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Abstract

This paper presents capital utilization corrected measures of technology shocks for aggregate and disaggregated (two digit Standard Industrial Classification code) industries. We correct for variations in capital utilization by employing industrial electrical use as a measure of capital services. In contrast, the standard measures of technology shocks used in the Real Business Cycle literature are based on economy wide data and assume that capital services are proportional to the stock of measured capital. To assess the impact of these differences, we contrast selected properties of the competing technology shock measures. We argue that the properties of technology shocks for the manufacturing sector are quite different than those used in the RBC literature. We also find that correcting for capital utilization has important implications for the properties of the Solow residual.

Keywords: Business Cycles, Productivity, Solow Residual.
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1. Introduction

This paper presents capital utilization corrected measures of technology shocks for aggregate and disaggregated (two digit Standard Industrial Classification (SIC) code) industries. We correct for variations in capital utilization proxying capital services by electricity use. In contrast, the standard measures of technology shocks used in the Real Business Cycle (RBC) literature are based on economy wide data and assume that capital services are proportional to the stock of measured capital. To assess the impact of these differences, we contrast selected properties of the competing technology shock measures.

Our decision to employ electricity use as a proxy for capital services is motivated by results in Burnside, Eichenbaum and Rebelo (1995). There we argue that (i) electricity use is a good measure of capital services; and that (ii) once we correct for capital utilization, there is virtually no evidence against the hypothesis of constant returns to scale. These findings suggest the importance of correcting for capital utilization when measuring technology shocks. The main findings in this paper can be summarized as follows.

1. For the manufacturing sector our capital utilization corrected technology shocks are much less volatile relative to output than the measure of technology shocks used in the RBC literature. Specifically, our corrections lead to a roughly 70% drop in the volatility of the growth rate of productivity shocks relative to output. Given that labor and capital inputs are measured much more accurately at the manufacturing level, this casts doubts on the volatilities of technology shocks relative to output that are standard in RBC models.

2. The correlation between the growth rate of productivity shocks and the growth rate of output is dramatically lower when we use electricity as a measure of capital services. Indeed, after correcting for capital utilization, we cannot reject the hypothesis that the two growth rates are completely uncorrelated for aggregate manufacturing. We know of no model that is capable of explaining this surprising regularity.

3. Standard Solow residuals imply that the probability of technological regress in manufacturing industries is roughly 40% lower than in the aggregate economy. Correcting for capital utilization leads to a further 50% reduction in the probability of technological regress in the manufacturing sector. In fact, when we work with annual data we find *no* instance of technological regress, once we correct for capital utilization. Given

our priors that the probability of technological regress in the US during the post-war era is very small, we believe that this finding provides strong corroborating evidence in favor of the plausibility of our measure of technology shock measures, at least relative to the measure used in the RBC literature.

4. We find substantial evidence of heterogeneity across 2 digit SIC industries in the nature of technology shocks. This provides a strong motivation for moving beyond simple aggregate models of the economy.

2. Measuring Productivity Shocks

In this section we consider three specifications of technology that we use to measure productivity shocks.

Our Benchmark Specification

According to our benchmark specification, gross output (Y_t) is produced by combining materials (M_t) and value-added (V_t) according to the Leontief technology:

$$Y_t = \min(a_M M_t, a_V V_t), \tag{2.1}$$

where a_M and a_V are constants. One motivation for using this specification is that it can be implemented with quarterly data, despite the absence of data on materials inputs at this frequency. Moreover, Basu (1993) has provided evidence that the Leontief assumption is a good approximation to the structure of production in manufacturing. Below we assess the robustness of our results to this assumption by implementing an alternative production technology using annual data.

Value added is produced according to a constant returns to scale production function that combines capital services (S_t) with total hours worked (L_t):

$$V_t = Z_t F(L_t, S_t). \tag{2.2}$$

Here Z_t represents the time t exogenous shock to productivity. We assume that total electricity consumption, E_t, is proportional to capital services:

$$E_t = \phi S_t. \tag{2.3}$$

Burnside, Eichenbaum and Rebelo (1995) consider alternative specifications for the relationship between electricity and capital services and find that their results are robust to this proportionality assumption.

Given this production structure and the hypothesis of perfect competition in factor markets, the growth rate in the productivity shock can be computed as:

$$\Delta z_t^1 = \Delta v_t - (1 - \alpha_t)\Delta l_t - \alpha_t \Delta e_t \tag{2.4}$$

where we used the symbol Δ to denote first differences and lower case variables to represent the logarithms of the different variables. The variable α_t denotes the share of capital in total time t value added.

The Conventional Solow Residual

It is useful to contrast our measure of technology shocks with the conventional Solow residual. The latter is based on the assumption that capital services are proportional to the stock of capital, K_t,

$$S_t = \lambda K_t. \tag{2.5}$$

This implies that the growth rate of the Solow residual can be computed as:

$$\Delta z_t^2 = \Delta v_t - (1 - \alpha_t)\Delta l_t - \alpha_t \Delta k_t. \tag{2.6}$$

A key shortcoming of this measure of technology shocks is that it based upon the proportionality assumption in equation (2.5). This assumption is very much at odds with the facts. All of the evidence that we have for manufacturing industries–data on the workweek of capital, on electricity use and shift data–suggests that capital utilization varies significantly over the business cycle.

An Alternative Specification

To assess the sensitivity of our findings to the assumption that materials usage is proportional to gross output, we also report results for annual data, generated under the assumption that gross output is a differentiable function of capital services, hours worked, energy (N_t), and materials (M_t):

$$Y_t = Z_t F(S_t, L_t, N_t, M_t) \tag{2.7}$$

We implement this technology by assuming that equation (2.3) holds, that is, capital services are proportional to electricity usage, and that factor markets are perfectly competitive.

Taking a first order log-linear approximation to this production function we obtain:

$$\Delta z_t^3 = \Delta y_t - c_{St}\Delta s_t - c_{Lt}\Delta l_t - c_{Nt}\Delta n_t - c_{Mt}\Delta m_t$$

where c_{jt} denotes the share of factor j in total time t revenue.

3. Results

We implement our benchmark specification using the quarterly and annual data sets described in Burnside, Eichenbaum and Rebelo (1995). The quarterly and annual data cover the periods 1972:1–1992:4 and 1972–1992, respectively. We implement the alternative specification using an updated version of the Jorgenson, Gollop, and Fraumeni (1987) data set, together with our data series for electricity. This data set also includes time series for factor shares at the annual frequency. To produce our quarterly results we assumed that these shares were constant within the year. In addition we display results for the economy as a whole using the data set constructed by Burnside and Eichenbaum (1995).

Aggregate and Manufacturing Sector Results

Table 1 reports statistics computed using economy wide-data and aggregate manufacturing data. Panels (a) and (b) are based on quarterly and annual data, respectively. Column one reports properties of the standard measure of technology shocks, the conventional Solow residual, computed using the economy wide data set constructed by Burnside and Eichenbaum (1995). Column 2 displays the properties of the conventional Solow residual for aggregate manufacturing. Column 3 reports the properties of the capacity utilization corrected technology shock measures for aggregate manufacturing, given our benchmark specification. Rows one through three report the variance of Δz_t (denoted by σ_ε^2), the relative volatility of Δz_t and Δy_t ($\sigma_\varepsilon^2/\sigma_y^2$) and the correlation between Δz_t and Δy_t ($\rho_{\varepsilon y}$). Row 4 reports on the probability of technological regress implied by the different measures. These were estimated by calculating the proportion of times in our sample that the estimated level of technology declined.

Comparing the properties of the economy-wide and the aggregate manufacturing Solow residuals we find that the volatility of technology shocks relative to output is dramatically lower in manufacturing (it is 62% lower in quarterly data and 54% lower in annual data). A number of interesting results emerge from considering the impact of correcting the manufacturing measure of technology shocks for capital utilization using the benchmark technology specification. First, the point estimate of $\sigma_\varepsilon^2/\sigma_y^2$ is reduced by 21% in the quarterly data and by 24% in annual data. The total effect of moving from the economy-wide residual to the manufacturing residual corrected for electricity is to reduce $\sigma_\varepsilon^2/\sigma_y^2$ by 70% in quarterly data and by 65% in the annual data. Second, there is a dramatic decline in the correlation between the growth rate of productivity shocks and the growth rate of output when we use electricity as a measure of capital services. Working with the manufacturing data, the decline in the correlation is even more dramatic when compared with the correlation emerging from the economy wide data. Notice that for both quarterly and annual data, once we correct for capacity utilization, we cannot reject the hypothesis that $\rho_{\varepsilon y} = 0$. This is difficult to reconcile with existing RBC models.

An important criticism of the standard measures of technology shocks is that they exhibit an implausibly large frequency of technological regress. For the economy wide residual this probability was 37% for quarterly data and 30% for annual data. At the other extreme, for the capacity utilization-corrected measure of the Solow residual in manufacturing this probability is 11% (quarterly) and 0% (annually). In our view this provides strong corroborating evidence for the relative plausibility of the capacity utilization corrected technology shock measures.

Industry Level Results

Figures 1 and 2 display selected properties of the estimated technology shocks for the different 2 digit SIC industries (industry codes are presented in Table 2). Because of space constraints we report only results generated using annual data. Figures 1 and 2 display results for the benchmark and alternative specifications, respectively. The length of the bars in Panels (a), (b) and (c) correspond to the estimated values of $\sigma_\varepsilon^2/\sigma_y^2$, $\rho_{\varepsilon y}$ and the probability of technological regress. The length of the dashed lines in each bar represent a two standard deviation band about the point estimate. A number of results are worth noting. First, the qualitative properties of the estimated technology shock measures do not depend sensitively on whether we work with the benchmark or alternative specification. Second, there is obvious heterogeneity across industries. Consider for example our results for the benchmark specification. Here the estimated values for $\sigma_\varepsilon^2/\sigma_y^2$ range from a low of

0.25 for leather goods (SIC 32) to a high of 1.28 for chemicals (SIC 28). The estimated value of $\rho_{\varepsilon y}$ ranges from a low of -0.09 for furniture (SIC 25) to a high of 0.74 in paper (SIC 26). The estimated probability of technological regress ranges from a low of 0 in electrical machinery (SIC 36) to a high of 0.55 in petroleum refining (SIC 29). Third, there is evidence of misspecification for certain industries. For example, it seems very unlikely that the true probability of technological regress equals 0.82 in printing and publishing (SIC 27). This argues for the usefulness of detailed industry studies. Nevertheless, viewed as a whole, the overall picture that emerges from the industry level results is that the measure of technology shocks used in RBC studies imply values of $\sigma_\varepsilon^2/\sigma_y^2$, $\rho_{\varepsilon y}$ and the probability of technological regress that are implausibly large.

4. References

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Table 1

Properties of the Solow Residual
Aggregate Data

(a) Quarterly Data			
Statistic	Standard		Corrected
	Economy Wide	Manufacturing	
σ_ε^2	3.9×10^{-5} (7.3×10^{-6})	6.6×10^{-5} (1.4×10^{-5})	5.3×10^{-5} (1.2×10^{-5})
$\sigma_\varepsilon^2/\sigma_y^2$	0.435 (0.063)	0.165 (0.033)	0.131 (0.041)
$\rho_{\varepsilon y}$	0.856 (0.032)	0.700 (0.088)	0.200 (0.166)
Pr(Regress)	0.374 (0.053)	0.217 (0.045)	0.108 (0.034)
(b) Annual Data			
Statistic	Standard		Corrected
	Economy Wide	Manufacturing	
σ_ε^2	1.3×10^{-4} (4.0×10^{-5})	3.0×10^{-4} (7.3×10^{-5})	2.3×10^{-4} (8.4×10^{-5})
$\sigma_\varepsilon^2/\sigma_y^2$	0.257 (0.080)	0.117 (0.027)	0.089 (0.039)
$\rho_{\varepsilon y}$	0.768 (0.069)	0.734 (0.123)	0.105 (0.283)
Pr(Regress)	0.300 (0.103)	0.100 (0.067)	0.000 (0.000)
c) Annual Data (Alternative Specification)			
Statistic	Standard		Corrected
	Economy Wide	Manufacturing	
σ_ε^2	–	1.9×10^{-4} (6.9×10^{-5})	1.4×10^{-4} (5.2×10^{-5})
$\sigma_\varepsilon^2/\sigma_y^2$	–	0.074 (0.036)	0.055 (0.029)
$\rho_{\varepsilon y}$	–	0.567 (0.102)	0.272 (0.160)
Pr(Regress)	–	0.294 (0.111)	0.235 (0.103)

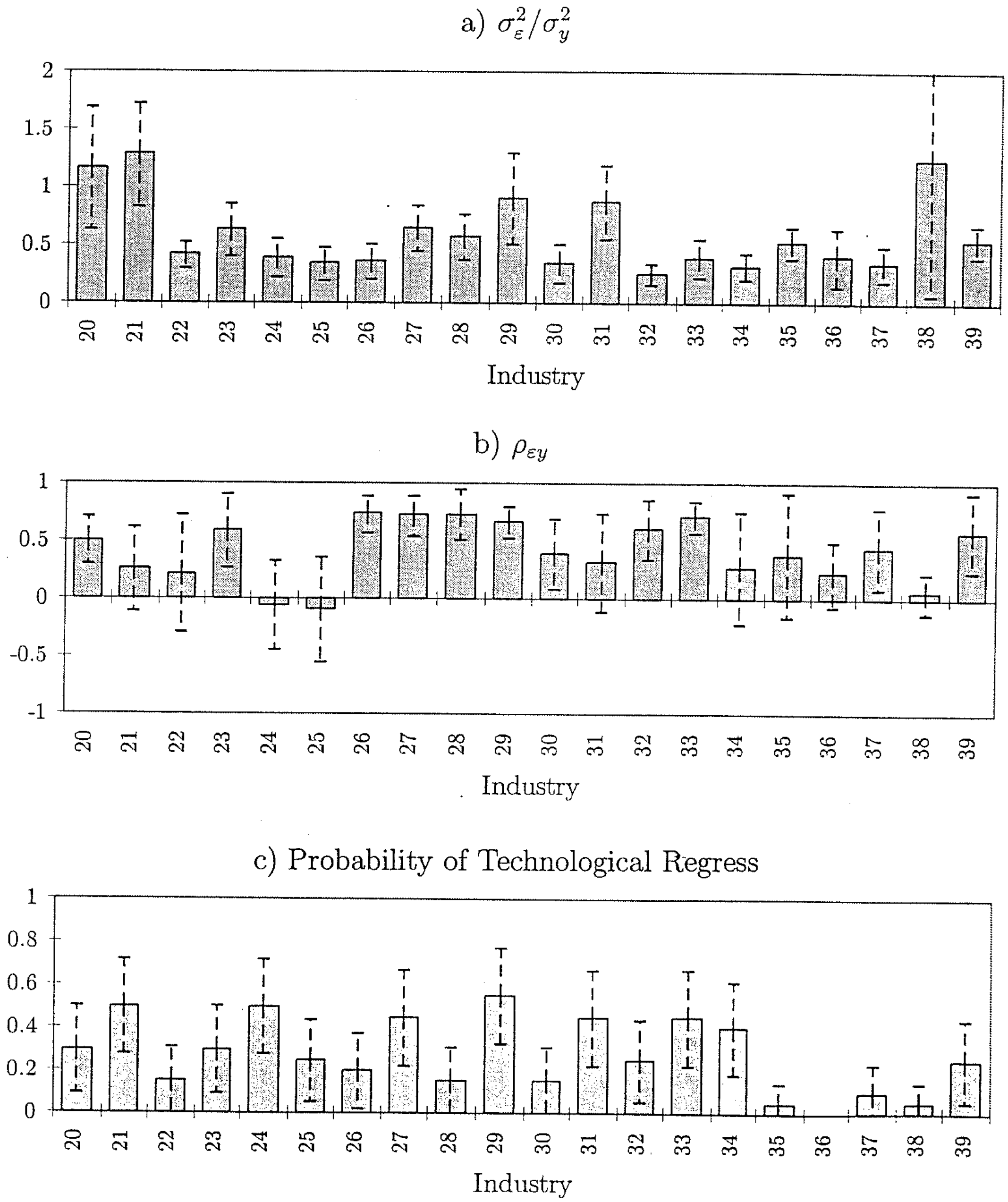
Table 2

Industry Definitions and Shares of Manufacturing Output

SIC Code	Industry	Share
20	Food and kindred products	0.135
21	Tobacco manufactures	0.007
22	Textile mill products	0.023
23	Apparel	0.034
24	Lumber and wood products	0.026
25	Furniture and fixtures	0.013
26	Paper	0.041
27	Printing and publishing	0.044
28	Chemicals	0.076
29	Petroleum refining	0.068
30	Rubber	0.043
31	Leather	0.005
32	Stone, clay, glass and concrete	0.027
33	Primary metals	0.070
34	Fabricated metals	0.058
35	Nonelectrical machinery	0.089
36	Electrical machinery	0.068
37	Transportation equipment	0.129
38	Instruments	0.029
39	Miscellaneous	0.014

FIGURE 1

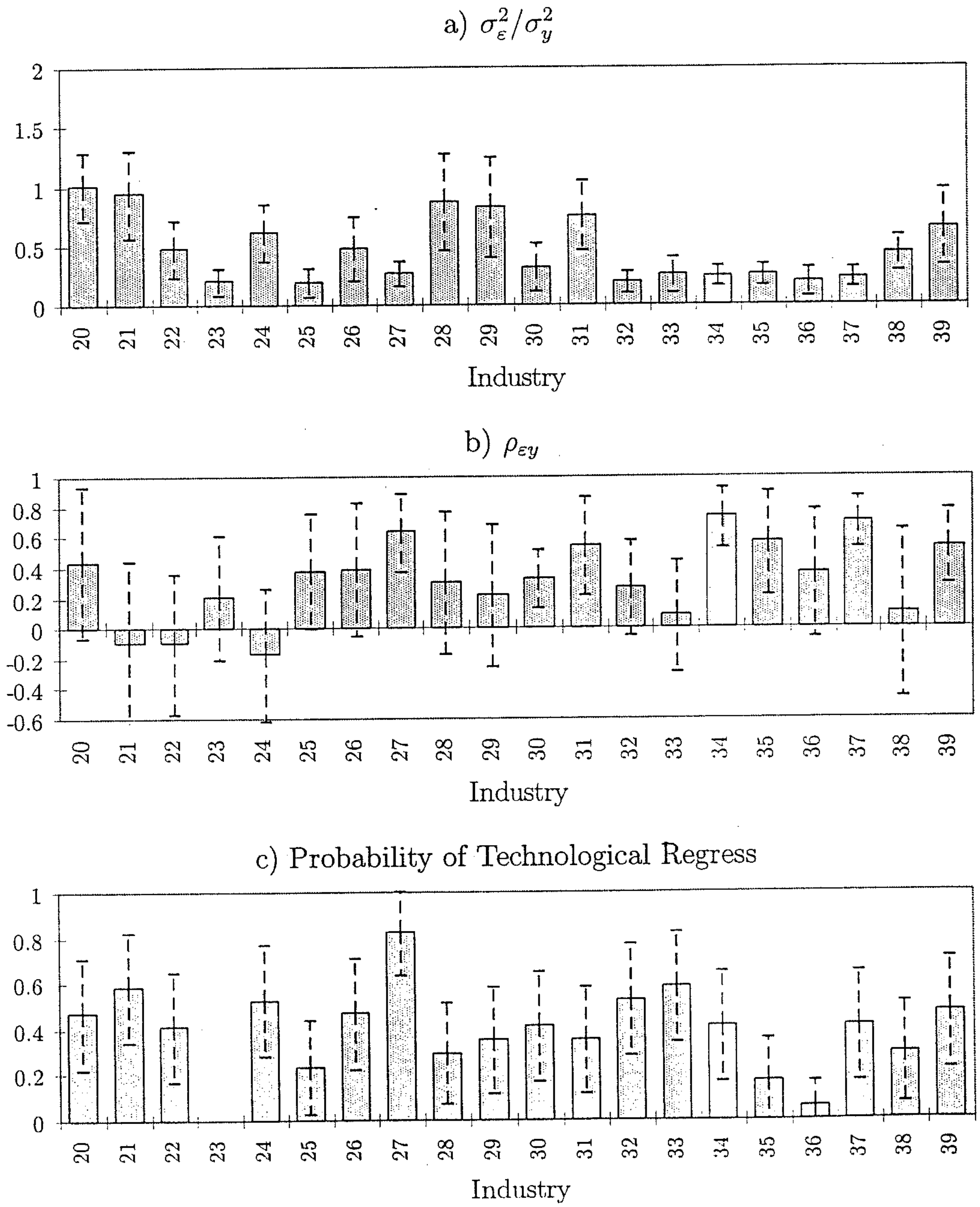
Properties of the Industry Level Solow Residuals
Benchmark Specification



Each statistic was computed using the benchmark specification. Each bar represents the value of the statistic for the industry indicated on the x-axis. The dashed line represents a two standard error band around the point estimate.

FIGURE 2

Properties of the Industry Level Solow Residuals
Alternative Specification



Each statistic was computed using the alternative specification. Each bar represents the value of the statistic for the industry indicated on the x-axis. The dashed line represents a two standard error band around the point estimate.