Measures of Technology and the Short-Run Responses to Technology Shocks

Is the RBC-Model Consistent with Swedish Manufacturing Data?*

Mikael Carlsson✉

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Abstract

This paper estimates technology growth using several variants of the Hall (1988, 1990) method on data for Swedish two-digit manufacturing industries. I first apply and evaluate two different approaches to control for varying factor utilization developed by Basu *et al.* (1998) and Burnside *et al.* (1995). Second, I propose a generalization of the latter specification. Finally, the cyclical behavior of the resulting technology measure is studied and the responses of hours and output to a technology shock are estimated using a variant of the standard VAR-approach. The main finding is that a positive technology shock has, on impact, a contractionary effect on hours and non-expansionary effect on output. This finding is inconsistent with the predictions of the standard real business cycle model.

Keywords: technological change, cyclical factor utilization, business fluctuations, panel data, manufacturing

JEL classification: C33, D24, E32, L60

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✉ Department of Economics, Uppsala University, Box 513, S-751 20 Uppsala, Sweden.
Phone +46 18 4711129, Fax +46 18 4711478, e-mail: Mikael.Carlsson@nek.uu.se

1 Introduction

The notion that improvements in technology cause a positive response of both output and inputs is at the core of real business cycle (RBC) theory, whereas models that emphasize price stickiness or sectoral heterogeneity imply that inputs, and under certain conditions even output, should fall initially. Thus, estimating these responses allows us to discriminate between the two classes of business cycle models.

Several recent studies have presented evidence that technology shocks have a contractionary short run effect on labor input while the results for output are somewhat mixed. Galí (1998) finds a contractionary effect on labor input in aggregate data for a majority of the G7 countries and Kiley (1998) finds it in U.S. manufacturing data, both using long-run restrictions in a structural VAR to identify technology shocks. The same result is also reported by Basu *et al.* (1998), who study aggregate U.S. data employing a production function approach. Since the results of these studies have strong implications for business cycle theory it is important to further investigate whether the results are similar for other countries. In this paper I analyze panel data for Swedish two-digit manufacturing industries using a production function approach. An advantage of studying data from a small open economy, such as the Swedish one, is that it opens up for using instruments that are not likely to be neither valid nor relevant for economies such as the U.S.

To study the responses of technology shocks we first need an adequate measure of technology. One alternative would be to use the technology measure proposed by Solow (1957). It is however unlikely that the assumptions underlying the Solow residual, i.e. (i) competitive markets, (ii) constant returns to scale and (iii) full factor utilization, are empirically satisfied.[1] The method used in this paper builds instead on the extension of Solow's (1957) methodology proposed by Hall (1988, 1990). While Hall's parametric approach allows for imperfect competition in the output market and non-constant returns to scale, the problem of varying factor utilization is left unresolved. A solution to the latter problem is then to extend Hall's original specification by including proxy variables for unobserved variation in factor utilization. In order to identify which variables to include as proxies, two different methods have been used in the literature. For expositional ease, I will refer to them as the indirect and the direct approach. The indirect approach identifies proxy variables indirectly by using the restrictions that follow

[1] It should be noted that Solow (1957) recognized that varying factor utilization causes the observed use of inputs to differ from the service flow stemming from these inputs and tried, accordingly, to control for varying capital utilization by multiplying the capital series by the fraction of unemployed. The utilization problem is however generally ignored when the Solow residual is calculated.

from agents' *optimal* behavior. This requires an explicit specification of the costs of increased utilization, i.e. postulating the problem facing the agents, so that one can use the implied first order conditions to derive a relationship between factor utilization and observable variables. This approach is taken by Basu *et al.* (1998) who use the first order conditions from a dynamic cost minimization problem to derive a relationship between factor utilization and hours per employee, the relative value of materials and capital and the investment to capital ratio. The direct approach relies instead on direct assumptions about the *technology* to legitimize the use of observable input data to control for varying utilization. For example, Burnside *et al.* (1995) assume that the flow of capital services is proportional to electricity consumption in order to control for varying capital utilization. [2]

In this paper, I first apply and evaluate both the indirect specification of Basu *et al.* (1998) and the direct specification of Burnside *et al.* (1995) to correct for unobserved variation in factor utilization on data for eight Swedish manufacturing industries. As it turns out, the indirect specification does not seem able to control for neither labor nor capital utilization, whereas the direct specification appears to be robust to the latter phenomenon. Second, I propose a generalization of the direct specification by allowing for a fixed baseload of electricity and including the rate of industrial accidents per hour worked as a proxy for unobserved variation in labor utilization. Allowing for a fixed baseload of electricity provides a slight improvement. However, including industrial accidents do not give rise to any discernible advantages relative to the original direct specification. Overall, the estimation results of the specifications above imply that the Swedish manufacturing sector is characterized by mildly increasing returns to scale, substantial variation in factor utilization and a significant heterogeneity across industries.

Finally, I turn to the properties of the resulting technology measure. In comparison to the Solow residual I find that the variance of the technology measure is only about 40 percent of the variance in the Solow residual. Moreover, when studying unconditional correlations a striking result is that I find a *negative* correlation between the growth rate of the technology measure and the growth rate of hours. Another interesting result is that the technology measure is *uncorrelated* with output growth. Thus, the standard result of procyclical productivity seems to be the result of poor measurement of technology growth.

The correlations discussed above are unconditional on what type of shocks that are causing them. In order to separate the responses of hours and output to technology shocks from those associated with other shocks I use a variant of the standard VAR-approach. The empirical

impulse response functions of hours and output to a technology shock imply that the growth rate of both hours and output fall below normal on impact in response to a positive technology shock, but the latter effect is not statistically significant. The main conclusion to be drawn from the empirical impulse response functions is that they are not consistent with the predictions of the standard RBC-model. However, more research is needed in order to discriminate between the competing business cycle models that are consistent with the observed behavior. Overall, the findings in this paper add to the international evidence that technology shocks have a contractionary short-run effect on the economy.

This paper is organized as follows. Section 2 outlines the specifications used to estimate technology growth. Section 3 discusses the data, instruments and other estimation issues. Section 4 discusses the choice of estimator and the results. Section 5 examines the properties of the estimated technology measure and presents the estimated responses of hours and output to a technology shock. Section 6 concludes.

2 Specifications to estimate technology growth

The following firm-level production function is assumed:

$$(1) \qquad Y_t = F(S_t, \widetilde{L}_t, M_t, A_t) = A_t S_t^{\alpha_1} \widetilde{L}_t^{\alpha_2} M_t^{\alpha_3},$$

where Y denotes gross output, A is an index measuring technology, S is effective capital input, $\widetilde{L}$ is the flow of labor services and M is intermediate material less electricity. Let effective capital input be determined by the following CES-production function, combining the flow of capital services, $\widetilde{K}$, and the consumption of electricity, V:

$$(2) \qquad S_t = \left[\varphi \widetilde{K}_t^{\rho} + (1-\varphi)(\beta_1 V_t - \beta_2 K_t)^{\rho}\right]^{\frac{1}{\rho}},$$

where K is the capital stock. Note that the formulation of the sub-production function for effective capital input allows for a fixed baseload of electricity, measured as a fraction, β_2, of the capital stock. This reflects heating, light etc. The term $(\beta_1 V_t - \beta_2 K_t)$ is then interpreted as production electricity, which, of course, would amount to the total consumption of electricity if

[2] Examples of other papers taking one of the two approaches, although not necessarily within the Hall (1988, 1990) framework, are Costello (1993), Basu (1996), Hokkanen (1998) and Wilson (2000) who follows the direct approach and Burnside *et al.* (1993) and Burnside and Eichenbaum (1996) who takes the indirect approach.

β_2 was equal to zero. Finally, let the flow of labor services be defined as the product of effort per hour, E, times total hours worked, L, and define the flow of capital services analogously as the product of capital utilization, Z, times the capital stock, i.e.:

(3) $$\widetilde{L}_t = E_t L_t,$$

(4) $$\widetilde{K}_t = Z_t K_t.$$

The motive for this two-level structure of the production function is that the elasticity of substitution between the service flow of capital and production electricity may be very low in the short-run. To allow for this possibility, the sub-production function for effective capital is specified as a CES-technology.

By differentiating the log of equation (1) with respect to time and invoking cost minimization we arrive at the following gross output version of the standard Hall (1988, 1990) specification, generalized to allow for variable factor utilization:

(5) $$dy_t = \eta\left(c_S ds_t + c_L d\widetilde{l}_t + c_M dm_t\right) + da_t,$$

where η denotes the overall returns to scale and c_j is the cost share of factor J in total costs defined as $P_J J / \sum_J P_J J$ for $J = S, L, M$, where $P_S S$ is the sum of capital and electricity costs.[3] Although the three specifications considered in the empirical work differ in how the unobservable growth rates of capital and labor utilization are handled, they all share the basic form of equation (5).[4] Thus, the specifications derived below yield measures of technology growth, i.e. da, that are robust to imperfect competition in the output market, increasing returns to scale and, under various conditions, varying factor utilization. Moreover, we will also obtain a robust estimate of the returns to scale under the same conditions. The first specification derived below employs the indirect approach (first order conditions) while the second and third specifications considered take the direct approach (technological assumptions) to correct for unobserved variation in utilization.

[3] See Carlsson (2000) for the details of the derivations in this paper.

[4] Thus, the first and second specification of Burnside *et al.* (1995) will not be considered in the empirical work. The reason is that multicollinearity problems (especially apparent when these specification are augmented to include intermediate materials) does not leave much hope of estimating these specifications with any precision. The specification referred to as the Burnside *et al.* (1995) specification is hence their third specification.

2.1 The indirect specification

If we disregard the fixed baseload in electricity, set β_1 equal to unity and let ρ go to zero in the sub-production function for effective capital input (2), we arrive at the following limiting form of the overall production function:

$$(6) \qquad Y_t = A_t \widetilde{K}_t^{\varphi\alpha_1} V_t^{(1-\varphi)\alpha_1} \widetilde{L}_t^{\alpha_2} M_t^{\alpha_3},$$

which is just a restatement of the Cobb Douglas production function assumed by Basu and Kimball (1997) when deriving the indirect specification used by Basu *et al.* (1998). Using equations (3) and (4), equation (5) can be rewritten as:

$$(7) \qquad dy_t = \eta dx_t + \eta(c_K dz_t + c_L de_t) + da_t,$$

where dx_t is defined as $c_K dk_t + c_V dv_t + c_L dl_t + c_M dm_t$. However, utilization growth, $(c_K dz_t + c_L de_t)$, is generally not observable. Thus, in order to obtain an empirically operational specification of equation (7) we need to find an expression for utilization growth in terms of observable variables.

An intuitive idea, that is useful when trying to control for unobservable utilization growth, is that a cost-minimizing firm should be indifferent between different margins of adjustment in optimum (given that the costs associated with adjustment are well-behaved). Basu and Kimball (1997) formalize this idea and derive a relationship between observable variables and utilization growth from the first order conditions of a dynamic cost-minimization problem. Inserting this expression into (7) we get the specification used in Basu and Kimball (1997) and Basu *et al.* (1998):

$$(8) \qquad dy_t = \eta dx_t + \gamma_1[c_L dh_t] + \gamma_2[c_K(dp_{M,t} + dm_t - dp_{I,t} - dk_t)] + \gamma_3[c_K(di_t - dk_t)] + da_t,$$

where dh is the growth rate of hours per worker, dp_M is the growth rate in the price of materials, dp_I is the growth rate in the price of investment goods and di is the growth rate of investments. Due to the assumed form of labor compensation hours per worker will move together with both effort and capital utilization, where the latter relation stems from the assumption of a shift premium. Thus, hours per worker will be a proxy for both labor and capital utilization. Second, increased capital utilization is assumed to increase the rate of capital depreciation. This depreciation cost induces, in itself, two effects associated with increased capital utilization that are

reflected by the third and the fourth term of equation (8). The third term corresponds to the benefit of increased capital utilization (i.e. the expected sign of γ_2 is positive) and the fourth term reflects the cost of higher capital utilization in terms of the increased depreciation it implies (implying that the expected sign of γ_3 is negative). Expression (8) is the "indirect specification", which is the first specification considered in this paper.

2.2 Direct Specifications

The first step of the direct approach is to impose some kind of restriction on the production function. The route taken by Burnside *et al.* (1995) to control for variable capital utilization follows Griliches and Jorgensen (1967), Costello (1993) and others by using electricity consumption as a proxy for the flow of capital services. This approach can be legitimized by assuming that equation (2) takes the form of a Leontief production function, i.e. $\rho \rightarrow -\infty$, implying that the elasticity of substitution between capital and (production) electricity is to equal zero. If we also assume that there is no fixed baseload of electricity, i.e. β_2 equals zero, we arrive at the sub-production function for effective capital in Burnside *et al.* (1995):

(9) $$S_t = \min\left[\tilde{K}_t, \beta_1 V_t\right].$$

Moreover, if it is assumed that labor utilization is constant over time we arrive at the Burnside *et al.'s* (1995) specification:

(10) $$dy_t = \eta d\hat{x}_t + da_t,$$

where $d\hat{x}_t$ is defined as $c_S dv_t + c_L dl_t + c_M dm_t$. This is the "direct specification", which is the second specification considered in the empirical work below.

As a first extension of the Burnside *et al.* (1995) specification, I allow for a fixed baseload of electricity originating from e.g. heating up buildings, light etc. When studying high frequency data on electricity demand for two Swedish manufacturing plants, Anxo and Sterner (1994) found a non-negligible baseload of electricity consumption.[5] Although one should not draw any general conclusions from a sample of two plants, these findings do indicate that a

[5] The plants studied are two Swedish manufacturing plants with non-continuos production processes (producing cars and fridges). The baseload in the study is measured, when lacking an exact measure, as the minimum demand during weekend nights (when the production process is shut down). The baseload is used e.g. for ventilation and lighting but also for more energy demanding round the clock tasks such as supporting pressurized air systems and paint stirring to avoid clogging.

specification that allows for a fixed baseload of electricity is desirable. Allowing for this yields the following limiting form (as $\rho \rightarrow -\infty$) of the sub-production function for effective capital input:[6]

$$(11) \qquad S_t = \min\left[\tilde{K}_t, \beta_1 V_t - \beta_2 K_t\right].$$

As a second extension of the Burnside *et al.* (1995) approach, an indicator variable is introduced to control for variation in labor effort. Following the suggestion of Shea (1990) and Hokkanen (1998), I use the frequency of industrial injuries per hour worked as a proxy for unobservable labor effort. Formally, the following relationship between labor effort and the injury-rate, *INJ*, is assumed:

$$(12) \qquad E_t = \xi INJ_t^{\lambda}.$$

Labor utilization may vary due to variation in the fraction of reported hours worked that employees actually work and the number of tasks performed per actual working hour, and the injury-rate should proxy for both these dimensions of labor utilization. First, accidents in the workplace should only occur when workers are actually working. Hence, if workers are given longer breaks or if standby times lengthen during a recession the injury-rate should fall. Second, the injury-rate should fall if the workers perform fewer tasks per hour that they actually work.[7] Using equations (11) and (12), expression (5) can be rewritten as:

$$(13) \qquad dy_t = \eta d\tilde{x}_t + \eta\phi\left[c_S(dv_t - dk_t)\right] + \eta\lambda\left[c_L dinj_t\right] + da_t,$$

where $d\tilde{x}_t$ is defined as $c_S dk_t + c_L dl_t + c_M dm_t$ and ϕ is the electricity elasticity of effective capital.[8] This is the "extended direct specification", which is the third specification considered in the empirical work.

Note that both of the direct specifications rely on assumptions about the technology to legitimize the use of observable variables to control for unobserved factor utilization. Thus, in contrast to the indirect specification they do not require any assumptions about the structure of

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[6] Capital for which electricity demand is independent of the utilization rate is not considered explicitly. However, under the assumption of proportionality between the stocks and the utilization rates for such capital and capital for which electricity demand is dependent of the utilization rate, allowing for both types of capital does not change the form of the extended direct specification, i.e. expression (13).

[7] This notion is supported by the ergonomic research of Ayoub *et al.* (1983) and Mital and Manivasagan (1983), who finds that an increased lifting pace increases the likelihood of injury.

[8] Note that the electricity elasticity of effective capital is modeled as a time invariant parameter. See Carlsson (2000) for a discussion of this approximation.

the costs associated with increased factor utilization. Moreover, the indirect specification builds on an assumption of a unit elasticity of substitution between capital services and electricity, whereas the two direct specifications rely on a zero elasticity of substitution. Although the Cobb Douglas assumption of Basu and Kimball (1997) could be justified as a first order approximation to any differentiable production function, it would represent a rather crude approximation if the true elasticity of substitution between capital services and electricity is close to zero.

3 Data, implementation and choice of instruments

The data used in this paper are collected from official sources and consists of annual data for eight Swedish two-digit manufacturing industries (SNI31-SNI38) covering the period 1967 to 1993 (see Carlsson 2000 for a detailed description of the data set).[9]

Using the injury-rate as a proxy for labor utilization gives rise to some empirical considerations since there might be other variables affecting the injury-rate beside the utilization of labor. One approach to control for this potential problem would be, as in Hokkanen (1998) and Shea (1990), to augment the proxy relationship (12) with potentially relevant variables until only a random error is expected to remain. Since IV-techniques will be used in the estimation the problem would then be solved if the remaining error is uncorrelated with the instruments. There are however problems with this approach. First, there is no solid theoretical framework within the economic literature to guide the choices of functional form and which variables to include. Thus, it is not obvious that this approach reduces the risk of misspecification. Second, all but one of the variables included by Hokkanen (1998) are strongly procyclical, hence estimation will be difficult due to multicollinearity.[10] Given these problems, I choose not to augment the proxy relationship (12). If there is a severe misspecification problem associated with this specification a Sargan-test should reject the joint null hypothesis of a correctly specified model and valid

[9] Two related studies estimating production functions on Swedish manufacturing data are Lindström (2000) and Hokkanen (1998). Lindström uses the CoSta database to study the question of external economies at the firm-level by including different measures of aggregate activity in the production function. The CoSta database lacks however information on electricity consumption, the injury-rate and total usage of intermediate inputs, thus rendering it impossible to implement the specifications in this paper. Hokkanen examine different explanations for procyclical productivity on two-digit industry data, e.g. the relevance of the labor hoarding hypothesis is investigated by including the injury-rate variable in the production function. Both Lindström and Hokkanen use value-added data. I use, however, gross output data because if the returns to scale is different from unity and/or if output markets are imperfectly competitive the use of value added data may give rise to spurious results. This is due to that under these circumstances the productive contribution of intermediary inputs is not accounted for correctly when compiling real value-added (see e.g. Basu and Fernald (1995) for a discussion). However, the use of aggregate data makes the parameter estimates presented below subject to the aggregation bias noted by Basu and Fernald (1997). Unfortunately, nothing can be said *a priori* about the sign and the size of this bias.

[10] The variables included by Hokkanen (1998) are overtime hours, the (machinery) investment to capital ratio, hiring and the share of non-production workers. All variables, but the share of non-production workers, are strongly procyclical.

instruments. However, this joint null hypothesis can not be rejected on the five-percent level for any industry, for any specification using the instrument set chosen below.

To implement the specifications empirically, the cost shares are approximated by their respective empirical time averages and first log differences are substituted for the continuous growth rates.[11] Moreover, the first difference of the log of the technology index is modeled as: $\Delta a_t = \alpha + \theta_t$. Where α is a deterministic growth rate in technology and θ is a random shock to α.

An appropriate estimator of the specifications above should be based on an IV-technique. The need of instruments arises because the firm considers the current state of technology when making its input choices. To solve this endogeniety problem we need instruments that are exogenous relative to variations in the growth rate of technology. Moreover, for the instruments to be relevant they must be correlated with economic activity.

If technology shocks are persistent, but not completely permanent, as is often assumed in the RBC-literature, low order lags of explanatory variables are not valid instruments, and high order lags of explanatory variables are not likely to be relevant instruments. Hence, the search for valid and relevant instruments should be conducted elsewhere and natural candidates are factors that shift aggregate demand. A standard set of demand instruments in the literature is the Hall (1988, 1990) and Ramey (1989) set, i.e. current and lagged values of the annual growth rate of real military spending and the real oil price as well as a dummy variable for the political party of the president. Contrary to the U.S., Sweden has not been involved in any military conflicts during the sample period (1967 - 1993) so the growth rate of real military spending is not likely to be a relevant instrument, and it is therefore not included in the instrument set. Beside the real oil price and a political dummy, I also consider the instruments proposed by Hokkanen (1998): the growth rate of foreign demand and the growth rate of the nominal exchange rate. Foreign demand is constructed as an export-share weighted index of industrial production indices for Sweden's fourteen main trading partners. The nominal exchange rate is constructed analogously as a weighted index of nominal exchange rates.

For validity of the proposed instruments the following assumptions have to be made: First, I assume, in line with Hall (1988, 1990), that neither changes in demand nor changes in the real oil price shift the production function in the short run. This should be reasonable because changes in factor prices or demand do not imply that new technologies become available.[12]

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[11] The use of the time average of the cost share is implied by the assumption of an overall Cobb Douglas production function and is also consistent with the data since the cost shares have remained quite stable over the sample period.
[12] Although, the incentives for research and development should change, so technology growth might be affected in a longer perspective.

Second, like Hokkanen (1998) I assume that Sweden can be treated as a small open economy. The small open economy assumption implies that foreign demand and the real oil price can be regarded as exogenous. Third, it is assumed that variations in the growth rate of technology do not affect the nominal exchange rate in the short run. Since Sweden, from before the start of the sample period until November 1992, was maintaining a fixed exchange rate regime with a small number of discrete devaluations, this is a reasonable assumption. Finally, to ensure validity of the political dummy variable it is assumed that neither left- nor right-wing governments pursued policies that had a systematic short-run effects on the growth rate of technology.

The proposed set of instruments now includes four variables and low ordered lags of these variables should also be valid instruments. However, given the limited sample it seems reasonable to use only a small number of instruments. Moreover, the finite sample properties of IV-estimators are seriously affected when low-relevance instruments are used (see e.g. Nelson and Startz 1990). The natural question that arises then is how to decide which variables, and how many lags, to include in the instrument set. Since pre-testing for relevance might actually worsen the small sample properties of IV-estimators, as noted by Hall *et al.* (1996), I will let *a priori* reasoning guide these choices and use a measure of relevance as an *ex post* diagnostic tool.

The growth rate of the nominal exchange rate should, under a fixed exchange rate regime, capture monetary policy shocks. Hence, this instrument is the fixed exchange rate equivalent of the monetary shock measure proposed by Christiano *et al.* (1994).[13] In practice this variable is close to a dummy variable for devaluations. Since the effects of monetary policy, i.e. devaluations in the Swedish case, tend to be lagged, I will include the first and the second lag of the growth rate of the nominal exchange rate index in the instrument set. The growth rate of the foreign demand index should be relevant for an open economy, such as the Swedish, and in particular for the manufacturing sector where most industries export a large fraction of their output. Again we would expect lagged effects as fluctuations in exports have indirect effects on investments, costs etc. Hence, the current and the once lagged value of the growth rate of foreign demand are included in the instrument set. When estimating fiscal policy reaction functions for government expenditures and revenues on Swedish data for the fiscal years 1969/70 - 1991/92, Ohlsson and Vredin (1996) found that although right-wing governments have both lower expenditures and revenues (controlling for economic activity), the latter effect dominates. To capture this partisan effect on the fiscal surplus a political dummy variable, taking on the value one for years with right-wing governments and zero otherwise, is included in the instrument set.

[13] The basic idea behind Christiano *et al.*'s (1996) measure is to use the residuals from an estimated reaction function for the monetary authority as a measure of monetary policy shocks.

Real oil price shocks tend to have an impact on the economic activity, but to limit the number of instruments only the contemporaneous growth rate of the real oil price is included.

4 Estimation method and results

In this section, I first estimate a specification that ignores varying factor utilization. This will serve as a reference point to the specifications that are supposed to take account of this phenomenon. Second, the indirect specification and the two direct specifications are estimated and evaluated. Finally, the relevance of the instrument set is investigated. All estimates are obtained using standard linear 3SLS methods. For each specification cross-industry restrictions are tested and the restricted estimates are also presented. However, the validity of cross-industry parameter restrictions, allowing for fixed industry effects, are rejected in all of the systems estimated below, as can be seen in tables 1 and 2. An estimation approach that employs cross industry restrictions is thus highly likely to introduce non-technology-related variation in the estimated technology growth series (i.e. the disturbance terms). I still present the restricted estimates for comparability with other studies.

The results of estimating the following *non-corrected specification*:

$$\Delta y_{i,t} = \alpha_i + \eta_i \left[\bar{c}_{K,i} \Delta k_{i,t} + \bar{c}_{V,i} \Delta v_{i,t} + \bar{c}_{L,i} \Delta l_{i,t} + \bar{c}_{M,i} \Delta m_{i,t} \right] + \theta_{i,t}, \tag{14}$$

are presented in table 1. The point estimates of the returns to scale are all above one and all but one industry, i.e. the Chemicals/Petroleum industry (with a point estimate of 1.086), displays statistically significant, increasing returns to scale with estimates ranging from 1.248 to 1.450.

The estimation results for the *indirect specification*, presented in table 1, are quite disappointing.[14] There is at least one parameter estimated with the "wrong" sign in each industry. Since the results do not support the notion that the cost of depreciation is an important determinant for the level of capital utilization, the two regressors implied by this cost are dropped from the specification. Note that, when omitting the depreciation cost, the Basu and Kimball (1997) model implies that both capital and labor utilization should move together with hours per employee. However, re-estimating the system defined by this reduced indirect specification still

[14] Note that the γ coefficients in the indirect specification are actually the product of η and underlying structural parameters from the cost minimization problem postulated by Basu and Kimball (1997). Restricting the γ coefficients (or some of them) to be equal over industries while allowing η to vary over industries, as done by Basu *et al.* (1998), thus imply the implausible restriction that the underlying structural parameters differ in such a way over industries that they balance the differences in η over industries such that $\gamma_{j,i} = \gamma_j$, where subscript i index industries. Moreover, following Basu *et al.* (1998) do not solve the problem with the indirect approach since the resulting γ

yields statistically insignificant and even negative point estimates of γ_1 as can be seen in table 1. Moreover, the estimates of the returns to scale are very similar to those obtained by the non-corrected specification. When compiling manufacturing-level correlations I find that the growth rate of hours per employee is acyclical, whereas the growth rate of total hours worked is significantly procyclical at the one-percent level (0.67). It thus seems that, in Swedish manufacturing, the cyclical adjustment in the number of hours worked, over the time span of a year, is handled on the extensive number of employees margin rather than on the intensive number of hours per employee margin. Overall, the indirect approach of Basu *et al.* (1998) does not seem to provide any improvements relative to the non-corrected specification and is therefore not considered in the rest of the empirical work.

The estimation results of the *direct specification* are presented in table 2. The point estimates of the returns to scale are all still above one, although comparing with the results of the non-corrected specification we see that the point estimates of the returns to scale are lower in all industries. This is expected since ignoring utilization implies that the cyclical variation in production factors is underestimated if utilization is procyclical. Only five industries now display statistically significant increasing returns to scale, i.e. the Food, the Textile, the Wood, the Primary Metals and the Fabricated Metals industries. Thus, the results of this specification indicate slightly increasing returns to scale in the manufacturing sector.

Table 2 shows the results of the estimation of the *extended direct specification*. Although there is a positive correlation between the growth rate of the injury-rate and output growth in all industries, the point estimates of the structural injury-rate parameter λ are all statistically insignificant and even negative for several industries.[15, 16] Since the injury-rate variable has little explanatory power and a negative sign of the structural parameter for the injury-rate variable is inconsistent with the notion that the injury-rate is a proxy for labor utilization, the injury-rate variable is dropped from the specification.[17]

What now separates the direct and the extended direct specification, after having dropped the injury-rate variable, is that the latter allows for a fixed baseload of electricity in the sub-production function for effective capital input. Since the lack of a fixed baseload of electricity

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estimates are not significant on any reasonable level of significance and γ_1 is still estimated with the wrong sign (-0.614, with a standard error of 0.375).

[15] A potential estimation problem associated with this specification is the changes in the legislation and the administration of the work-injury insurance that took place in 1992 and 1993. However, dummies included to control for this problem do not turn out significant. For a brief survey of the changes and for a more elaborate discussion of the dummy structure see Carlsson (2000).

[16] Dropping the growth rate of the electricity to capital ratio does not alter this result.

implies that the electricity elasticity of effective capital in equation (13), ϕ, equals its theoretical lower bound, i.e. unity, it follows that the extended direct approach reduces to the direct approach in this case. However, restricting ϕ to unity when the true ϕ is larger than one should bias the estimates of the returns to scale downward since capital utilization, captured by the $\phi(\Delta v_t - \Delta k_t)$ term, is expected to be procyclical. Table 2 presents the results of estimating this reduced extended direct specification. As predicted above, we find the largest drops in the estimates of the returns to scale, relative to the direct approach, in those industries with the largest estimates of ϕ. However, for three industries (i.e. the Food, the Paper/Publishing and the Fabricated Metals industries) the point estimates of ϕ are below one, although not significantly so, and only the estimate of ϕ for the Primary Metals industry is significantly larger than one. Without the injury-rate variable, both the non-corrected specification (14) and, as discussed above, the direct specification are nested as special cases of the extended direct specification. That is, if ϕ equals unity the extended direct approach reduces to the direct approach and if ϕ equals the ratio of the share of energy costs to the share of energy and capital costs, the extended direct specification reduces to the non-corrected specification. We can thus use the estimates of ϕ in order to try to discriminate between these three specifications. In table 3, we see that although the estimate of ϕ is larger than unity in five industries the null hypothesis of $\phi = \bar{c}_V / \bar{c}_S$, implicit in the non-corrected specification, is only rejected for three industries, i.e. the Wood, the Chemicals/Petroleum and the Primary Metals industries. Moreover, the null hypothesis of ϕ being equal to unity is only rejected in one case, i.e. for the Primary Metals industry, and then in favor of the extended direct approach. Even though the data in most cases does not allow us to discriminate between the different specifications, the direct specification generally seems to fit the data better than the non-corrected specification. The extension of the direct specification does, however, only seem to provide a slight improvement relative to the original specification.

Although allowing for a fixed baseload of electricity only provides a slight improvement, the preferred specification should allow for this possibility. Thus, in order to minimize the amount of noise in the technology series we should also control for this source. However, since the assumptions underlying the direct approach imply that ϕ should be larger than or equal to unity, the system is re-estimated with ϕ restricted to unity for those industries exhibiting a point estimate of ϕ below unity (i.e. the Food, Paper/Publishing and the Fabricated Metals industries).

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[17] Hokkanen (1998) finds, however, a statistically significant positive relationship between the injury-rate variable and output in a production function regression on Swedish two-digit manufacturing data. One reason for this might be that he uses value added as output measure.

Since this restriction is intrinsic in the direct specification, the restriction is implement by substituting the direct specification for the extended direct specification in those industries where the point estimate of ϕ is below unity. The estimation results of this *preferred specification* are presented in table 4. When comparing these results with the results obtained when estimating the direct specification we see that the differences are generally small. The main differences between the point estimates of the returns to scale are found in the Minerals and the Primary Metals industry, where we also have the largest estimates of ϕ. It should be noted though that the only qualitative difference regarding the returns to scale estimates is that the estimate for the Primary Metals industry is no longer significantly larger than one. Thus, the conclusion of mildly increasing returns to scale in the manufacturing sector is not reversed by the results of this specification.

Table 4 also presents estimates of the average growth rate of technology, i.e. the α term, expressed in percent per year. Most industries have an estimate of the average annual growth rate of technology in the range of 0.614 to 0.914 percent per year, although the Food and the Textile industries stand out with estimates of 0.004 and 2.802 percent per year respectively. Finally, table 4 presents a comparison between the estimates of the returns to scale from this specification with the estimates of the returns to scale from the non-corrected specification. We can see that the difference is negative for all industries, as expected, and significantly so for the Paper/Publishing and the Primary Metals industry on the one-percent level.

It is interesting to compare the measure of capital utilization implied by the preferred specification, i.e. $\Delta z_t = \phi(\Delta v_t - \Delta k_t)$, to other utilization measures.[18] Two such measures are the growth rate of the capital operating time measure (based on data on shift work) presented by Anxo and Sterner (1995) and the growth rate of the qualitative resource utilization index presented by the National Institute of Economic Research (based on survey data). The correlations between these measures and output growth are presented in table 5. All utilization measures, including the one implied by the preferred specification are significantly procyclical. Moreover, all cross correlations between the different utilization measures are significant at the one-percent level – thus supporting the notion that this specification does control for variation in capital utilization (the corresponding results for the direct specification are very similar, as can be seen in table 5).

[18] This expression follows from (4) and (11). To obtain an aggregate measure of capital utilization, the industry-level measures Δz_i, where Δz_i is calculated using the estimate or the restriction of ϕ from the preferred specification, are weighted together using gross output weights.

The returns to scale in Swedish manufacturing are found to be slightly higher than the results found on gross output data for U.S. manufacturing industries. Burnside (1996) reports in his overview that the average U.S. manufacturing industry exhibits constant returns to scale, although he also finds a significant heterogeneity across U.S. manufacturing industries. In a study on aggregate Swedish manufacturing gross output data, Hansson (1991) estimates the overall returns to scale for the manufacturing sector to 1.29 and 1.36 using two different versions of a flexible cost function approach. [19] These estimates are closer to the weighted average returns to scale for the manufacturing sector implied by the estimates of the non-corrected specification (1.25), than to the corresponding average for the preferred specification (1.15). One reason for this might be that Hansson (1991) does not control for the measurement errors due to using the capital stock as measure of the service flow of capital, which should bias his estimates upwards if capital utilization is procyclical.

Finally, I regress each regressor from the specifications above on the chosen instrument set in order to examine the relevance of the chosen instruments. The R^2's from these regressions are presented in table 6. The results show that there is some heterogeneity in the relevance of the instrument set over industries. This is to be expected because of the inherent heterogeneity over industries, e.g. in the relative importance of demand from foreign markets as a determinant of output. Overall, the relevance of the instrument set does not give rise to any large concerns, and for the regressors pertaining to the direct and the preferred specification the explanatory power of the instrument set is considerable.

5 Is the RBC-model consistent with the properties of technology growth?

In this section, I examine the properties of the estimated measure of technological progress. The technology measure analyzed in this section is obtained by adding the estimates of the constant term and the residuals from the preferred specification. [20] The resulting series is henceforth denoted the technology residual. Since we are interested in assessing the empirical relevance of different business cycle models the resulting eight technology series are aggregated into one series

[19] Both versions control for imperfect competition and non-constant returns to scale. The version yielding the higher estimate also controls for quasi-fix capital. For an overview and a comparison between second order approaches, including the one taken by Hansson (1991), and the approach taken in this paper see Basu and Fernald (forthcoming).

[20] The choice of which estimates to compile the technology growth series from is of little practical importance for all industries but the Primary Metals industry. However, the estimate of the electricity elasticity of effective capital, i.e. ϕ, for the Primary Metals industry is significantly larger than one, thus making the estimates from the preferred specification a natural choice when compiling the technology residual in this case.

for the entire manufacturing sector, using the share of respective industry's gross output in total manufacturing gross output as weights.[21]

Despite its limitations as a measure of technology, the Solow residual is often used as such. Thus, it is interesting to compare the properties of the Solow residual to the technology residual that comes out of the estimates in this paper. The gross output Solow residual for the aggregate manufacturing industry, Θ_M, is calculated as:

$$\text{(15)} \qquad \Theta_{M,t} = \sum_{i=SNI31}^{SNI38} \omega_{i,t} \left[\Delta y_{i,t} - s_{L,i,t} \Delta l_{i,t} - s_{M,i,t} \Delta m_{i,t} - s_{V,i,t} \Delta v_{i,t} - (1 - s_{L,i,t} - s_{M,i,t} - s_{V,i,t}) \Delta k_{i,t} \right],$$

where ω_i denotes the i:th industry's weight in manufacturing gross output and s_J is the share of cost for factor J in gross revenue.[22] An alternative approach would be to calculate the aggregate gross output Solow residual directly from the aggregates, but this yields an almost identical series. Table 7 presents descriptive statistics of the technology residual and the Solow residual. The mean of the technology residual is slightly lower than the mean of the Solow residual. However, the variance of the Solow residual is almost two and a half times larger than the variance of the technology residual, implying that the standard deviation of the technology residual is less than two thirds of the standard deviation of the Solow residual. The relative volatility is also visible in figure 1, which presents plots of the two series.

Table 7 and 8 presents descriptive statistics for the growth rates of output, input and hours and correlation between these series and the Solow residual and the technology residual respectively. The measure of input growth (including the service flow from capital utilization) is defined as implied by the preferred specification, i.e.:

$$\text{(16)} \qquad \Delta x^I_{M,t} = \sum_{i=SNI31}^{SNI38} \omega_{i,t} \left[\bar{c}_{S,i} (\hat{\phi}_i \Delta v_{i,t} + (1 - \hat{\phi}_i) \Delta k_{i,t}) + \bar{c}_{L,i} \Delta l_{i,t} + \bar{c}_{M,i} \Delta m_{i,t} \right],$$

where ω_i denotes the i:th industry's weight in manufacturing gross output and $\hat{\phi}$ denotes the estimate of ϕ for the i:th industry obtained, or restricted to, when estimating the preferred specification. The contemporaneous correlations presented in table 8 are difficult to reconcile

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[21] Using the aggregation method employed by Basu *et al.* (1998) yields very similar results to those presented below. This aggregation method differs in that it defines technical change as the change in output holding not only aggregate inputs fix (as above) but also the distribution of production factors across sectors.

[22] Note that when compiling the industry-level Solow residual the shares in gross revenue are used as weights instead of the shares in total cost times the returns to scale. However, under the assumptions of constant returns to scale and competitive markets (assumed by Solow 1957) these weights are equal.

with the predictions of the standard RBC-model. First, the technology residual is uncorrelated with output growth. Second, the correlations between the technology residual and the growth rates of input and hours are negative. However, only the latter result is statistically significant. To illustrate these correlations the growth rates of output, input and hours are plotted together with the technology residual series in figure 2.

As seen in table 8, there is a statistically significant positive contemporaneous correlation between the technology residual and the Solow residual. The technology residual and the Solow residual are both measures of technology growth and should therefore be positively correlated. However, when technology is measured by the Solow residual the contemporaneous correlations with output, input and hours are positive. With the results from the previous section in mind, the Solow residual should be contemporaneously positively correlated with output growth and other procyclical variables. That is, if the underlying assumptions are not valid, the Solow residual becomes contaminated with cyclical noise (see Hall 1990 for a discussion).

The results in this section are qualitatively similar to the ones found by Basu *et al.* (1998) for U.S. manufacturing data.[23] Moreover, for Swedish manufacturing data Hansson (1991) also reports low correlations between his two technology growth measures and output growth (0.27 and -0.10). The result presented above thus adds more evidence in favor of the notion that the procyclicality of productivity is a figment of poor modeling of technological change, as suggested by Hansson (1991) and others.

When examining figure 2 it is natural to investigate whether the correlation results are driven by the deep recession period in the end of the sample. To this end, I re-estimated the preferred specification using the sample 1968 to 1990, compiled a new technology growth series and then re-calculated the correlations presented above. However, dropping the last three years does not change the correlation results presented in table 8 qualitatively.[24]

The correlations calculated in this section are crude indicators of the dynamic behavior in the sense that they are unconditional on the type of shocks that have caused the outcomes of output, input and hours growth. It might very well be the case that the dynamic responses to other past and contemporaneous shocks, beside adjustments to technology shocks, lead us to the wrong conclusions. To isolate the dynamic effects of a technology shock a variant of the standard

[23] It should be noted that Basu *et al.* (1998) transform their technology residual to a value added series and makes the comparison with the value added Solow residual. Consequently, Basu *et al.* (1998) define their input measure as a factor share (in value added) weighted index of the growth rates of primary inputs of capital and labor. The correlation between this input measure, aggregated with gross output weights, and the aggregate technology residual is significantly negative on the five-percent level (-0.42), as found by Basu *et al.* (1998) on U.S. data.

VAR-approach is used. The structural dynamic system focused on is:

$$(17) \qquad \Gamma_0 \begin{bmatrix} \Delta\hat{a}_t \\ \Delta y_t \\ \Delta l_t \end{bmatrix} = \mathbf{c} + \sum_{j=1}^{2} \Gamma_j \begin{bmatrix} \Delta\hat{a}_{t-j} \\ \Delta y_{t-j} \\ \Delta l_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{a,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{bmatrix},$$

Where **c** is a three-by-one vector of constant terms and the Γ's denotes three-by-three matrices containing structural parameters for $\Delta\hat{a}$, Δy and Δl at different lags. Moreover, the diagonal terms of the matrix containing contemporaneous structural parameters, i.e. Γ_0, have been normalized to unity.[25] Note that the input measure used is the growth rate of hours and not the weighted input index defined in expression (16). This is due to that the latter measure is highly correlated (0.99) with output growth, which, in turn induces a serious multicollinearity problem when trying to estimate the reduced form of system (17).[26]

In order to identify the VAR, the standard ordering assumptions that Γ_0 is lower triangular and that the structural disturbances, i.e. the ε's, are mutually orthogonal are imposed. The ordering assumption and the econometric practice above then entails that the structural disturbance term ε_a can be identified as a structural technology shock. However, since a firm with market power makes, theoretically, only one decision, we cannot separately identify ε_2 as an innovation to demand and ε_3 as an innovation to factor supply. However, for the purpose of this paper it is enough to be able to identify the structural disturbance ε_a as a technology shock. In addition to the assumptions above, it is assumed that the growth rate of technology is exogenous. This additional assumption implies that the restriction of Γ(1,2) = Γ(1,3) = 0 are imposed on all Γ matrices, where Γ(R,C) denotes the R,C:th element of Γ. Note that the latter assumption is the key identifying assumption of the previous sections.

Since the disturbance terms of the reduced form are linear combinations of the structural disturbance terms, the exogeneity assumption of the growth rate of technology implies that the requirements for the SUR-estimator to be more efficient than OLS are fulfilled by

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[24] The correlation between the technology residual and the growth rate of hours is now statistically negatively correlated at the five-percent level, (-0.48), instead of the one-percent level as before.

[25] Thus, cointegration techniques are not applied. That is, because levels of output and inputs do not necessarily need to be cointegrated with technology. For example, credit market deregulation as well as changes in trade and industrial policy may have induced permanent changes in the level of output and input that are unrelated to the level of technology. Moreover, changes in immigration flows or other changes in the demographic structure may cause permanent changes in the level of the labor force that are unrelated to technology, as noted by Basu *et al.* (1998).

construction. Hence, the SUR-estimator will be employed instead of OLS.[27] The impulse responses to output and inputs growth are then derived using the Cholesky decomposition and confidence bands are obtained using the standard bootstrap technique proposed by Runkle (1987). Note that the impulse responses we are interested in, i.e. the responses of hours and output growth to a technology shock, are not sensitive to the internal ordering between hours and output growth because the latter two variables are in both cases ordered below technology growth.[28] A caveat regarding the procedure outlined above is however appropriate since the technology growth variable is treated as data while it is in fact a generated regressor.[29]

Figure 3 presents the impulse responses resulting from estimation of the system (17). The lag length of the model is set to two.[30] The point estimates imply that both the growth rate of hours and output fall below normal on impact in response to a positive technology shock, but only the response of hours is statistically significant. These results confirm the findings from studying unconditional correlations. The initial contraction in both variables is followed by a hump-shaped dynamical pattern where output and hours attains growth rates that are above normal after three and four years respectively and then fall back to normal about seven years after impact. The response paths are imprecisely estimated, however. Basu *et al.* (1998) also finds a contractionary response on impact for both hours and output on aggregate U.S. data. Again, only the impact response for hours is statistically significant, although they do find a statistically significant increase in the level of output after two years. Using a different approach, Galí (1998) and Kiley (1998) also report a short run tendency for labor input to fall when technology improves. Galí (1998) observes this pattern in aggregate data for a majority of the G7 countries[31] and Kiley (1998) in U.S. manufacturing data. Both these studies use long-run restrictions in a structural VAR to identify technology shocks, where the main identifying assumption is that only

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[26] Estimation is, however, still possible and yields point estimates of the impulse responses that are similar to those presented in figure 3, although statistically insignificant at all points. The wide confidence bands is however not surprising when recalling the multicollinearity problems between output and input growth mentioned above.
[27] An alternative estimator is the implied FIML-estimator. However, FIML-estimates are generally sensitive to deviations from the underlying assumption of a multivariate normal distribution of the errors terms. Moreover, there are no asymptotic advantages to be gained from using the FIML-estimator instead of the SUR-estimator. Thus, to be on the safe side the more robust SUR-estimator is used. However, the impulse responses presented in figure 3 are qualitatively unchanged when the FIML-estimator is used instead of the SUR-estimator.
[28] Although the impulse responses of output and hours growth to an innovation in technology are invariant to the internal ordering of the former two variables it might still be wrong to impose any causal ordering between the two.
[29] The generated regressor problem can be thought of as classical measurement errors, with the variance of the measurement error tending asymptotically to zero. Although in finite samples the parameter estimates are likely to suffer from an attenuation bias which, in turn, also affect the estimated residuals used in the bootstrap.
[30] Since information criterion tests for lag length is based on the value of the maximized likelihood function these tests are unavailable when the SUR-estimator is used. However, when using the FIML-estimator instead of the SUR-estimator the Schwarz (1978) information criterion indicates a lag length of two.
[31] Galí (1996) reports a statistically significant negative impact effect for the U.S., Canada, U.K. and Italy, a negative but statistically insignificant impact effect for Germany and France, and no impact effect for Japan.

technology shocks can affect labor productivity in the long run. Moreover, Galí (1998) also finds a non-significant impact response of output, although with a positive point estimate, in aggregate U.S. data. However, for the remaining G7 countries Galí (1996) reports a statistically significant positive impact response of output to a technology shock.

To assess the robustness of the findings above a series of exercises were conducted. First, standard diagnostic tests do not indicate that the model suffers from any problems with autocorrelation or heteroscedasticity. Moreover, adding another lag to the model does not change the results in any significant way, although the expansion following upon the initial contraction are amplified for both hours and output growth. Second, a Granger causality test cannot reject the null hypothesis that the technology residual is exogenous in the Granger sense ($F(4,17) = 2.18$ with a p-value of 0.12). It should be noted though that this test is not a test of the exogeneity assumption above. The Granger test it is only a test of the prediction power of *lagged* growth rates of hours and output on the growth rate of the technology residual controlling for lagged growth rates of the technology residual. Third, I have also employed the dynamic approach of Basu *et al.* (1998) and analyzed a series of two variable systems consisting of the technology residual and one of the output or hours growth series. The conclusions above are however robust to using this approach instead of the three variable system (17). Fifth, the corresponding industry-level results, presented in Carlsson (2000), are similar to the aggregate results of this section. Finally, to investigate whether the results are driven by the recession years 1991 to 1993 I re-estimated the VAR using the technology growth series from the re-estimated preferred specification (discussed above). However, the properties of the impulse response functions presented in figure 3 are qualitatively unchanged from dropping the last three years.

Thus, overall, the robustness exercises do not give rise to any results that give us reason to question the main findings of a contractionary impact effect on hours worked and a non-expansionary impact effect on output growth in the manufacturing sector due to a positive technology shock.

6 Concluding discussion

In this paper I estimate technology growth in the Swedish manufacturing sector using several extensions of the Hall (1988, 1990) method, which are robust to non-constant returns to scale, imperfect competition on the output market and, under various conditions, unobserved variation in factor utilization. More specifically, two different approaches have been employed to obtain estimates of technological progress that are robust to unobserved variation in factor utilization. That is, the indirect approach, using first order conditions, represented by the specification used by Basu *et al.* (1998) and the direct approach, employing technological

assumptions, of Burnside *et al.* (1995). When evaluating the results of these two specifications I find that the indirect specification does not seem able to control for neither labor nor capital utilization in Swedish manufacturing data. The main cause of this failure seems to be that the utilization proxy used by Basu *et al.* (1998), i.e. hours per employee, is not an important adjustment margin in the Swedish manufacturing sector, at least not over the time span of a year. The direct specification, on the other hand, appears capable of controlling for variation in capital utilization. In addition to these two specifications, I also proposed a generalization of the direct specification allowing for a fixed baseload of electricity and including the rate of industrial accidents per hour worked as an indicator variable for unobserved variation in labor utilization. Allowing for a fixed baseload of electricity provides a slight improvement, but the injury-rate variable does not work well as a proxy for unobserved labor effort.

Since the specifications above allow for non-constant returns to scale we are able to obtain estimates of the returns to scale that are robust to imperfect competition on the output market and varying capital utilization. Generally, the estimation results imply that the Swedish manufacturing sector is characterized by mildly increasing returns to scale, substantial variation in factor utilization and a significant heterogeneity across industries.

When studying the manufacturing wide series of the resulting technology residual several conclusions can be drawn. First, when comparing the technology residual with the Solow residual, I find that the variance of the technology residual is only about 40 percent of the variance in the Solow residual. Second, there is a *negative* correlation between the technology residual and the growth rate of hours. Third, the technology residual is *uncorrelated* with output growth. Thus, the standard result of procyclical productivity, replicated in this paper when studying the Solow residual, seems to be a figment of poor measurement of technology growth. Fourth, the empirical impulse response functions of hours and output to a technology shock imply that both the growth rate of hours and that of output fall below normal on impact in response to a positive technology shock. However, only the negative response of the growth rate of hours is statistically significant. The initial contraction of both variables is followed by a hump-shaped dynamical pattern where output and hours attain growth rates that are above normal after three and four years respectively and then fall back to normal about seven years after impact. The response paths are imprecisely estimated, however. Finally, the industry-level results are similar and the aggregate results are robust to different aggregation methods, thus implying that the findings above are not due to the aggregation method.

What is the mechanism driving the contractionary response of hours and the non-expansionary response of output to a technology shock in the short run? Although an answer to

this question is beyond the scope of this paper it is interesting to see in what direction the evidence points. First, it should be emphasized that the contractionary response is not compatible with the behavior implied by the standard RBC-model. As Basu *et al.* (1998) put it "Given that the central stylized fact of business cycles [to be reproduced by RBC-models] is the comovement between inputs and output, if technology shocks drive the cycle then almost any sensible calibration implies that technology improvements increase inputs and outputs"[32]. Potentially more fruitful explanations of the findings above include instead notions such as sectoral shifts, sticky prices and cleansing effects.

The basic idea of the sectoral shifts literature is that because reallocation of production factors over sectors is slow and costly, times with high levels of reallocation between sectors should also be times with low output and input growth (see the seminal paper by Lilien 1982). To put the notion into the context of this paper, if aggregate technology shocks are unevenly distributed over industries it gives rise to incentives to reallocate production factors. Thus, a multisectoral RBC-model, with idiosyncratic technology shocks and reallocation lags might explain why an aggregate technology shock is contractionary on impact. However, if this mechanism explains the results for manufacturing as a whole, the response patterns found on industry-level due to an industry specific technology shock should mimic the responses of a standard RBC-model. This is not what I find. Thus, it is hard to believe that a multisectoral RBC-model can explain the findings above. Although, it might be the case that the aggregation level is still too high to tell.

The explanation advocated by Basu *et al.* (1998), Galí (1999) and Kiley (1998) as the reason for the findings above is price stickiness. Basu *et al.* (1998) show that both output and inputs might fall in fall in response to a positive technology shock in a sticky price model. However, this depends crucially on the assumption that the monetary authority does not counteract the effects of the technology improvement.

A third explanation of the results is that the direction of the causation is the other way around. Even if firm level technical change is exogenous, the distribution of inputs over firms with varying levels of technology might be driven by changes in demand. Thus, if inefficient production units are driven out of the market in recessions, aggregate technology should rise. Thus, recessions have a cleansing effect that causes technology growth to be countercyclical. This Schumpeterian explanation casts doubt on the basic identifying assumption of the method used in the paper, i.e. that the growth rate of technology is exogenous relative to the demand

[32] Basu *et al.* (1998) page 25.

instruments. However, the Sargan and the Granger causality tests above do not support the notion of reversed causation.

Although the evidence does not support neither the sectoral shifts nor the Schumpeterian explanation, more research, preferably using micro data, is needed in order to invalidate them. Moreover, it would be interesting to empirically evaluate the relevance of the sticky price explanation. More research is needed in order to understand the mechanisms behind the contractionary response of hours and the non-expansionary response of output to a technology shock in the short run. The main conclusion, however, is that the standard RBC-model can not explain the findings of this paper.

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Table 1
The Indirect Approach

	Non-Corrected	Indirect				Indirect (reduced)	
Industry	RTS	RTS	γ_1	γ_2	γ_3	RTS	γ_1
Food	1.248**	1.099	0.621	0.790*	0.121	1.203*	0.304
	(0.094)	(0.085)	(0.684)	(0.381)	(0.370)	(0.102)	(0.960)
Textile	1.450**	1.861*	-1.171	-1.098	-0.208	1.467**	-0.919
	(0.090)	(0.360)	(0.899)	(1.450)	(0.359)	(0.105)	(0.519)
Wood	1.264**	1.045	-0.643	1.983**	-0.378	1.255**	0.393
	(0.050)	(0.095)	(1.441)	(0.734)	(0.335)	(0.060)	(1.177)
Paper/Publishing	1.267**	1.356**	-0.788	-0.191	-0.137	1.265**	-1.092
	(0.071)	(0.076)	(0.609)	(0.358)	(0.133)	(0.082)	(0.871)
Chemicals/Petroleum	1.086	0.979	-0.288	0.087	0.720	1.089	-0.147
	(0.110)	(0.098)	(1.204)	(0.206)	(0.421)	(0.117)	(1.693)
Minerals	1.419*	0.886	-1.292	1.335	0.253	1.377*	-1.039
	(0.198)	(0.424)	(2.153)	(1.183)	(0.296)	(0.161)	(2.865)
Primary metals	1.258**	0.827	-1.925	1.244	0.084	1.272**	0.280
	(0.068)	(0.320)	(2.487)	(0.870)	(0.150)	(0.075)	(2.091)
Fabricated metals	1.270**	1.050	0.359	1.149	0.414	1.270**	0.232
	(0.052)	(0.119)	(0.777)	(1.113)	(0.302)	(0.074)	(0.882)
χ^2	15.152*	6330.635**				53.674**	
	[0.034]	[0.000]				[0.000]	
Restricted Estimates	1.269**	1.215**	-0.308	0.236	0.027	1.267**	-0.321
	(0.037)	(0.045)	(0.332)	(0.202)	(0.070)	(0.040)	(0.309)

Notes: * and ** indicates statistical significance on the 5% and 1% level respectively. H(0): Average growth rate of technology = 0, RTS = 1, $\gamma_1 = 0$, $\gamma_2 = 0$ and $\gamma_3 = 0$. Heteroscedasticity robust standard errors (White's 1980 method) in parenthesis. The H(0) of the Wald-test is equal slope parameters across industries, p-value inside brackets. The restricted estimates are the estimate resulting from imposing the cross-industry restriction above.

Table 2
The Direct Approach

	Non-Corrected	Direct	Extended Direct					Extended Direct (Reduced)		
Industry	RTS	RTS	RTS	El./Cap.	ϕ	INJ	λ	RTS	El./Cap.	ϕ
Food	1.248**	1.242*	1.252**	0.699	0.558	-0.090	-0.072	1.245**	0.924	0.742
	(0.094)	(0.109)	(0.088)	(1.141)	(0.902)	(0.203)	(0.161)	(0.090)	(1.031)	(0.808)
Textile	1.450**	1.407**	1.377*	1.033	0.750	0.198	0.144	1.395**	1.633*	1.171
	(0.090)	(0.106)	(0.146)	(1.356)	(1.022)	(0.238)	(0.173)	(0.146)	(0.806)	(0.644)
Wood	1.264**	1.197**	1.141	1.751*	1.534	0.096	0.084	1.192**	1.446*	1.213
	(0.050)	(0.041)	(0.147)	(0.701)	(0.792)	(0.379)	(0.341)	(0.064)	(0.572)	(0.532)
Paper/Publishing	1.267**	1.075	1.024	1.132	1.106	0.288	0.282	1.139	0.881	0.774
	(0.071)	(0.056)	(0.369)	(0.788)	(1.121)	(0.847)	(0.918)	(0.143)	(0.521)	(0.544)
Chemicals/Petroleum	1.086	1.023	0.974	1.526*	1.567	0.134	0.137	0.992	1.494**	1.507
	(0.110)	(0.093)	(0.088)	(0.636)	(0.699)	(0.184)	(0.191)	(0.091)	(0.538)	(0.594)
Minerals	1.419*	1.152	0.844	1.201	1.423	0.492	0.583	1.025	1.900	1.854
	(0.198)	(0.147)	(0.287)	(1.164)	(1.616)	(0.364)	(0.553)	(0.265)	(1.219)	(1.594)
Primary metals	1.258**	1.188**	1.097	2.410**	2.196	-0.137	-0.124	1.045	2.344**	2.242*
	(0.068)	(0.060)	(0.087)	(0.559)	(0.612)	(0.171)	(0.152)	(0.080)	(0.520)	(0.609)
Fabricated metals	1.270**	1.179**	1.394**	0.851	0.611	-0.267	-0.191	1.210**	0.993	0.820
	(0.052)	(0.049)	(0.145)	(0.867)	(0.658)	(0.173)	(0.107)	(0.051)	(0.589)	(0.500)
χ^2	15.152*	21.733**	101.773**					36.834**		
	[0.034]	[0.003]	[0.000]					[0.001]		
Restricted Estimates	1.269**	1.163	1.135**	1.100**	0.969	0.109	0.096	1.164**	1.091**	0.937
	(0.037)	(0.031)**	(0.045)	(0.179)	(0.171)	(0.107)	(0.097)	(0.036)	(0.163)	(0.153)

Notes: * and ** indicates significance on the 5% and 1% level respectively. H(0): RTS = 1, The reduced form Electricity / Capital parameter (b_1)= 0, ϕ = 1, The reduced form Injury Rate parameter (b_2) = 0, λ = 0. Heteroscedasticity robust standard errors (White's 1980 method) in parenthesis. Standard errors for ϕ (= b_1/η) and λ (= b_2/η) are computed using the delta method. The H(0) of the Wald-test is equal slope parameters across industries, p-value inside brackets. The restricted estimates are the estimate resulting from imposing the cross-industry restriction above.

Table 3
P-values for t-tests of nested specifications

Industry	Estimate of ϕ	$\bar{c}_V / \bar{c}_S$	P-values of t-tests	
			H(0): $\phi = \bar{c}_V / \bar{c}_S$	H(0): $\phi = 1$
Food	0.742	0.090	0.420	0.750
Textile	1.171	0.063	0.085	0.791
Wood	1.213	0.121	0.040*	0.689
Paper/Publishing	0.774	0.188	0.281	0.678
Chemicals/Petroleum	1.507	0.170	0.025*	0.394
Minerals	1.854	0.123	0.278	0.592
Primary metals	2.242	0.204	0.001**	0.041*
Fabricated metals	0.820	0.083	0.140	0.719

Notes: * and ** indicates significance on the 5% and 1% level respectively. Standard error for ϕ (= b_1/η) in parenthesis, computed using the delta method based on White's (1980) heteroscedasticity robust covariance matrix estimator.

Table 4
The Preferred Specification 3SLS

Industry	Average Growth Rate of Technology	RTS	Electricity /Capital	ϕ	RTS DIFF
Food	0.004	1.243*		1	-0.004
	(0.192)	(0.102)			
Textile	2.802**	1.409**	1.575*	1.118	-0.041
	(0.821)	(0.133)	(0.741)	(0.572)	
Wood	0.614**	1.188**	1.498**	1.260	-0.076
	(0.199)	(0.065)	(0.567)	(0.532)	
Paper/Publishing	0.745**	1.086		1	-0.181**
	(0.206)	(0.056)			
Chemicals/Petroleum	0.871**	0.990	1.543**	1.558	-0.096
	(0.307)	(0.091)	(0.546)	(0.606)	
Minerals	0.701	1.004	1.942	1.933	-0.415
	(0.980)	(0.250)	(1.200)	(1.597)	
Primary metals	0.914**	1.048	2.362**	2.253**	-0.210**
	(0.310)	(0.080)	(0.487)	(0.576)	
Fabricated metals	0.892**	1.194**		1	-0.076
	(0.229)	(0.048)			

Notes: * and ** indicates significance on the 5% and 1% level respectively. H(0): Average growth rate of technology = 0, RTS = 1, The reduced form Electricity / Capital parameter (b_1) = 0, ϕ = 1, RTS DIFF = 0. RTS DIFF is measured as the difference between the RTS estimate from this specification and the RTS estimate from the non-corrected specification. Heteroscedasticity robust standard errors (White's 1980 method) in parenthesis. Standard errors for ϕ (= b_1/η) computed using the delta method. Both the point and the standard error estimates of the constant term (i.e. the average growth rate of technology) are scaled by factor of 100. The estimate of the average growth rate of technology is thus stated in percent per year.

Table 5
Correlations between utilization measures

	Δy^1	$\Delta z^{D\,1}$	$\Delta z^{PS\,1}$	RU^2	COT^2
Output growth: Δy	1				
Capital Utilization growth, Direct specification	0.64**	1			
Capital Utilization growth, Preferred specification	0.66**	1.00**	1		
Resource Utilization growth: RU	0.79**	0.74**	0.76**	1	
Capital Operating Time growth: COT	0.57**	0.55**	0.56**	0.63**	1

Notes: * and ** indicates estimates significantly different from zero on the 5% and 1% level respectively. Sample period 1969 – 1990. 1) Δ Denotes first log differences of variable. Y is aggregated by summation to total manufacturing before log differencing. Δz^D and Δz^{PS} are aggregated by gross output weights 2) Measured as the percentage change.

Table 6
First stage R^2 for the instrument set.

Industry	$\Delta\hat{x}$	$\Delta\breve{x}$	$\bar{c}_s(\Delta v - \Delta k)$	$\bar{c}_L \Delta inj$	Δx	$\bar{c}_L \Delta h$	$\Delta RVMC$	ΔIC
31	0.20	0.20	0.46	0.24	0.20	0.34	0.61	0.23
32	0.54	0.51	0.23	0.20	0.51	0.25	0.70	0.32
33	0.73	0.72	0.55	0.26	0.72	0.30	0.67	0.41
34	0.73	0.70	0.68	0.19	0.71	0.20	0.59	0.51
35	0.45	0.42	0.51	0.35	0.43	0.32	0.82	0.36
36	0.45	0.41	0.51	0.26	0.41	0.13	0.56	0.34
37	0.50	0.47	0.44	0.35	0.48	0.11	0.58	0.45
38	0.49	0.50	0.41	0.31	0.50	0.21	0.53	0.48

Notes: The R^2's are obtained by regressing each regressor on the instrument set. The instrument set consists of a constant term; growth rate of the exchange rate index, lags 1-2; growth rate of the foreign demand index, lags 0-1; growth rate of the real oil price, current value and a political dummy (taking on the value 1 for years with right-wing governments, zero otherwise), current value. Δ Denotes the first log difference. Finally, $\Delta RVMC = \bar{c}_K(\Delta p_M + \Delta m - \Delta p_I - \Delta k)$ and $\Delta IC = \bar{c}_K(\Delta i - \Delta k)$.

Table 7
Descriptive statistics for the Technology and the Solow residual

	Mean	Standard deviation	Min	Max
Solow Residual	1.00	1.05	-0.92	2.77
Technology Residual	0.78	0.67	-0.36	2.45

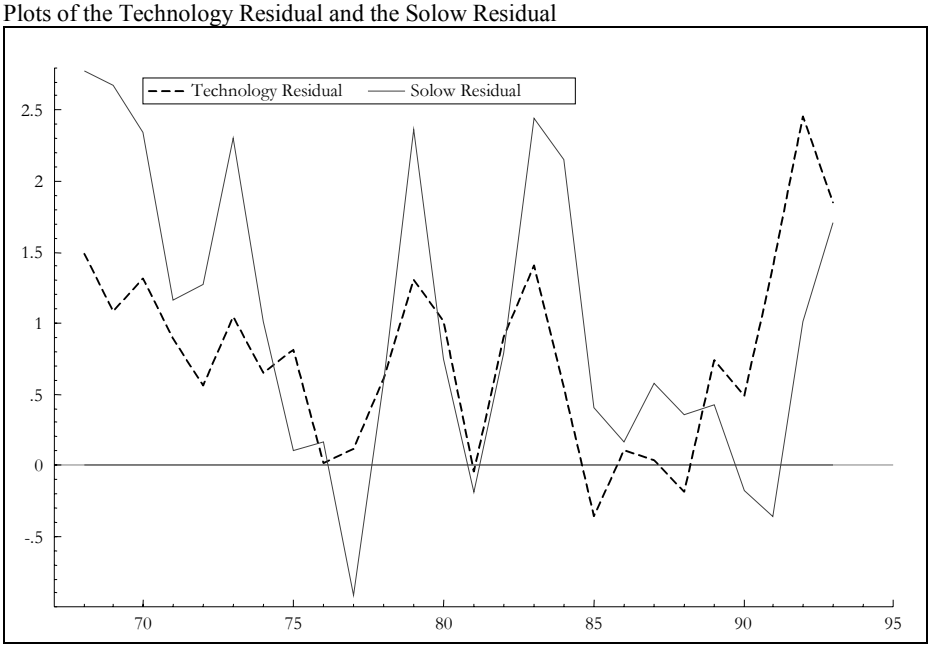
Notes: Statistics are scaled by a factor of 100. Both series are aggregated by gross output weights.

Table 8
Basic Correlations

	Δy	Δx^I_M	Δl	Solow Residual	Tech. Residual
Output growth: Δy	1				
Input growth: Δx^I_M	0.99**	1			
Hours growth: Δl	0.67**	0.75**	1		
Solow Residual	0.77**	0.68**	0.19	1	
Tech. Residual	0.00	-0.16	-0.56**	0.54**	1

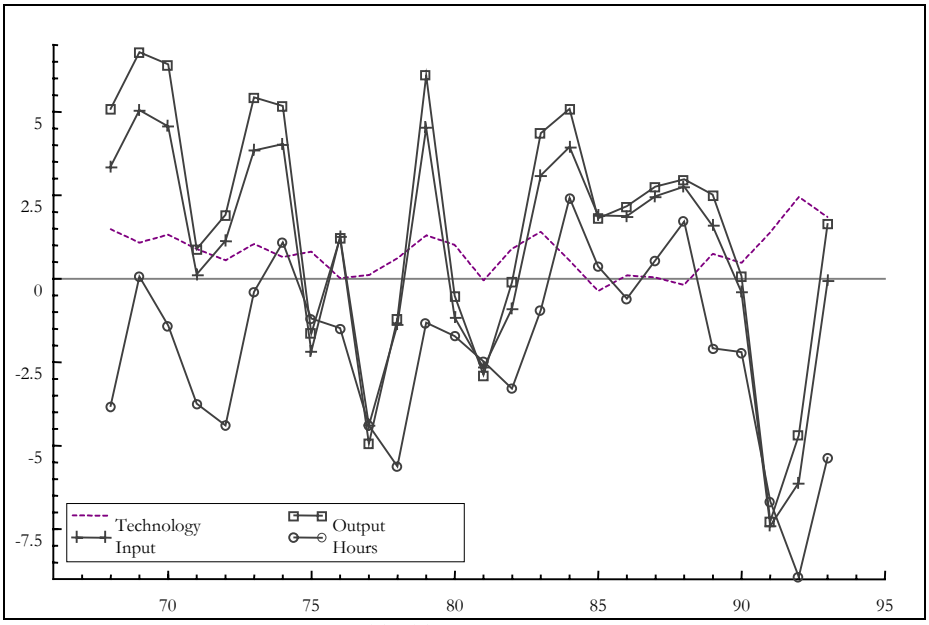
Notes: * and ** indicates estimates statistical significantly different from zero on the 5% and 1% level respectively. Δ Denotes first log differences. Y and L are aggregated by summation to total manufacturing before log differencing. All other series are aggregated by gross output weights.

Figure 1
Plots of the Technology Residual and the Solow Residual



Notes: Series scaled by a factor of 100. Both series are aggregated by gross output weights.

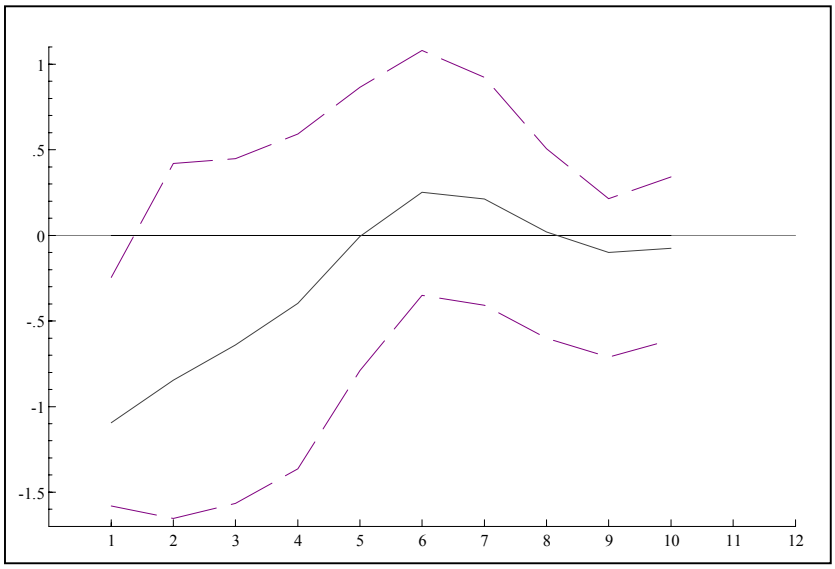
Figure 2
Plots of the Technology Residual, Output Growth, Input Growth (Δx_M^I) and Hours Growth



Notes: Series scaled by a factor of 100. The Technology Residual is aggregated by gross output weights. Output and Hours Growth are aggregated by summation to total manufacturing before log differencing. Input growth is defined as in expression (17).

Figure 3
Responses to a one s.d. innovation to Technology Growth using Hours growth as input measure

Response of Hours growth to a one s.d. innovation to Technology growth



Response of Output growth to a one s.d. innovation to Technology growth

Notes: 95 Percent confidence interval based on 1000 bootstrap replications.
A one standard deviation innovation to technology corresponds to a 0.55 percentage increase in the growth rate of technology in aggregate manufacturing.