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On the Contribution of Technology Shocks to Business Cycles

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The paper "Time to Build and Aggregate Fluctuations" by Kydland and Prescott (1982) has led to a controversy in the literature on business cycles concerning the extent to which technology shocks are responsible for aggregate fluctuations in the U.S. economy. Prescott (1986b, p. 29) has suggested that "technology shocks account for more than half the fluctuations in the postwar period, with a best point estimate near 75 percent." Since then, several people have questioned this conclusion and suggested that the contribution of technology shocks is much lower than the figure calculated by Prescott.[1]

The policy importance of figuring out the relative contribution of different sources of economic fluctuations arises from the following considerations.[2] Sometimes the choice of a policy instrument can depend on the relative contribution of different shocks to fluctuations.[3] Sometimes the exact nature of a desirable policy rule can depend on the nature of shocks. That is, how government policy variables should respond to observable variables like output and investment can depend on whether fluctuations are due to technology shocks or some other shocks.[4] If the root sources of fluctuations are not observable directly (unlike, say, the weather) or indirectly, then the government has to solve a signal extraction problem to determine optimal government policy. The solution of any signal extraction problem depends on the relative contribution of different sources of fluctuations to observables.[5] Therefore, it becomes important to determine the contribution of different shocks to economic fluctuations.

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[1]Summers (1986) offers a particularly blunt and negative assessment of Prescott's conclusion, suggesting that it is plagued by various types of measurement errors and that the true contribution of technology shocks is probably very small and may even be zero. Since then, several researchers—including Hall (1987, 1988), Eichenbaum (1991), and Burnside, Eichenbaum, and Rebelo (1993)—have also argued that Prescott's measure of the importance of technology shocks is very imprecise and may be too high.

[2]Of course, I am presuming that there are some market imperfections which make some government policy other than laissez-faire desirable. I should note that the models of Kydland and Prescott (1982) and Prescott (1986a) are of competitive market economies in which aggregate fluctuations are socially optimal. The models of some of their critics who argue that the contribution of technology shocks is much lower than that calculated by Prescott have the same feature. Hence there is no useful role for policy in any of these models. I am also presuming that fluctuations are not the result of random variations in government policy variables unrelated to economic variables. If this were not the case, then the solution to the policy problem would seem simple. Since it is hard to imagine how such government policy shocks can contribute to welfare, it seems desirable to eliminate them entirely or at least follow appropriate procedures to minimize such policy shocks.

[3]For example, in an IS/LM model, Poole (1970) shows that whether the monetary authority should use a money supply rule or an interest rate rule depends on the relative variances of shocks to the IS curve (like animal spirits, saving propensity, government consumption, or taxes) and the LM curve (like liquidity preference shocks).

[4]For example, consider an economy in which lump-sum taxes are not feasible and revenues must be raised by a proportional labor income tax. In such an economy, a policy to smooth taxes over time is very likely to be desirable. However, whether the policy should be procyclical or countercyclical can depend on whether the fluctuations are due to changes in government consumption or changes in technology and may also depend on whether or not changes in technology are highly persistent.

[5]Lucas (1972) was the first to use a signal extraction model of optimal behavior at the individual level to explain the positive comovement of prices and output known as the *Phillips curve*. In his model, individuals observe only the price level and cannot tell if a movement in the price level is due to a monetary shock or a supply shock. Their labor supply decision depends on the price level, and the decision rule depends on the relative variances of these two shocks. Consequently, movements in the monetary shock lead to movements in the price level and thereby to movements in labor supply and output.

In this article, I will argue that the various measures of the contribution of technology shocks to business cycles calculated using the real business cycle (RBC) modeling method are not supported by corroborating evidence. I should emphasize that this criticism is not specifically against the number put forth by Prescott but applies to most such studies regardless of whether the particular number they yield is large or small. One—or none—of these numbers may be right, but there is no way to know based solely on the properties of these models and the data.

Then I will describe a different and much simpler method for calculating the extent to which technology shocks contribute to business cycles, which is the main focus of my article. This method is designed to take account of facts concerning the productivity/labor input correlation and the variability of labor input relative to output and has the following implications:

- Under the standard assumptions of competitive markets, no external economies of scale, and no measurement errors,
  - ▷ Either the contribution of technology shocks must be large (at least 78 percent), or the predictions concerning the productivity/labor input correlation and the variability of labor input relative to output will be incorrect.
  - ▷ A large magnitude of the aggregate intertemporal labor supply elasticity is not necessary for explaining the observed fluctuation in labor input. Hence some of the work in RBC modeling that has attempted to modify the basic growth model by increasing the intertemporal labor supply elasticity has been quite unnecessary. Instead, work should have focused on incorporating shocks other than technology into these models.
  - ▷ Contrary to the argument of Eichenbaum (1991), the contribution of technology shocks can be estimated fairly precisely.
- The point estimate of the contribution of technology shocks can be lower than 78 percent under alternative assumptions involving imperfect competition, external economies of scale, overtime wage premiums, and measurement errors (especially systematic errors in measuring labor input) while still resulting in correct predictions for the productivity/labor input correlation and the variability of labor input relative to output.

In view of the second implication, the argument of Prescott's critics that the contribution of technology shocks is much lower should be understood to imply some departure from the standard assumptions. I will conclude by suggesting that it may be possible to use empirical evidence from micro studies at the firm and household level to determine whether the standard assumptions or some alternative assumptions are appropriate. Thus it may be possible to narrow the range of disagreement regarding the contribution of technology shocks.

Problems With Measures Based on Real Business Cycle Models

Perhaps the best way to explain the problems with current RBC model–based measures of the importance of technology shocks is by analogy with the price and quantity determination in a single market, in terms of the usual supply/demand apparatus. Suppose that the supply and demand curves are being shifted by many random influences, one of these being random changes in technology. (For simplicity, I will assume that any particular shock affects either supply or demand, but not both, and that the various shocks are mutually independent.) Clearly, equilibrium price and quantity will be fluctuating randomly. A modeler of such a market, who is interested in how much technology shocks contribute to quantity fluctuations, could specify a supply/demand model in which only technology shocks enter (say, on the supply side), calculate the variance of quantity (which is a measure of how much quantity fluctuates in the model), express this as a ratio to the variance of quantity in the data, and report that as the contribution of technology shocks to quantity fluctuations. Let us call this ratio ϕ.

How would one defend the calculated value of ϕ as plausible? One possibility is to compare the model's predictions for the price/output correlation and the variance of price with the data. However, if ϕ is not close to unity, then such a comparison would not make sense since, admittedly, the model is omitting some shocks which are present in the data and which significantly affect the price/output correlation and the degree of price fluctuation. Therefore, there is no way to judge if the calculated value of ϕ is plausible or not. Further, given that the model is missing some quantitatively significant shocks, it would appear to be better if the model's predictions were wrong. But, again, there is no way to say by how much they would have to be wrong in order for the calculated value of ϕ to be right.

RBC models are basically similar to a supply/demand model except that the RBC analysis is of a general equilibrium nature and may include some shocks in addition to technology shocks. The RBC modeler specifies the technology and the preferences and endowments of the individuals in the model economy using particular functional forms and parameter values. These are used to calculate the unconditional variance of output in the model economy when only technology shocks are present. This is expressed as a fraction (denoted ϕ) of the variance of output in the U.S. economy, and ϕ is taken to be an estimate of the contribution of technology shocks to output fluctuation.

The view underlying many RBC models (certainly those with only technology shocks in them) seems to be that the models are missing quantitatively important sources of fluctuations.[6] As Prescott (1991, p. 6) has said, "To estimate the model is to implicitly assume that technology shocks are the only significant source of fluctuations. That is not a hypothesis we were willing to maintain." That is, under this view, a close match of model statistics with those in the data cannot be used to corroborate the calculated value of ϕ.[7] Indeed, as noted in the supply/demand example, it would appear to be better if the model statistics were not close to the values in the data. As Prescott has noted (1991, p. 6), "Mimicking is not always good." However, as noted earlier, for this to be useful in practice, one needs to know by how much the model statistics should miss those in the data. Since this is often not possible, it is difficult to evaluate the plausibility of these models and thereby defend the contribution of technology shocks implied by them.

The above comments apply also to the models of some of Prescott's critics. Sometimes the output variance generated by their models is significantly lower than that of the data, suggesting that their models are missing some shocks that explain the remaining portion of output variance. One cannot then defend the calculated value of ϕ by comparing model statistics with those in the data (using either informal or formal econometric methods), since it is hard to maintain that the data were (even approximately) generated by the model at hand.

As an example, consider the work of Burnside, Eichenbaum, and Rebelo (1993), who incorporate a labor hoarding feature (as suggested by Summers 1986) into an RBC model. Some versions of this model (with both technology shocks and government consumption shocks) generate output variance that is only 30–40 percent of that of U.S. data. (See the values of λ for "Labor Hoarding I" and "Laboring Hoarding II" in their Table 4.) Hence the contribution of technology shocks alone is implied to be even lower. On this basis, Burnside, Eichenbaum, and Rebelo (1993) argue that the contribution of technology shocks may be much lower than Prescott's figure. And yet they suggest (p. 255) that "the labor hoarding model does at least as well as the Hansen-Rogerson model at accounting for the volatility of hours worked and the relative volatility of consumption, investment, average productivity, and government consumption" (Hansen 1985, Rogerson 1988). Elsewhere (p. 260) they state, "Burnside et al. (1991) argue that the labor hoarding model is better able to account for the joint behavior of average productivity and hours worked than the standard model." It cannot be a good feature of a model that it matches various correlations in the data while missing shocks that account for possibly as much as 70 percent of output variance.[8]

Clearly, the contribution of technology shocks to business cycles calculated using RBC models is unsupported by corroborating evidence.

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[6]As Prescott (1986b, p. 29) notes in his response to Summers, "I only claim that technology shocks account for more than half the fluctuations in the postwar period, with a best point estimate near 75 percent. This does not imply that public finance disturbances, random changes in the terms of trade, and shocks to the technology of exchange had no effect in that period." Note that Prescott's model only has technology shocks in it.

[7]Comparing selected model statistics with those of the data appears to be a common practice. (See, for example, Kydland and Prescott 1982; Hansen 1985; Christiano and Eichenbaum 1990; Benhabib, Rogerson, and Wright 1991; and Burnside, Eichenbaum, and Rebelo 1993.) The typical statistics that these studies focus on are the standard deviations (relative to output) and cross-correlations (with output) of variables like consumption, investment, labor input, and productivity. However, it may be possible to compare aspects of the model's predictions which are somewhat insensitive to the shocks that are not included. For instance, one may try to compare impulse response properties of the model (for those shocks that are included) with those in the data. This is the method adopted by King (1991) and Rotemberg and Woodford (1992). Of course, the assumption that the impulse responses for the included shocks are somewhat insensitive to the shocks the model is abstracting from is essential, but without this, the only alternative is to try to include all the shocks one thinks are important. In that case, there is no advantage to looking at impulse responses, as opposed to looking at standard deviations and cross-correlations.

[8]In fact, in RBC models, there is no guarantee that the contribution of technology shocks will come out to be at most 100 percent; that is, one may be led to the nonsensical conclusion that technology shocks account for a lot more than 100 percent of output fluctuations. For an example of this, see Burnside, Eichenbaum, and Rebelo 1992. They consider the Hansen (1985) model with technology shocks and government consumption shocks. As can be seen from their Table 5 (columns labeled "Hansen-Rogerson"), the ratio of output variance generated by the model (with both shocks) to that of U.S. data (denoted by λ in the table) may be as high as 168 percent. Since government consumption shocks contribute negligibly to output variance, I can conclude that in these examples technology shocks contribute significantly more than 100 percent to output variance. (Compare values of λ for variable government and constant government in Eichenbaum 1991, Table 1.) Even if the contribution of technology shocks alone is less than 100 percent, the fact that technology and government consumption shocks together generate much more output variance than in the data makes the model unattractive.

A Simpler Method of Measuring

Here I will present a different and much simpler method that is based on a variance decomposition procedure, imposes a minimum of theoretical structure on the data, uses only information on contemporaneous correlations, and does not rely on measures of Solow residuals.[9] This is in contrast to the elaborate dynamic theoretical structure imposed in RBC modeling methods and the use of measured Solow residuals.

In my method, a lower bound for the contribution of technology shocks is derived by calculating the relative strength of technology versus other shocks, which is required to match two key features of the data: the contemporaneous productivity/labor input correlation and the variability of labor input relative to output. (These two numbers determine all the other standard deviations and cross-correlations among the three variables: output, labor input, and productivity.) The intuition behind how the observed values of the productivity/labor input correlation and the variability of labor input relative to output can be used to deduce the contribution of technology shocks and nontechnology shocks to business cycles is as follows. Suppose, for the sake of illustration, that the production technology satisfies diminishing returns to labor input. If nontechnology shocks were the only source of fluctuations, then clearly labor input would fluctuate more than output, and the productivity/labor input correlation would be close to negative unity. If technology shocks were the only source of fluctuations, however, then labor input would generally fluctuate less than output, and the productivity/labor input correlation would be close to unity. Therefore, the empirically observed values of these two statistics can be used to deduce the relative strengths of technology versus nontechnology shocks and hence the contribution of technology shocks to business cycles.[10]

There are three key steps in my analysis. The first is the specification of technology. This is specified as

$$(1)\qquad y_t = \alpha(n_t + z_t)$$

for $\alpha > 0$, where y_t, n_t, and z_t denote the logarithms of these economywide variables in period t: output, labor input, and technology level, respectively.

The essential features of equation (1) are omission of capital input and log-linearity. Effectively, capital is being treated as a fixed input so that its role in production need not be specified. This is justified by appealing to the following fact.

FACT 1. *Movements in capital are small and contribute negligibly to movements in output over short periods of time corresponding to the length of a typical business cycle.*[11]

The log-linear specification may be justified as a locally valid approximation to the production function.[12]

The second key step of my analysis is the following representation of the effects of technology and other shocks on labor input:

$$(2)\qquad n_t = \delta_0 z_t + \sum_{j=1}^{\infty}\delta_j z_{t-j} + \sum_{j=0}^{\infty}\xi_{1j}x_{1,t-j} + \sum_{j=0}^{\infty}\xi_{2j}x_{2,t-j} + \sum_{j=0}^{\infty}\xi_{3j}x_{3,t-j} + \dots$$

where $x_{1,t}$, $x_{2,t}$, $x_{3,t}$, and so on, are the different nontechnology shocks in period t. Equation (2) may be thought of as the decision rule for labor input resulting from some dynamic equilibrium model.[13] The specification in (2) is quite general (except for the log-linearity) since labor input in a period depends on all current and past values of random shocks to the economy.

I will assume that the nontechnology shocks are uncor-

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[9]The Solow residual in period t is defined as $\exp[y_t - \theta_k k_t - \theta_n n_t]$, where y_t, k_t, and n_t are the logs of output, capital, and labor input in period t, respectively, and θ_k and θ_n are the shares of capital and labor income in output. Under some assumptions, the Solow residual in period t coincides with the technological change index. (See Solow 1957.)

[10]The definition of business cycle fluctuations used here is that of Hodrick and Prescott (1980). That is, the correlations from the data that I will use are calculated using the deviations of the logarithms of output, labor input, and productivity from their respective Hodrick-Prescott trends. The main reason for this is to maintain comparability with RBC studies since this is a commonly used procedure in most RBC studies. In general, the contribution of technology shocks can differ based on the detrending procedure used. By using the Hodrick-Prescott definition of business cycle fluctuations, I am implicitly measuring the contribution of technology shocks at the frequencies emphasized by this detrending procedure. The way this difference will show up in my framework is that the values of the correlations that are used will generally differ with different detrending procedures.

[11]Empirically, most short-run fluctuations in output are due to fluctuations in the labor input, and fluctuations in capital are small. According to postwar U.S. data (Hansen 1985, Table 1), the correlation between output and capital stock is 0.04; that is, movements in output and capital are almost unrelated over short periods of time. Further, the standard deviation of capital relative to that of output is only 0.36, compared to 0.94 for the standard deviation of labor input relative to that of output (Hansen 1985, Table 1).

[12]The specification in (1) can be consistent with variable capacity utilization as long as capacity utilization varies one-for-one with the labor input. Note that I have not restricted the value of α to be less than unity, which corresponds to diminishing returns. Diminishing returns may be reasonable even with variable capacity utilization if increasing labor input (and capacity utilization) leads to more frequent breakdowns of capital equipment and larger (total and marginal) maintenance expenditures, so that output net of maintenance expenditures is subject to diminishing returns.

[13]One such example is Kydland and Prescott 1982, in which past leisure is used as an argument in the utility function. The effects of lagged z's are absent in the simpler models of Hansen (1985) and Christiano and Eichenbaum (1990).

related with the technology shock at all leads and lags. I will interpret the $x_{i,t}$'s as either innovations in other exogenous nonpolicy variables (like the weather) or as policy shocks, that is, shocks in the decision rules for policy variables. Under this interpretation, my assumption is reasonable.[14]

The third key step of my analysis is to decompose the influences on labor input into two mutually orthogonal parts: one arising from the current technology shock and the other capturing everything else that is uncorrelated with the current technology shock. Using this idea, I can rewrite equation (2) as

$$(3) \qquad n_t = \gamma z_t + \zeta_t$$

where

$$(4) \qquad \gamma = \text{cov}(n_t,z_t)/\text{var}(z_t) = \delta_0 + \sum_{j=1}^{\infty} \delta_j \text{cov}(z_t,z_{t-j})/\text{var}(z_t)$$

$$(5) \qquad \zeta_t = \omega_t + x_t$$

$$(6) \qquad \omega_t = \sum_{j=1}^{\infty} \delta_j z_{t-j} - z_t\Big[\sum_{j=1}^{\infty} \delta_j \text{cov}(z_t,z_{t-j})\Big] \Big/ \text{var}(z_t)$$

$$(7) \qquad x_t = \sum_{j=0}^{\infty} \xi_{1j} x_{1,t-j} + \sum_{j=0}^{\infty} \xi_{2j} x_{2,t-j} + \sum_{j=0}^{\infty} \xi_{3j} x_{3,t-j} + \ldots$$

Note that ζ_t is uncorrelated with z_t; that is, $\text{cov}(\zeta_t,z_t) = 0$, because ω_t and x_t are uncorrelated with z_t. Consequently, the variance of output is also decomposed into two mutually orthogonal parts: one arising from variability in the current technology shock and the other from everything else that is uncorrelated with the current technology shock. In this way, the large number of unknown coefficients (δ_j) and the variance of x relative to z are replaced by a single unknown coefficient γ and the variance of ζ relative to that of z. To show how these latter two objects can be determined, let π denote the logarithm of labor productivity so that

$$(8) \qquad \pi_t \equiv y_t - n_t = \alpha z_t - (1-\alpha)n_t = [\alpha - (1-\alpha)\gamma]z_t - (1-\alpha)\zeta_t$$

and let

$$(9) \qquad q = \text{var}(\zeta)/\text{var}(z)$$

$$(10) \qquad \rho = \text{corr}(\pi_t,n_t)$$

$$(11) \qquad \sigma = [\text{var}(n_t)/\text{var}(y_t)]^{1/2}.$$

Using equations (1), (3), (8), and (9), I can derive the following expressions for ρ and σ:

$$(12) \qquad \rho^2 = \{\gamma[\alpha - (1-\alpha)\gamma] - (1-\alpha)q\}^2 \div ((\gamma^2+q)\{[\alpha - (1-\alpha)\gamma]^2 + (1-\alpha)^2 q\})$$

$$(13) \qquad \sigma^2 = (\gamma^2+q)/\{\alpha^2[(1+\gamma)^2 + q]\}.$$

If I have a value for the parameter α in (1), then equations (12) and (13) can be used to find values of γ and q, such that the resulting values of ρ and σ will match the values in the data. These values of γ and q can then be used in the following way to calculate a lower bound (denoted ϕ^*) for the contribution of technology shocks.

Let $\text{var}(y|x)$ denote the variance of output conditional on the x-shocks; equivalently, it is the variance of output when only technology shocks are present. Let $\text{var}(y)$ denote the variance of output when technology shocks as well as other shocks are present. Then a measure of the contribution of technology shocks to output fluctuation is given by $\text{var}(y|x)/\text{var}(y)$ and is denoted by ϕ. It can be seen that ϕ takes the value unity if all of the variation in output is due to technology shocks and the value zero if all of the variation in output is due to other shocks. The expression for ϕ is given as

$$\begin{aligned}(14) \qquad \phi &= \text{var}(y|x)/\text{var}(y) \\ &= \alpha^2[(1+\gamma)^2\text{var}(z) + \text{var}(\omega)] \div \{\alpha^2[(1+\gamma)^2\text{var}(z) + \text{var}(\zeta)]\} \\ &> (1+\gamma)^2\text{var}(z)/[(1+\gamma)^2\text{var}(z) + \text{var}(\zeta)] \\ &= (1+\gamma)^2/[(1+\gamma)^2 + \text{var}(\zeta)/\text{var}(z)] \\ &= (1+\gamma)^2/[(1+\gamma)^2 + q] \\ &\equiv \phi^*.\end{aligned}$$

The intuition described earlier in this section can be seen in the above equations. Suppose, for simplicity, that lagged z's are absent in (2) so that $\gamma = \delta_0$, $\omega_t = 0$, and $\zeta_t = x_t$. (For examples, see the model of Hansen 1985 and the basic growth model of Prescott 1986a.) Note that $\phi =$

[14]If some of the x's represent policy shocks (such as a shock to the policy rule for government consumption), then the implicit view underlying this assumption is that any correlation between corresponding policy variables (government consumption) and the technology shock is due to endogenous policy rather than the effects of policy variables on technology. That is, that part of the effect of government consumption on labor input that is due to the correlation between government consumption and the technology shock is taken to be the result of endogenous policy and is attributed to the technology shock. Some assumption of this sort is necessary in order to talk about the contribution of technology shocks.

ϕ^* in this case. If nontechnology shocks were the only source of fluctuations, then $\phi = 0$ and $q = \infty$, and (12) and (13) would imply that $\rho = -1$ and $\sigma = 1/\alpha$. If returns to labor input are diminishing so that $\alpha < 1$, then $\sigma > 1$. Thus the productivity/labor input correlation is negative unity, and labor input fluctuates more than output. If technology shocks were the only source of fluctuations, then $\phi = 1$ and $q = 0$, and (12) and (13) would imply that $\rho = 1$ and $\sigma = \gamma/[\alpha(1+\gamma)]$.[15]

In the general case, the values of γ and q calculated using (12) and (13) can be used in (14) to calculate ϕ^*, which provides a lower bound for ϕ (the fraction of output variance arising from technology shocks).

Implications Under Standard Assumptions

I will now implement this method under the following standard assumptions (common in many RBC models) and facts regarding the U.S. economy.

ASSUMPTION 1. *Perfect Competition*
Product and labor markets are competitive; that is, firms behave as price takers in product as well as labor markets.

ASSUMPTION 2. *No External Economies*
The response of output to labor input is the same at the individual firm and the economywide levels and exhibits diminishing returns to labor.

ASSUMPTION 3. *No Measurement Errors*
There are no (significant) measurement errors in output or labor input.

FACT 2. *The correlation between productivity and labor input* (ρ) *is about zero.*[16]

FACT 3. *The variability of labor input relative to output* (σ) *is about* 0.85.[17]

FACT 4. *The share of labor income in output, denoted* θ, *is about* 0.64.

By virtue of Assumptions 1 and 2 and profit maximization, it follows that α equals the labor share and hence is about 0.64.[18] Using this value for α, I display in Chart 1 graphs of ϕ^* (the lower bound on the contribution of technology shocks) versus ρ (the productivity/labor input correlation) for three different values of σ (the relative variability of labor input).[19]

I will now display the various implications of my method under standard assumptions (Assumptions 1–3). Later I will display the implications of several alternative assumptions.

Large Technology Shock Contribution

First, I will show that under the standard assumptions, any RBC model must either yield a large contribution of technology shocks (above 78 percent) or make counterfactual predictions concerning the productivity/labor input correlation and the variability of labor input relative to output. This follows from two considerations. First, when $\rho = 0$ and $\sigma = 0.85$ (as dictated by Facts 2 and 3), Chart 1 indicates (and my calculations confirm) that $\phi^* = 0.78$. Second, my value for ϕ^* is constructed under the standard assumptions and in such a way that the values of ρ and σ match those in the data. Now recall that ϕ^* is a lower bound for ϕ, the contribution of technology shocks to output fluctuations. Therefore, under the standard assumptions, the contribution of technology shocks to output variation must be at least 78 percent, or the values of ρ and σ from the model will not match the values in the data.

Using my method, I can also show that the contribution of technology shocks was likely lower in the 1950s and 1960s than in the 1970s and 1980s. Many economists have noted that the latter two decades were more subject to adverse supply shocks than were the former. Some examples are the oil price shocks of 1973 and 1979 and the

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[15]In the typical RBC model, since the technology shock is fairly persistent, γ is small, which leads to the usual result that σ is significantly less than unity. Thus the productivity/labor input correlation is unity, and labor input fluctuates less than output.

[16]Christiano and Eichenbaum (1990) and Baxter and King (1991) report point estimates of ρ equal to –0.20 and –0.04, respectively (using slightly different time series). My own calculation, based on data from the first quarter of 1950 to the fourth of 1988, yields a value of –0.13. The standard error of 0.11 reported in Christiano and Eichenbaum 1990, Table 4a, suggests that one cannot reject, at the 5 percent level, the hypothesis that ρ is zero.

[17]Hansen (1985) and Prescott (1986a) report point estimates for σ of 0.94. Christiano and Eichenbaum (1990), Baxter and King (1991), and Benhabib, Rogerson, and Wright (1991) report the value 0.85. Kydland and Prescott (1993) suggest that if differences in the quality of various types of labor input are taken into account, then the relative variability of labor input may be reduced by a factor of 0.75; that is, it may be as low as 0.64.

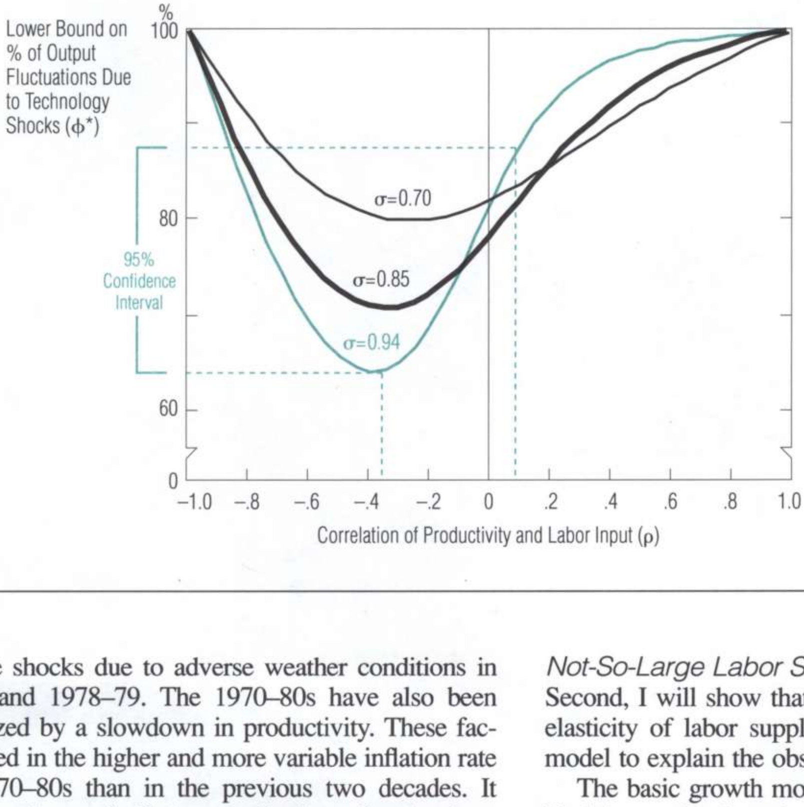
[18]The technology in (1) can be written as $Y = (ZN)^{\alpha}$, where Y, Z, and N are output, level of technology, and labor input, respectively. Profit maximization implies that the marginal product of labor equals the real wage (denoted W), so that $\alpha(ZN)^{\alpha-1}Z = W$. Therefore, the labor share $\theta \equiv WN/Y = \alpha$.

[19]It may seem puzzling that the relation between ϕ^* and ρ is not monotonic and that when ρ is sufficiently negative, ϕ^* starts getting close to unity. For instance, when ρ equals negative unity, it would seem that ϕ^* ought to be zero, since with only nontechnology shocks, labor input and productivity would be perfectly negatively correlated. However, with only nontechnology shocks, it is not possible to match the value of σ because in this case the model implies $\sigma = 1/\alpha$, which is a lot bigger than the empirical value of σ. The way to match both ρ and σ is to have only technology shocks and a negative value of γ; that is, labor input has to vary negatively with the technology shock so that productivity and labor input move in opposite ways. This is the reason why ϕ^* starts rising toward unity when ρ gets closer to negative unity. As can be seen in Chart 2, the value of γ turns negative at exactly the same value of ρ at which the value of ϕ^* reaches a minimum.

Chart 1

Estimating How Much Technology Shocks Contribute to Output Fluctuations

Based on Standard Assumptions in Real Business Cycle Models and U.S. Data in 1950–88 for Likely Range of Variability of Labor Input Relative to Output (σ)



food price shocks due to adverse weather conditions in 1973–74 and 1978–79. The 1970–80s have also been characterized by a slowdown in productivity. These factors resulted in the higher and more variable inflation rate in the 1970–80s than in the previous two decades. It seems natural to ask if the contribution of technology shocks might also have been higher in the 1970–80s.[20] Using quarterly data, I have calculated the values of ρ and σ separately for the periods 1952–69 and 1970–88 and found that in the former period, ρ was about -0.40 and σ was about 1.05, whereas in the latter period, ρ was about 0 and σ was about 0.90. Clearly, the productivity/labor input correlation was significantly more negative in 1952–69, which suggests that the contribution of technology shocks could have been lower then. (See Chart 1.) Using the above values of ρ and σ, my calculations indicate that the contribution of technology shocks could have been as low as 55 percent in 1952–69 compared to 79 percent in 1970–88.

Not-So-Large Labor Supply Elasticity

Second, I will show that a large aggregate intertemporal elasticity of labor supply is not necessary for an RBC model to explain the observed fluctuation in labor input.

The basic growth model with log-linear utility, divisible labor, and only technology shocks (Prescott 1986a, p. 16) has been considered deficient for two reasons:

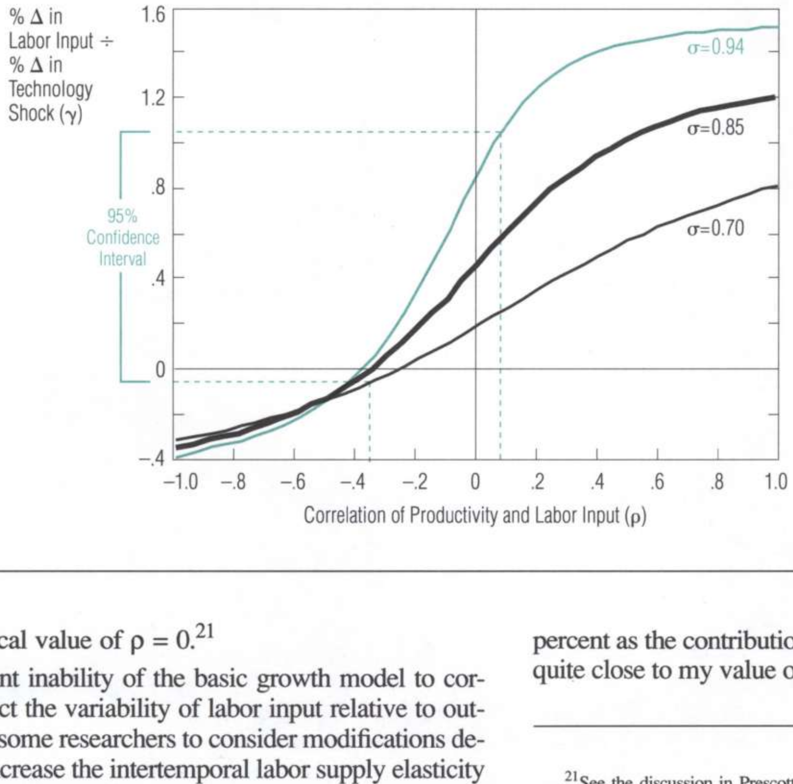
- The model leads to labor input varying only about half as much as output compared to the empirical value of $\sigma = 0.85$.
- The model also leads to a productivity/labor input correlation that is close to unity as compared to the

[20]An oil price rise may be regarded as an adverse technology shock since it reduces oil input in production and, when oil and labor input are complements, reduces the amount of output that can be produced for a given level of labor input. Thus an oil price rise has the same effect as a reduction in z in equation (1) specifying the technology.

Chart 2

Labor Input's Response to a Technology Shock

Based on Standard Assumptions in Real Business Cycle Models and U.S. Data in 1950–88
for Likely Range of Variability of Labor Input Relative to Output (σ)



empirical value of $\rho = 0$.[21]

The apparent inability of the basic growth model to correctly predict the variability of labor input relative to output has led some researchers to consider modifications designed to increase the intertemporal labor supply elasticity and thereby increase the variability of labor input relative to output. For instance, Kydland and Prescott (1982) consider past leisure as an argument in agents' utility functions, and Hansen (1985) considers indivisible labor.[22]

However, I will show that these modifications to increase the aggregate intertemporal labor supply elasticity were unnecessary. Refer to Charts 1 and 2, and note that when ρ is zero and σ is 0.85, the values of γ and ϕ^* based on my method are 0.44 and 78 percent, respectively. Also note that the basic growth model maintains the standard assumptions. The value of γ for a version of the basic growth model is 0.45, which is close to my value of γ. (See Campbell 1991, Table 2, where v_2 stands for γ and a stands for z.) Further, the basic growth model yields 75 percent as the contribution of technology shocks, which is quite close to my value of ϕ^*.[23] Therefore, I can conclude

[21]See the discussion in Prescott 1986a, pp. 16–20. Regarding the basic growth model, Prescott notes, "The most important deviation from theory is the relative volatility of hours and output." Also note that the observation that the "empirical labor elasticity of output" (Prescott 1986a, p. 19) is approximately unity (and hence significantly higher than the labor share) is equivalent to the observation that the productivity/labor input correlation is approximately zero. This follows because $\eta = \text{cov}(n,y)/\text{var}(n) = [\text{cov}(n,\pi) + \text{var}(n)]/\text{var}(n)$. This has also been noted by Christiano and Eichenbaum (1990).

[22]The basic growth model of Prescott (1986a) implies an elasticity of labor supply with respect to a temporary change in the real wage of 2. The Kydland and Prescott (1982) model implies a value of over 6 for the corresponding elasticity, and the indivisible labor model of Hansen (1985) implies a value of infinity for this elasticity. See Prescott 1986a, pp. 14–19.

[23]If somewhat different parameter values for preferences, and the like, are used, then the value of γ for such a model could range from 0.24 to 0.49. Christiano and Eichenbaum (1990, Table 2) report values of 0.30 and 0.49. (The coefficient e_n corresponds to my γ.) Campbell (1991, Table 2) reports a value of 0.24. However, these alternative values can be quite consistent with my analysis. As I will show momentarily, given the sampling variability in the values of ρ and σ, values of γ ranging from 0.23 to 0.49 can also provide quite a good match with the data.

that the basic growth model is quite capable of matching features of the data regarding output, labor input, and productivity, once nontechnology shocks are included.

The intuition behind this conclusion is simple. Recall that with only technology shocks, the basic growth model predicts a productivity/labor input correlation near unity and one-half as much variability in labor input relative to output.[24] Adding in shocks to something other than technology—which I will call the *x-shocks*—serves to bring both of these model statistics close to the empirical values. The *x*-shocks make productivity and labor input move in opposite directions and serve to bring their correlation down to about zero. The *x*-shocks also make labor input vary more than output, because the parameter α in equation (1) is less than unity; a 1 percent change in labor input due to the *x*-shocks will change output by less than 1 percent. Thus the *x*-shocks raise the relative variability of labor input toward the value implied by the data.

It follows that attempts to modify the basic growth model by increasing the intertemporal elasticity of labor supply were unnecessary. Instead, work should have focused on incorporating shocks other than technology into the model.

More Measurement Precision

I will now show that under the standard assumptions, and contrary to Eichenbaum's (1991) argument, the contribution of technology shocks can be estimated fairly precisely. To demonstrate this, I can use Chart 1, since it is constructed by forcing the model's predictions for ρ and σ to match the values in the data. I take the 95 percent confidence interval for ρ to be [–0.35, 0.09] and the 95 percent confidence interval for σ to be [0.70, 0.94].[25] As ρ ranges from –0.35 to 0.10 and σ ranges from 0.70 to 0.94 (in Chart 1), the values of ϕ^* range, roughly, from 0.65 to 0.90.[26] While there is some uncertainty regarding the value of ϕ due to sampling variability in the values of ρ and σ, the extent of uncertainty in ϕ is much less than has been suggested by Eichenbaum (1991).

Eichenbaum (1991) argues that there is a considerable degree of imprecision attached to Prescott's measure of the importance of technology shocks due to sampling variability in some of the estimated parameters. (See Eichenbaum 1991, Table 1, Figure 1, and the accompanying discussion on p. 614.) Referring to a model in which technology shocks are the only shocks, he writes that (p. 614) "we ought to be very comfortable believing that the model explains *anywhere* between 5% and 200% of the variance in per capita US output." This conclusion ignores the mismatch between the model's predictions for ρ and σ and the values in the data that will result if the contribution of technology shocks is too low or too high.[27] Ignoring values over 100 percent as inadmissible, consider the possibility that the contribution of technology shocks could be as low as 5 percent (or as high as 95 percent). In order to entertain this possibility, one would also have to entertain the possibility that when other shocks that account for the remaining 95 percent (or 5 percent) of output variance are put into the model, the values of ρ and σ will match those in the data. In fact, my calculations show that this cannot happen. When proper attention is paid to matching the model's predictions for ρ and σ with the values in the data, the sampling variability in ϕ is much lower.

Implications Under Alternative Assumptions

In this section, I will show how the contribution of technology shocks can be lower than 78 percent under several alternative assumptions considered in the literature while still resulting in correct predictions for ρ and σ. I will consider the following alternatives to the standard assumptions:

- Monopolistic competition in product markets.
- External economies of scale.
- Overtime wage premiums.
- Monopsonistic competition in labor markets.
- Errors in the measurement of output and labor input.

Note that Assumptions 1 and 2 together with Fact 4 were only used in deriving an estimate of the parameter α and that the first four alternatives involve changing either Assumption 1 or Assumption 2. Therefore, I only need to analyze how those alternatives will change the value of α. Then this value of α can be used to calculate γ and ϕ^* just as before. In each case, the result will be to

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[24] The productivity/labor input correlation will be near unity, provided γ is between zero and $\alpha/(1-\alpha)$. As noted earlier, negative values of γ will lead to a negative productivity/labor input correlation. (See Charts 1 and 2.)

[25] I use the standard errors for ρ and σ reported in Christiano and Eichenbaum 1990, Table 4a, of 0.11 and 0.06, respectively, along with the point estimates of –0.13 and 0.85, respectively.

[26] It is also possible to take account of sampling error in the measurement of labor share in output which is used to calculate α. However, the standard error reported in Christiano and Eichenbaum 1990, Table 1a, suggests that the labor share is determined quite precisely. Values of θ are unlikely to be outside the range from 0.63 to 0.65.

[27] The models of Hansen 1985 and Prescott 1986a have the feature that ϕ^* and ϕ coincide because lagged values of z do not appear in the labor input decision rule. [See equation (2).]

deliver a higher value of α, which turns out to lower the value of ϕ^*.

Monopolistic Competition

Suppose that firms are monopolists in the product markets and face a downward-sloping demand curve with price elasticity equal to η. Then profit-maximizing behavior on the part of firms implies that firms will equate the marginal revenue product of labor to the real wage. It follows that θ, the share of labor income in output, equals $\alpha[1 - (1/\eta)]$. As can be seen, a particular value of the labor share will imply a higher value of α under monopolistic competition as compared to perfect competition ($\eta = \infty$).

In order to come up with a value for α, I will also need to have some idea of the elasticity of demand in product markets. Work by Hall (1987, 1988) suggests that values of η range from about 2 to about 6 depending on the industry. If I take 4 as a benchmark value for η, then using the value of 0.64 for the labor share, I find that α must be about 0.85. Using this value, my calculations indicate that when $\rho = 0$ and $\sigma = 0.85$, the value of $\phi^* = 0.54$. Thus taking account of monopolistic competition can lower the contribution of technology shocks.

External Economies of Scale

Here I relax the part of Assumption 2 which states that the relation between output and labor input is the same at the individual firm level as well as the economywide level. In particular, I assume that the production technology at the firm level exhibits external economies of scale. Baxter and King (1991) argue that such external economies may be important and have presented some evidence in support of this view. The following formulation of individual firm technology is borrowed from their paper:

$$(15) \quad y_t(f) = \varepsilon y_t + \alpha'[n_t(f) + z_t]$$

where $y(f)$ and $n(f)$ represent the logarithms of individual firm output and individual firm labor input, respectively, and ε represents the effect of external economies.

Assuming that all firms are identical, I can aggregate the above relationship over all firms [by setting $y(f)$ and $n(f)$ equal to y and n, respectively] and obtain the following relationship between aggregate output and aggregate labor input:

$$(16) \quad y_t = [\alpha'/(1-\varepsilon)](n_t+z_t).$$

By comparing (16) and (1), I find that

$$(17) \quad \alpha = \alpha'/(1-\varepsilon).$$

Note that according to the technology in (15) and (16), when markets are competitive, α' equals the labor share of income, which I have taken to be 0.64. Therefore, equation (17) implies that $\alpha > \alpha' = 0.64$. In order to come up with a value for α, I will now need to have an estimate for ε in addition to θ, the share of labor income in output. Baxter and King (1991) discuss the existing empirical evidence regarding ε and use a value of $\varepsilon = 0.23$, which if combined with a labor share of 0.64 yields a value of $\alpha = 0.83$. This is very close to the value of 0.85 for α that was used in the monopolistic competition case. Therefore, I can conclude that when $\rho = 0$ and $\sigma = 0.85$, the value of $\phi^* \cong 0.54$. Thus taking account of external economies of scale can also lower the contribution of technology shocks to output fluctuation.

Overtime Wage Premiums

Lucas (1970) suggests that the real wage may be procyclical even in the absence of any technology shocks if overtime labor is more expensive to hire than normal straight-time labor. One way to capture this in my framework is to assume that the firm faces an upward-sloping schedule relating the marginal wage to labor input.[28] Like the previous two factors, this factor causes an increase in the value of α to be used in my calculations and thereby reduces the contribution of technology shocks.

To see this, let $w(s)$ be the (increasing) marginal wage paid when labor input is s. Let

$$(18) \quad \kappa = Nw(N) \Big/ \Big[\int_0^N w(s)ds \Big]$$

be the elasticity of the total wage bill with respect to total labor input (denoted N). From profit maximization, the marginal product of labor (denoted MPL) equals $w(N)$. Therefore, the labor share of output is

$$\begin{aligned}(19) \quad \theta &= \Big[\int_0^N w(s)ds \Big] \Big/ Y \\ &= Nw(N)/(\kappa Y) \\ &= [(N \times MPL)/Y]/\kappa.\end{aligned}$$

Using the form of the production function (1), I then have

[28]Recall (from footnote 12) the interpretation of the production function (1) as arising from a fixed coefficients technology with possible diminishing returns to higher-capacity utilization.

$\theta = \alpha/\kappa$. Since $w(\cdot)$ is increasing, $\kappa > 1$ and therefore $\alpha > \theta$. Hence the contribution of technology shocks can be lower. To say how much lower, I would need an estimate of the elasticity parameter κ.[29]

Monopsonistic Competition

The analysis is similar under monopsony. To see this, let ψ be the elasticity of the wage with respect to the labor input. Profit-maximizing behavior on the part of the firm now implies that the firm will set the marginal product of labor to equal $W \times (1+\psi)$, where W is the wage. Therefore, the share of labor income in firm output is

$$\theta = WN/Y = [(N \times MPL)/(1+\psi)]/Y = \alpha/(1+\psi). \quad (20)$$

It follows that a given value of the labor share, θ, will now imply a larger value of α if ψ is positive. Therefore, the contribution of technology shocks can be lower. To go beyond this and say how much lower, I would need an estimate of the elasticity parameter ψ.

Measurement Errors

In Assumption 3, I assumed that output and labor input were measured without error. Here I address departures from this assumption. There are three types of measurement errors: sampling errors, unsystematic measurement errors, and systematic measurement errors. I have already covered sampling error in my discussion of Eichenbaum's (1991) criticism of the models of Hansen (1985) and Prescott (1986a). Here I will discuss the other types of measurement errors.

□ *Unsystematic*

Several researchers argue that unsystematic measurement errors, especially in the measurement of labor input, may be quite important (Hansen 1985, Prescott 1986a, and Christiano and Eichenbaum 1990). Unsystematic measurement error in labor input will result in an overstatement of the relative variability of labor input (σ) and an understatement of the productivity/labor input correlation (ρ). That is, the measured relative variability will be higher than the true variability, and the measured correlation will be less than the true correlation. Since the measured correlation is about zero, the true correlation is positive. This suggests that the contribution of technology shocks can be even greater than my calculations indicate. (See Chart 1.) The overstatement of the relative variability of labor input has an ambiguous effect.

Unsystematic measurement error in output also affects both the productivity/labor input correlation and the relative variability of labor input. If labor input is measured accurately, unsystematic measurement error in productivity is introduced and the magnitude of the productivity/labor input correlation is reduced without affecting its sign. Thus the measured correlation is biased toward zero. It follows that if the measured correlation is positive, then the true correlation will be higher and thereby imply a larger value of ϕ^* than before. (See Chart 1.) Conversely, if the measured correlation is negative, then the true correlation will be more negative and imply a smaller value of ϕ^* than before. (Again, see Chart 1.)[30]

Unsystematic measurement error in output also makes the measured relative variability of labor input smaller than the true one, since the measured variability of output is larger. Therefore, on this account also, it suggests that the value of ϕ^* may be smaller than before.[31] In order to go beyond this, I would need some idea of the likely extent of measurement error in output.

□ *Systematic*

I will now consider the impact of taking account of possible systematic measurement errors, especially in labor input. It has been observed by proponents of theories of labor hoarding (such as in Summers 1986) that labor hoarding leads to systematic measurement errors in labor input, which could explain the relevant facts concerning measured output, measured labor input, and measured productivity without any technology shocks. Labor hoarding can be captured in a simple way by positing that the variation in measured labor input is smaller than that in actual labor input. Suppose that due to a systematic measurement error of this type, a 1 percent change in actual labor input translates into only a λ percent change in measured labor input, where λ is less than one.[32] Now let

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[29]In the fixed coefficients example, Lucas (1970) takes α to be known and equal to unity and uses his theory to show that the labor share θ can be less than α and that the real wage (which equals the labor share) can be procyclical. The alternative considered here is to treat α (reflecting the extent of diminishing returns to capacity utilization) as unknown and use the observed value of θ and an estimated value of κ to calculate α.

[30]The 95 percent confidence interval for the productivity/labor input correlation shows that this correlation is quite possibly negative and may be as low as –0.35. Therefore, measurement error in output implies that the true productivity/labor input correlation would be lower than –0.35, that is, even more negative.

[31]Compare the values of ϕ^* in Chart 1 corresponding to ρ equal to –0.20 and σ equal to 0.70, 0.85, and 0.94, respectively. However, for slightly larger values of ρ, the relation between σ and ϕ^* is not necessarily monotonic. For still higher values of ρ, ϕ^* is increasing in σ.

[32]The dynamics of mismeasurement are being ignored here. In general, the extent of systematic mismeasurement can vary over the cycle and have implications for the dynamic correlations between measured productivity, measured output, and measured labor input. This would require looking not only at the contemporaneous correlations, as I do, but also at the dynamic correlations.

$$\text{(21)} \quad \alpha' = (\%\ \Delta \text{ in total output} \div \%\ \Delta \text{ in actual total labor input})_{z\,=\,\text{constant}}.$$

It follows from equations (1) and (21) that

$$\text{(22)} \quad \alpha = \alpha'/\lambda$$

for $0 < \lambda < 1$. As before, using Assumptions 1 and 2 and Fact 4, I can conclude that α' must equal the labor share, which is 0.64. However, as can be seen from equation (22), the implied value of α will be higher than this. As I demonstrated earlier in the discussion of monopolistic competition, higher values of α can lower the contribution of technology shocks.[33] In order to go beyond this, I would need an estimate of the parameter λ.

Summary

In this article, I have shown that under the standard assumptions of competitive markets, no external economies of scale, and no measurement errors, either the contribution of technology shocks must be large (at least 78 percent), or the predictions concerning the productivity/labor correlation (ρ) and the variability of labor input relative to output (σ) will be incorrect.

However, the point estimate of the contribution of technology shocks can be lower than 78 percent under alternative assumptions involving imperfect competition, external economies of scale, overtime wage premiums, and measurement errors (especially systematic errors in measuring labor input) while still resulting in correct predictions for ρ and σ. In view of this point, it follows that whether the contribution of technology shocks is large or small depends on a number of empirical questions concerning the extent of imperfect competition, external economies of scale, overtime wage premiums, and measurement errors in labor input and output. Consequently, in order to determine the exact contribution of technology shocks to aggregate fluctuations, one would need to have precise quantitative measures of each of the above factors. Currently, there exist some micro studies at the firm and household level which provide some empirical evidence regarding these factors. More work along these lines, especially with regard to accurate measurement of output and labor input, is likely to be very useful in narrowing the range of disagreement on the contribution of technology shocks to business cycles.

[33]Note that the monopolistic competition theory, the external economies theory, the overtime wage premiums theory, the monopsonistic competition theory, and the labor hoarding theory of systematic measurement error in labor input all work in the same fashion. The implications for the value of the parameter α (and hence for the value of ϕ^*) of these alternative assumptions are the same if the parameter λ in equation (22) equals $1 - (1/\eta)$ in the monopolistic competition theory, $1 - \varepsilon$ in the external economies theory, $1/\kappa$ in the overtime wage premiums theory, and $1/(1+\psi)$ in the monopsonistic competition theory.

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