish Results

Table 5 contains the results for the aggregate Swedish private non-farm economy. We compare six different technology measures: the Solow approach, the Basu and Kimball (1997) specification with hours worked as proxy for factor utilization, the Burnside et al. (1995) approach using energy consumption, the large, cointegrated six variable VAR of King et al. (1991), the Scandinavian five variable specification and the small two variable VAR of Galí (1999).

Focusing first on the relationship between the different approaches for identifying technology growth, we see that the measure from the Galí VAR model is significantly positively related both to the Basu and Kimball measure and the Solow residual on the five-percent level. The measures from the Scandinavian and the King models are, however, unrelated to both the Basu and Kimball residual and the Solow residual. Hence, only two out of six correlations between the technology measures from the two main approaches are significantly positive and the average correlation is 0.33. The two large VAR models, the King specification and the Scandinavian model, produce similar but not identical results in terms of technology growth. The correlation between the series is 0.71. The King model utilizes the same data on levels of output, consumption and investment as the Scandinavian model. It is the treatment of the monetary side of the economy differs between the two specifications. The Burnside et al. technology measure is compiled using data from the manufacturing industries only and can therefore not be compared to the economy-wide measures from the large VAR models. It is however similar to the Basu and Kimball specification as the correlation between the series amounts to 0.91.

The correlations between the cyclical variables are in line with what is expected. Output growth is strongly correlated to both input (0.78) and hours growth (0.78). Moreover, since hours is by far the most volatile part of the primary input index, defined in (9), the correlation between hours growth and the input index is almost unity (0.98).

Turning to cyclical behavior of the different technology measures, it is clear that we replicate the standard finding of a strongly procyclical Solow residual. The correlation between the Solow residual and output growth amounts to 0.71. The correlation between the Solow residual and hours and input growth is also positive, although not significantly so. It has been argued that the finding of a procyclical 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 from truly procyclical technological changes (see e.g. Basu and Fernald (2001) and the references therein). Our application of the Basu Kimball specification to Swedish data is robust to imperfect competition and increasing returns to scale but not to variable factor utilization since we were forced to drop the hours per employee variable for all groups but the mining industry. Because factor utilization is assumed to be procyclical, leaving out hours per employee is likely to bias the technology residual towards a positive correlation between the technology residual and output, input and hours growth. However, when studying the results for the Basu and Kimball measure, we find that it is acyclical. The correlation with output growth is 0.11 and insignificant. Moreover, the correlation between the Basu and Kimball measure and input and hours growth are significantly negative on the five-percent level, -0.49 and -0.49, respectively. The Burnside residual which takes variable factor utilization into account through the firms' consumption of electricity is even more countercyclical with a zero correlation with output growth and large negative correlations with input and hours worked (-0.65 and -0.57, respectively).

An interesting finding concerning the results from the VAR models is that the cyclical pattern of the technology measure derived from the Scandinavian five variable VAR and the two variable VAR of Galí are very similar to that of the Basu and Kimball and the Burnside et al. measures. The technology measure of the Scandinavian specification is acyclical with output growth (-0.23) and significantly negatively correlated to input (-0.44) and hours growth (-0.45). The technology measure of the two-variable VAR of Galí is also acyclical with output growth (-0.04), significantly negatively correlated with input growth

(-0.43) and negatively correlated with hours growth (-0.40) but insignificantly so. Thus, these measures imply that technological improvements are associated with periods of contractions in input and hours growth while output growth do not seem to increase to any large extent, at least not contemporaneously. These results are hard to reconcile with predictions from the standard RBC model, whereas they are in line with the predictions of e.g. a sticky price model (see e.g. Basu et al. (1998)). The technology measure from the King et al. specification, which may be argued to be less appropriate than the Scandinavian specification for Swedish data, are, however, not significantly correlated to any of the cyclical variables. It is nevertheless interesting to see that the point estimates for the correlations between the King et al. measure and input and hours growth are negative (-0.07 and -0.05, respectively).

4.2 U.S. Results

The correlations between our six different technology measures for the U.S. private non-farm economy and their relationship to cyclical variables are presented in Table 6. A first observation from Table 6 concerns the cross correlations of the different technology measures. All measures except the one derived from the Galí model are significantly positively related to the Solow residual on the five percent level. We also see that the technology measure from the Scandinavian model and the Galí model are positively related to the Basu and Kimball residual on the five-percent level. The correspondence between the two main approaches for identifying technology shocks is thus higher here than in the Swedish case. Four out of six correlations are significantly positive and the average correlation is 0.39.

Another encouraging finding in Table 6 is that all VAR technology measures are significantly positively related to each other on the five percent-level. The correlation between the King specification and the Scandinavian model is 0.72. The correlation between the refined Solow residuals of Basu and Kimball (1997) and Burnside et al. (1995), estimated using manufacturing data only, is 0.76.

Thus, the results from both the refined production function residuals and the structural VARs seem to be robust to changes in the empirical models.

As for Swedish data, we find the expected relationships between the business cycle variables. Input and hours growth are significantly procyclical as the correlations with output growth are 0.66 and 0.77, respectively, and hours growth is highly positively correlated to input growth (0.94). We also replicate the standard finding of the Solow residual being strongly positively correlated to output growth (0.81). Furthermore, the Solow residual is positively correlated to hours growth (0.29) and to the input index (0.09), but insignificantly so on the five-percent level in both cases.

When imperfect competition, increasing returns to scale, and cyclical factor utilization are allowed, the cyclical behavior of the technology measures from the production function approach change 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). The Burnside et al. energy corrected measure, which is estimated for the manufacturing industries only, is acyclical with output growth (0.20) and significantly negatively related to input (-0.43) and hours growth (-0.34).

Table 6 also shows that all three technology series derived from the VAR:s display a cyclical behavior that is similar to that of the refined Solow residuals. The VAR technology shocks are uncorrelated to output growth on the five-percent level, and the point estimates of the correlations between these technology measures and input and hours growth are all negative. The correlation between the Scandinavian VAR model is acyclical with output growth (0.18) and is negatively correlated to input (-0.29) and hours growth (-0.28) but not significantly so on the five-percent-level. We see a similar pattern for the measure derived from the King model. The correlations between the King measure and output, input and hours growth (0.17, -0.25 and -0.23, respectively). The Galí measure is also acyclical with output growth (0.01) and negatively correlated with input (-0.30) and hours growth (-0.35), and significantly so on the five-percent level in the latter case.

Overall, the U.S. evidence on input and hours movement in times of technology improvements 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 and the significantly positive cross correlations between the measures of the Basu and Kimball specification, the Scandinavian VAR and the VAR model of Galí leads us to the conclusion that these measures reflect the same underlying unobservable phenomenon.

4.3 Robustness of the VARs

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 on the cointegrating space can be imposed or not, and so on. We therefore study the sensitivity of the technology shocks with respect to the minor changes in the empirical specification.

We have estimated eight VAR models for the aggregate Swedish economy: Two King models using four and six lags but without restrictions on the cointegrating space (all restrictions suggested by economic theory were rejected by the data in this case), four Scandinavian models, also with four and six lags with and without restrictions on the cointegrating space, and two Galí models with four and five lags. None of the models display obvious signs of misspecification and they are all optimal choices using at least one criterion. Table 7 shows the results from this robustness analysis.

Changing the number of lags has a negligible influence of the technology shocks in case of the King model and the Galí model. These two correlations are 0.91 and 0.93, respectively. For the unrestricted Scandinavian model, the effect of adding two more lags is slightly larger as the correlation between the two sets of technology shocks falls to 0.73. Finally, the Scandinavian model with a full set of theoretical restrictions on the cointegrating space is quite sensitive to the number of lags which is indicated by a correlation of 0.41 between the technology measures derived from the four and the six lag versions of the model. Imposing permissible restrictions on the cointegrating space appears to have some effect on the results as the correlations between the Scandinavian specifications with the same number of lags, with and without restrictions are 0.62 and 0.50.

Overall, 11 of the 28 correlations between the technology shocks from different Swedish VAR specifications are significantly positive on the five-percent level. The main part of the insignificant correlations are cross correlations between variations of the Galí model and the large VAR:s. The two large, cointegrated VAR models produce similar technology shocks except for the restricted Scandinavian specification with six lags. The Swedish sample 1973-1993 is dominated by a few major monetary policy shocks, the large devaluations of the Swedish krona in 1981 and the deep recession from 1991 to the end of the sample which was induced by the defence of the fixed exchange rate with the interest rate hiked up to 500 percent. If the size of the deterministic trend component varies between the models, small differences in the extent to which the technology trends pick up these cyclical movements has a major impact on the results.[13] The qualitative conclusions about the relation between technology growth and cyclical variables also varies between the specifications of the VAR models. However, in no case we find a significant positive correlation between the technology and hours which we would expect in an RBC-world.

Table 8 shows the corresponding robustness results for eight US VAR models: Two King specifications with two and four lags, with and without restrictions on the cointegrating space, the Scandinavian model with two and four lags, and the small Galí model with three and four lags. The results in Table 8 provide support for the conclusion that the Scandinavian and the Galí VAR models reflect the same underlying phenomenon in US data. All cross correlations between these two measures are significantly positive. Moreover, all correlations

[13] Variations in the magnitude of the deterministic trend component μ has a similar effect to varying λ in a Hodrick-Prescott filter, i.e. if μ is large relative to the variance of the technology shocks in φ_t, the stochastic trend become more linear.

between the measures from the Scandinavian and the King model are significantly positive. The results for the correlations between the King and the Galí measures are more mixed, five out of eight correlations are significantly positive. Varying the number of lags in the VAR has negligible effects on the technology shocks as the relevant correlations are above 0.88. Similarly, imposing or not imposing permissible restrictions on the cointegrating space produces technology shocks with correlations of 0.88 and 0.70 for the two and four variable King specification, respectively.

The Scandinavian and the Galí models also produce similar technology measures as compared to the Basu and Kimball measure. All four correlations between these VAR measures and the production function measure from the Basu and Kimball model are significantly positive. However, non-of the correlations between the VAR measures derived from variations of the King model and the Basu and Kimball measure are significantly positive. As in the Swedish case, the qualitative conclusions about the cyclical behavior of technology growth are sensitive to the exact specification of the VAR models, although none of the VAR specifications implies that technology growth has an expansionary short-run effect on hours worked.

Structural VAR models can be used to obtain Forecast Error Variance Decompositions (FEVDs) at different horizons. Variance decompositions show how much of the variance of a variable that stems from a certain structural shock. At business cycle frequencies, the variance decompositions provide information about the share of business cycle variations in real output that is caused by technology shocks. The first column of Table 9 contain the three-year FEVDs of output for the six different VAR models applied to aggregate Swedish data: The King specification with four and two lags, and the Scandinavian specification with two and four lags, with and without restrictions on the cointegrating space. It is clear that technology shocks is a minor source of business cycle fluctuations in this data set. Only 7.4 to 15.4 percent of the variations are caused by technology shocks. While the results differ slightly between the empirical specifications, the qualitative conclusion remains the same across the variance decompositions for Swedish output growth. This can be interpreted as more evidence against the real business cycle model, since the standard RBC-model relies on technology shocks as the primary driving force behind business cycle movements. Since the correlations between the Swedish VAR technology shocks were generally to small to convincingly motivate the conclusion that the different specifications capture similar shocks, it is reassuring that the results in terms of the empirical relevance of business cycle models are robust to various permutations of the VAR models.

The share of technology shocks in the variance decomposition for US output growth at the three-year horizon appear in the second column of Table 9. Here, the different models yield slightly different conclusions. Five specifications arrive at a relative importance of technology shocks in the range of 12.3 to 16.0 percent. The restricted King specification with four lags produce a larger share of technology induced variations, i.e. 23.4 percent. However, these results do not support the view that technology shocks constitute the main driving force of business cycle variation in real output.

4.4 Evidence from industry data

In this section we study the coherence between the industry specific Basu and Kimball residual and the technology measure from the structural VAR approach of Galí (1999). To this end, we estimate two small VAR-models a'la Galí on annual gross output data for each industry, using one lag and four lags for both Sweden and the U.S. Thus, we supply the Galí model with exactly the same data as the Basu and Kimball specification. For the manufacturing industries, the technology measure from the Burnside et al. (1995) approach using consumption of electricity as proxy for capital utilization are included in the analysis.

Table 10 summarizes the Swedish results from this comparison on industry data. It also displays the number of significant correlations (on the five-percent level) as well as the number of significant correlations with a sign opposite to that of the average correlation. The correlation across the Galí specifications are

0.64 on average and all but one of the underlying correlations are significantly positive. The correlations between the VAR technology measures of Galí and the Basu and Kimball measure are about 0.3, with about one third of them significant. We also present the results for the Burnside et al. specification. These results are compiled using manufacturing data only. The Burnside measure is highly correlated with the Basu and Kimball measure on average (0.93) with all eight correlations significantly positive. Finally, we see that the Burnside measure is generally uncorrelated with the Galí measures, 0.16 (one lag) and 0.21 (four lags), respectively and only one correlation is significant in the four lag case and non in the one lag case. Thus, the coherence between the VAR and the production function measures are quite low also when applied to Swedish industry data.

Tables 11 presents the U.S. results from the comparison on industry data. The average correlations between the Galí technology measures with one and four lags and the Basu and Kimball measure are 0.55 and 0.45, with 27 and 26 out of 31 correlations significantly positive, respectively. Hence, the two approaches for capturing technology shocks are even more similar at the industry level than for aggregate data when applied to U.S. data. 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 measures are 0.50 and 0.40, with 17 and 14 correlations out of 21 significantly positive, respectively. The coherence within each approach is also high. The average correlation between the Basu and Kimball and Burnside et al. series amounts to 0.83, and the average correlation between the one and four lag measures from the Galí model is 0.78. In both cases all underlying correlations are significantly positive. These results can be compared to Kiley (1998) who finds a significant correlation between the Basu and Kimball (Burnside) measure and the Galí measure in 7 (9) out of 17 industries and an average correlation of 0.23 (0.22).

5 Conclusions

We have applied six different techniques to identify technology growth on Swedish and US data in order to investigate whether they capture the same phenomenon and whether the implications for macroeconomic theory are robust to the choice of method. Our results are somewhat mixed. Above all, the US and Swedish results differ in terms of the cohesiveness between the approaches to identify technology growth.

For the U.S., a robust finding is that the technology measures derived from the large Scandinavian VAR, the small VAR of Galí and the production function approach of Basu and Kimball are significantly positively correlated to each other. The technology measure derived from the large VAR model of King is however not related to the Basu and Kimball residual, and the relation to the Galí measure is not robust. The classic Solow residual is significantly correlated with all alternative measures except for the Galí measure. Hence, the different approaches for identifying technology shocks yield reasonably similar results when applied to US data.

The Swedish results are more dismal. The small Galí VAR model and the large VAR models do not yield technology series that are significantly correlated. This may be due to that the Swedish sample 1973-1993 is dominated by a few major demand related events. Small differences in the extent to which the models identify these cyclical movements as permanent technology shocks cause large differences in the resulting technology measures. However, the technology measure from our baseline specifications of the Galí VAR model are significantly correlated to comparable technology measures derived from the refined production function approaches and to the Solow residual. The latter finding turns out not to be robust to small variations in the baseline VAR. The Solow residual is not related to any of the measures derived from the large VAR models in the Swedish case.

Our U.S. industry level evidence on the relationship between technology shocks from a structural VAR versus the production function approach can be compared to the findings of Kiley (1998). About half of his correlations between the Galí VAR measure and the Basu and Kimball (Burnside) technology measures are significantly positive and the average correlation across the industries is only 0.23 (0.22). When controlling for differences in the data by providing these three approaches with exactly identical information, we find that different technology measures are much more similar. Between the Galí and the Basu and Kimball measures 27 of 33 correlations are significantly positive, and between the Galí and the Burnside measures 17 of 21 of the correlations are significantly positive. The average correlations across the industries are also more than twice as high as in Kiley (1998), 0.55 (0.50) for the Basu and Kimball (Burnside) measures. The Swedish industry evidence is, however, less encouraging. We find an average correlation between the Galí VAR measure and the Basu and Kimball (Burnside) measure of 0.27 (0.16), with 4 (0) out of 15 (8) of the underlying correlations significantly positive.

We are also interested in whether variations in the specification of the structural VAR results in small or large changes in the resulting technology measures. Again, the results differ between the two countries. For the US, all cross correlations between the measures derived from the large VAR models are significantly positive and also between the large Scandinavian VAR models and the small Galí VAR models. The results for the correlation between the measures derived from the large VAR models of King and the small VAR models of Galí are more mixed, with five out of eight correlations significantly positive. Overall, the structural VAR approach is remarkable robust in the U.S. case, both to major and minor variations in the empirical specification. For Sweden, the correlations between the structural VAR model are less robust.

Turning to the cyclical behavior of the technology shocks, we find similar patterns in both the refined versions of the Solow residual as well as in the technology measures derived from the baseline structural VARs. In the Swedish case, none of the measures derived from the refined Solow residuals or the baseline VARs are significantly correlated to output growth and 7 of the 10 correlations with inputs are significantly negative. In the U.S. case none of these measures are significantly correlated with output, whereas 5 out of the 10 correlations with inputs are significantly negative. Moreover, in both the Swedish and the U.S. case the point estimates of all of the remaining insignificant correlations with inputs are negative. Thus, the cyclical pattern that emerges is that technological improvements are associated with periods of contractions in inputs, whereas there is no significant (contemporaneous) increase in output. This finding can easily be reconciled with e.g. a sticky price model (see e.g. Basu et al. (1998)) but is clearly at odds with the standard RBC-model.

Refining the standard measure of technology by allowing for phenomena like imperfect competition, increasing returns to scale and cyclical factor utilization or applying a structural VAR model hence has a radical effect on the cyclical properties of technology growth relative to the stylized facts that refer to the classic Solow residual. More specifically, the correlation with output growth falls from about 0.75 for the classic Solow residual to about 0.15 for the Basu and Kimball specification in both the Swedish and the US aggregate data sets. Furthermore, the refined production function residuals are generally significantly negatively correlated with input and hours growth. The results from the structural VARs confirm that the refined Solow residuals constitute a more appropriate measure of technology at business cycle frequencies since they produce technology measures with similar cyclical behavior.

Another piece of evidence that points away from technology shocks as the prime driving force of business cycle fluctuations is the forecast error variance decomposition presented in the paper. Our baseline VAR models all indicate that technology shocks account for a small and insignificant fraction of the three-year variation of output growth, 10.4 to 16 percent, and the largest fraction observed for all of our variations of the large VAR specifications is 23.4 percent. Overall, the qualitative conclusions in terms of the empirical validity of different business cycle models are more robust across our methods for identifying technological change than the technology shocks themselves.

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6 Data Appendix

Table A1 present the industries in our disaggregate Swedish data set. The somewhat higher level of aggregation, relative to the U.S. data set, is due to the availability of data. Given the sample length at the current level of aggregation we choose not to disaggregate any further. SNI39 has been dropped because it is not a well defined industry.

Table A1: Industry Classification - Disaggregate Swedish Data

Industry	Description	SNI69 Classification
1	Mining	2
2	Food	31
3	Textiles	32
4	Wood	33
5	Paper	34
6	Chemicals	35
7	Minerals	36
8	Primary Metals	37
9	Fabricated Metals	38
10	Electricity, Gas and Water	4
11	Construction	5
12	Trade	6
13	Transportation and Communication	7
14	FIRE	8
15	Services	9

Table A2 presents the main sources and definitions used for the Swedish data sets. The quarterly **Investment** series for the business sector for the period before 1980:1 has been kindly provided from Lennart Berg from the SNEPQ database which, in turn, is collected from the National Accounts.

The **Capital Stock** series is calculated using the perpetual inventory method described in Hansson (1991).

The **Exchange Rate Index** series is an export-share weighted index of exchange rate series for OECD 14. The weights for each country are compiled as the time average of Swedish exports to the country divided by total Swedish exports to the fourteen countries. Nominal exchange rates are collected from OECD Main Economic Indicators (MEI).

The **Political Dummy** variable takes on the value one for years with right-wing governments (1977-1982, 1992-1993) and zero otherwise.

Table A2: Sources and Definitions of Swedish Variables

Variable	Source	Definition
Y ($A^{c,f}$,Q^f)	SM Series N	Gross output (A), Value added for non-farm business (Q)
M ($A^{c,f}$)	SM Series N	Value of used intermediary goods
H (A,Q)	SM Series N	Total hours worked, Total hours worked non-farm business (Q)
N (A)	SM Series N	Number of employees
P_HH (A^c)	SM Series N	Wage sum including collective fees
V (A)	SOS Industrin	Consumption of electricity in gWh
P_VV (A^c)	SOS Industrin	Electricity Cost
I ($A^{c,f}$,Q^f)	SM Series N	Investments (A), Investments for business (Q)
C (Q^f)	SM Series N	Private consumption
P (Q)	SM Series N	Consumer price index
R (Q)	IFS	Three-month Swedish treasury bill rate
M (Q)	Bank of Sweden	M3

.
A (Q) denote annual (quarterly) series. Superscript c denotes series in current values and f denotes series in fixed 1991 prices. SM Series N denotes the Statistics Sweden publication Statistiska Meddelanden Serie N (National Accounts). IFS denotes the IMF publication International Financial Statistics. OECD MI denotes the OECD publication OECD Main Indicators.

The **Foreign Demand Index** series is an export-share weighted index of indices for manufacturing production from MEI for OECD 14. Due to missing data, an index of total industrial production from the OECD MEI is used as a proxy for Germany for the period 1967-1991. For Denmark an index of industrial production, collected from Mitchell (1992) and linked in 1970 to an index of the production of consumer durable goods, collected from the OECD MEI, is used as a proxy for manufacturing production.

The **Real Oil Price** series is compiled by converting the world spot oil price series, obtained from IFS, to kronor using the exchange rate from the OECD MEI and deflating using the Swedish GDP deflator from the SM Series N.

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.

Table A3 present the main sources of the U.S. aggregate quarterly data set.

Table A3: Sources and Definitions of Quarterly US Variables

VARIABLE	SOURCE	DEFINITION
Y (Q)	BEA (NIPA)	Real value added for non-farm business
H (Q)	BLS	Total hours worked index for non-farm business
I (Q)	BEA (NIPA)	Real gross private fixed investment
C (Q)	BEA (NIPA)	Real personal consumption expenditures
P (Q)	BEA (NIPA)	The GDP deflator
R (Q)	FED BOG	Three-month U.S. treasury bill rate
M (Q)	FED BOG	M2

.
For Y, I and C both the volume index and the current price series are collected. These series are then used to construct chained 1987 dollar series (to match the base year used in the Jorgenson data).

The **M2** series before 1959:1 is taken from King et al. (1991). The series is available at Mark W. Watson's home page.

The **Real Oil Price** is measured as the PPI for crude petroleum, taken from the BLS web site, deflated with the GDP deflator, calculated from NIPA series taken from the BEA web site.

The **Real Defense Spendings** series is measured as national defense outlays deflated with the GDP deflator. Both series are taken (or compiled) from NIPA series taken from the BEA web site.

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. Real and nominal GDP is collected from the BEA web site.

Table 1: The Johansen (1991) trace test for cointegrating rank

	Sc4 Sw	Sc6 Sw	K4 Sw	K6 Sw	Sc2 US	Sc4 US	K2 US	K4 US
$r = 0$			164.58*	137.88*			124.66*	144.46*
$r = 1$	105.21*	84.19*	77.21*	83.79*	77.49*	75.09*	74.12*	84.30*
$r = 2$	45.35*	47.77*	47.54*	44.08*	49.26*	50.41*	45.48*	50.95*
$r = 3$	26.80*	26.85*	26.55	22.57	29.59*	29.15*	18.21	25.24
$r = 4$	11.66	9.91	13.14	9.83	11.43	13.96*	8.39	10.44
$r = 5$	2.72	2.58	2.87	2.91	0.01	0.06	2.57	4.18

.

* denotes significance using the 90-percent level from Osterwald-Lenum (1992).

Table 2: Point estimates of the cointegrating vectors

	y	c	i	$m-p$	R	π	m	p
Sc(4) Sw	-1.061*	1.0	0.0				-0.019	0.019
	-1.240*	0.0	1.0				0.101	-0.101
	-2.152*	0.0	0.0				1.0	-1.917*
Sc(6) Sw	-0.798*	1.0	0.0				0.008	-0.008
	-1.028	0.0	1.0				0.046	-0.046
	-2.992	0.0	0.0				1.0	-2.291
K(4) Sw	-0.652*	1.0	0.0	0.0	-0.009	-0.001		
	-2.907*	0.0	1.0	0.0	0.177*	0.015		
	-0.045	0.0	0.0	1.0	-0.036*	-0.017*		
K(6) Sw	-0.720*	1.0	0.0	0.0	-0.004	-0.004		
	-2.909*	0.0	1.0	0.0	0.061*	-0.066*		
	0.157	0.0	0.0	1.0	-0.018	0.001		
Sc(2) US	-1.311*	1.0	0.0				0.104*	-0.104*
	-1.068*	0.0	1.0				0.685*	-0.685*
	-1.332*	0.0	0.0				1.0	-0.886*
Sc(4) US	-1.261*	1.0	0.0				0.104*	-0.104
	-0.942*	0.0	1.0				-0.340*	0.340*
	-2.132	0.0	0.0				1.0	-0.358*
K(2) US	-0.863*	1.0	0.0	0.0	0.056*	-0.073*		
	-0.608*	0.0	1.0	0.0	0.116*	0.177*		
	-1.193*	0.0	0.0	1.0	-0.007	0.007		
K(4) US	-0.704	1.0	0.0	0.0	0.025*	-0.069*		
	-0.608	0.0	1.0	0.0	0.023	-0.110*		
	-1.193	0.0	0.0	1.0	-0.001	0.009*		

.
* denotes significance at the 90 percent level.

Table 3: Swedish Disaggregate Results

	Hours correction			Electricity correction	
Groups	ARTS	γ	Sargan	ARTS	Sargan
Mining	1.39	1.12 (0.30)	0.36	–	–
Non Durables	1.26	–	0.69	1.18	0.93
Durables	1.24	–	0.39	1.17	0.50
Services and Others	1.08	–	0.43	–	–

	NDF Correction			DF Correction		
Relevance Measures	$\Delta\widehat{x}$	Δhpe	$\Delta\widetilde{x}$	$\Delta\widehat{x}$	Δhpe	$\Delta\widetilde{x}$
Average R2	0.46	0.24	0.51	0.29	0.01	0.36
Average Partial R2	0.41	0.22	0.51	0.23	-0.03	0.36

.
Sample 1968-1993. The ARTS column presents the average returns to scale by group. The gamma column gives point estimates of the hours per employee coefficient (s.e. in parenthesis). The Sargan column presents the p-value of the Sargan-test of overidentfying restrictions. Average R2 and Average Partial R2 corresponds to averages of R2 and Partial R2:s (defined as in Shea (1997)) across all industries. DF/NDF indicates if a degrees of freedom correction is done or not, respectively.

Table 4: U.S. Disaggregate Results

	Hours correction			Electricity correction	
Groups	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	–	–

	NDF Correction			DF Correction		
Relevance Measures	$\Delta\widehat{x}$	Δhpe	$\Delta\widetilde{x}$	$\Delta\widehat{x}$	Δhpe	$\Delta\widetilde{x}$
Average R2	0.16	0.14	0.17	0.09	0.06	0.10
Average Partial R2	0.09	0.08	0.17	0.04	0.03	0.10

.
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 (s.e. in parenthesis). The Sargan column presents the p-value of the Sargan-test of overidentfying restrictions. Average R2 and Average Partial R2 corresponds to averages of R2 and Partial R2:s (defined as in Shea (1997)) across all industries. DF/NDF indicates if a degrees of freedom correction is done or not, respectively.

Table 5: Correlations - Swedish Private Economy

	Δy^A	Δx^A	Δh^A	S	BK	Sc(4)	K(4)
Output Growth	1						
Input Growth	0.78*	1					
Hours Growth	0.78*	0.98*	1				
Solow	0.71*	0.12	0.15	1			
BK	0.11	-0.49*	-0.49*	0.73*	1		
Scand (4)	-0.23	-0.44*	-0.45*	0.12	0.36	1	
King (4)	0.20	-0.07	-0.05	0.41	0.25	0.71*	1
Galí (4)	-0.04	-0.43*	-0.40	0.42*	0.50*	0.19	0.21
BER	-0.00	-0.65*	-0.57*	0.50*	0.91*	-	-

.
Sample 1972-1993. * denotes correlation significantly different from zero on the five-percent level. The correlations with BER are compiled on aggregates for the manufacturing sector.

Table 6: Correlations - U.S. Private Economy

	Δy^A	Δx^A	Δh^A	S	BK	Sc(2)	K(2)R
Output Growth	1						
Input Growth	0.66*	1					
Hours Growth	0.77*	0.94*	1				
Solow	0.81*	0.09	0.29	1			
BK	0.16	-0.49*	-0.34*	0.59*	1		
Scand (2)	0.18	-0.29	-0.28	0.47*	0.46*	1	
King (2) R	0.17	-0.25	-0.23	0.42*	0.31	0.72*	1
Galí (3)	0.01	-0.30	-0.35*	0.24	0.43*	0.63*	0.40*
BER	0.20	-0.43*	-0.34*	0.59*	0.76*	-	-

.
Sample 1955-1989. * denotes correlation significantly different from zero on the five-percent level. The correlations with BER are compiled on aggregates for the manufacturing sector. The R marker denotes models with restrictions imposed the cointegrating vectors

Table 7: Robustness of Correlations - Swedish Private Economy

	Δy^A	Δh^A	S	BK	K4	K6	Sc4	Sc6	Sc4R	Sc6R	G4
K(4)	0.19	-0.03	0.40	0.24	1						
K(6)	0.32	0.19	0.34	0.04	0.91*	1					
Sc(4)	-0.24	-0.46*	0.12	0.37	0.71*	0.55*	1				
Sc(6)	0.02	-0.07	0.13	0.09	0.68*	0.73*	0.73*	1			
Sc(4)R	0.13	0.04	0.19	0.05	0.60*	0.42	0.62*	0.62*	1		
Sc(6)R	0.29	0.34	0.15	-0.16	0.03	0.15	-0.11	0.50*	0.41	1	
G(4)	-0.08	-0.36	0.34	0.42	0.19	-0.10	0.19	-0.08	0.34	-0.05	1
G(5)	-0.06	-0.30	0.29	0.35	0.02	-0.20	0.10	-0.10	0.22	0.02	0.93*

.
Sample 1973-1993. K denotes the King model , Sc is the Scandinavian model and G is the Galí model. Number of lags in paranthesis. The R marker denotes models with restrictions imposed on the cointegrating vectors. * denotes correlation significantly different from zero on the five-percent level.

Table 8: Robustness of Correlations - US Private Economy

	Δy^A	Δh^A	S	BK	K2	K4	K2R	K4R	Sc2	Sc4	G3
K(2)	0.39*	-0.06	0.60*	0.31	1						
K(4)	0.43*	0.12	0.50*	0.15	0.88*	1					
K(2)R	0.23	-0.21	0.50*	0.31	0.88*	0.64*	1				
K(4)R	0.19	-0.19	0.43*	0.22	0.82*	0.70*	0.92*	1			
Sc(2)	0.20	-0.28	0.50*	0.46*	0.68*	0.51*	0.73*	0.58*	1		
Sc(4)	0.26	-0.24	0.57*	0.46*	0.77*	0.58*	0.87*	0.76*	0.90*	1	
G(3)	0.04	-0.34*	0.29	0.42*	0.40*	0.31	0.39*	0.33	0.63*	0.55*	1
G(4)	0.05	-0.33	0.32	0.41*	0.42*	0.33	0.39*	0.35*	0.64*	0.55*	0.98*

.
Sample 1956-1989. K denotes the King model , Sc is the Scandinavian model and G is the Galí model. Number of lags in paranthesis. The R marker denotes models with restrictions imposed on the cointegrating vectors. * denotes correlation significantly different from zero on the five-percent level.

Table 9: The Share of the Three-Year FEVD of Aggregate Output Growth Due to Technology Shocks.

	Δy^A, Sweden	Δy^A, U. S.
King (4/2)	15.4	15.3
King (6/4)	14.7	14.4
King (2) R		16.0
King (4) R		23.4
Scand (4/2)	10.4	13.1
Scand (6/4)	7.4	12.3
Scand (4) R	10.9	
Scand (6) R	11.8	

The R marker denotes models with restrictions imposed the cointegrating vectors.

Table 10: Average Correlations Across Industries - Swedish Data

	BK	BER	G(1)
BK	1		
BER	0.93	1	
	(8/0)		
Galí (1)	0.27	0.16	1
	(4/0)	(0/0)	
Galí (4)	0.30	0.21	0.64
	(5/0)	(1/0)	(15/1)

.
Sample 1968-1993. Averages over 15 Industries (8 industries for correlations with BER). Number of significant correlations on the five-percent level / Number of significant correlations on the five-percent level with other sign than reported for the average correlation in parenthesis.

Table 11: Average Correlations Across Industries - U.S. Data

	BK	BER	G(1)
BK	1		
BER	0.83	1	
	(21/0)		
Galí (1)	0.55	0.50	1
	(27/0)	(17/0)	
Galí (4)	0.45	0.40	0.78
	(26/0)	(14/0)	(33/0)

.
Sample 1953-1989. Averages over 33 Industries (21 industries for correlations with BER). Number of significant correlations on the five-percent level / Number of significant correlations on the five-percent level with other sign than reported for the average correlation in parenthesis.

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