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UNOBSERVED FACTOR UTILIZATION, TECHNOLOGY SHOCKS AND BUSINESS CYCLES

by Domenico J. Marchetti* and Francesco Nucci**

Abstract

We derive a measure of technological change using firm-level panel data and controlling for imperfect competition, increasing returns and unobserved factor utilization. We show that the latter variable accounts for a relevant portion of the cyclicality of the Solow residual. Our key finding is that technological shocks result in a contraction of inputs on impact. Whilst this result is hard to reconcile with the transmission mechanism of real business cycle models, it is consistent with simple sticky-price models**.** Using survey information on the frequency and size of price revisions, we show that the evidence on the contractionary effects of technology shocks is indeed much stronger for firms with stickier prices.

JEL classification: D24, E32.

Keywords: factor hoarding; technology shocks; business cycles.

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1. Introduction[1]

The procyclicality of productivity is a firmly established stylized fact of industrialized economies. Yet, assessing the source of such cyclical behavior remains an open issue, which has crucial implications for understanding the main impulses and propagation mechanisms underlying business cycles. Indeed, appraising the empirical relevance of each different explanation of the short-run behavior of productivity helps considerably in the evaluation of alternative macroeconomic models.

The basic mechanism underlying the standard Real Business Cycle model (RBC) suggests that business fluctuations are driven by exogenous technology shocks, which thus explain the cyclical behavior of productivity (e.g., Prescott, 1986; Cooley and Prescott, 1995). Another explanation, which dates back at least to Solow (1964), hinges on variations of unobserved factor utilization over the cycle. In this interpretation, the cyclical pattern of measured productivity originates endogenously from fluctuations in inputs and output.[2] It is argued that significant adjustment costs concerning both hiring and capital accumulation induce a form of factor hoarding, so that firms utilize inputs more intensively in booms than in recessions. Reported measures of labor and capital inputs do not properly consider the movements in effective input services, causing a cyclical mismeasurement in the standard Solow residual. A third explanation of procyclical productivity is advanced by Hall (1988; 1990) and is based on imperfect competition and increasing returns.[3]

It is important to recognize, however, that the different explanations of the procyclical behavior of productivity are not mutually exclusive. For example, increasing concern about the

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[2] Recent contributions include Gordon (1990), Bernanke and Parkinson (1991), Burnside, Eichembaum and Rebelo (1993), Basu (1996), Burnside and Eichembaum (1996), Sbordone (1996; 1997), Basu and Kimball (1997) and Imbs (1999).

[3] Among the other possible sources of procyclical productivity, Caballero and Lyons (1990; 1992) emphasize the role of productive spillovers operating at the firm level stemming from aggregate activity (increasing returns external to the firm), whereas Basu and Fernald (1997) ascribe part of the procyclicality to a reallocation of inputs during booms to more productive firms and industries.

reliance of early RBC models on large-scale, highly volatile technology shocks led scholars in the RBC tradition to augment the basic framework with non-technology shocks or with features that would act as an amplification mechanism, such as variable factor utilization. Indeed, when account is taken of the latter element, the remeasurement of technology impulses in RBC models seems to yield more plausible first and second moments as compared with the Solow residual, and a lower probability of technological regress (Burnside and Eichenbaum, 1996, and King and Rebelo, 2000).

The fact that unobservable factor utilization and other elements have been successfully incorporated into RBC models makes it harder to assess the empirical relevance of competing views of the business cycle on the basis of the procyclical productivity puzzle. However, a new test has been recently suggested in the literature. Basu, Fernald and Kimball (1998) and Galì (1999) have provided evidence that favourable technology shocks reduce input use on impact. The empirical finding of a negative short-run relationship between inputs and technology shocks is hard to reconcile with the RBC paradigm. In these models a technology improvement induces a positive impact on labor and output, via intertemporal substitution between labor and leisure, and this result holds no matter how extensively the baseline framework is augmented. On the contrary, a negative relationship between labor input and technology shocks has been shown to be consistent with business cycle models with sticky prices (see, e.g., Galì, 1999, and Kimball and Weil, 2000). Intuitively, if a positive technological shock occurs but output does not vary significantly because of nominal rigidities, firms will produce the same quantities as before by utilizing less labor.

Using firm-level panel data drawn from two high quality sources (the Bank of Italy Survey of Investment in Manufacturing and the Company Accounts Data Service), this paper contributes to the large empirical literature on the procyclical productivity puzzle, assessing the empirical relevance of the different explanations proposed. Moreover, it provides microeconomic evidence on the response of input use to a technology improvement, shedding some light on the role that technology shocks actually play in business cycles. To our knowledge, all the empirical studies focusing on these issues have been conducted on aggregate data at different levels of sectoral disaggregation.[4] Such data may have the

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[4] Malley, Muscatelli and Woitek (1999) use the most highly disaggregated data, i.e. the NBER 4-digit SIC level productivity database maintained by Bartelsman, Becker and Grey.

advantage of spanning the whole economy. However, in light of the significant heterogeneity across firms, theory calls for an investigation on firm-level data. An important advantage of using microeconomic panel data is that they allow us to control for unobservable individual idiosyncracies that reflect important characteristics of a firm. Moreover, panel data allows us to study dynamics for the individual firms, so that, for example, a more precise assessment can be made of how the firm's production plans and factor allocation evolve over time. By contrast, the use of more highly aggregated data, for example sectoral data, would cause individual idiosyncrasies to wash out in the aggregation process, inducing a potentially serious bias in the estimates.

Following Basu and Kimball (1997), the theoretical framework used in our investigation is based on a dynamic cost-minimization problem which allows us to control simultaneously for all potential sources of procyclical productivity. By imposing the optimality conditions from this model on a gross-output production function, a suitable empirical specification is derived. A clear advantage of this approach is to provide evidence on the importance of each component of the Solow residual: that stemming from imperfect competition and increasing returns, that due to variable intensity in factor use and that due to technology shifts. Of course, the intensity of labor and capital utilization are not observable. In order to identify these variable service flows, we assume that more intense utilization of installed capital implies faster depreciation and that effort per hour is related to the number of hours worked.

Estimations are conducted using the generalized method of moment (GMM) estimator for panel data developed by Arellano and Bond (1991). A highly refined estimate of technology change is obtained, where all the "non-technology" components of Solow residuals are net out. We investigate the cyclical properties of this measure and document, for example, that its correlation with standard measures of the cycle is weaker with respect to the Solow residual. This implies that a significant portion of the procyclicality of productivity is induced by unobservable factor utilization. Most importantly, we study the impact of a technology improvement on input growth and find that, unambiguously, a negative relationship emerges from our micro-data. Moreover, a notable feature of our data allows us to discriminate among the possible interpretations of this finding. In particular, the Bank of Italy Survey has collected information on the frequency and size of price revisions for each firm. This allows us to split the sample according to the degree of price stickiness present in each firm. We find that the negative relationship between input use and technology change is much stronger for firms whose product prices are more rigid. This result lends support to an interpretation of contractionary technology shocks based on business cycle models with nominal rigidities.

In order to verify if our model-based estimates of firm-level technology are sensible, we compare them with survey data on observable indicators of innovative activities. These indicators are expenditure for, respectively, research and development (R&D), purchases of patents and new product experimentation. The link between these indicators and our measure of technological shock is found to be highly significant (and stronger than that associated with the standard Solow residual). This provides independent evidence that the innovation process is well captured by our analytical approach. We also compare our model-based measure of factor utilization with sample information on the rate of capacity utilization, as assessed by each firm, and again find a strong relationship.

The remainder of the paper is organized as follows. Section two outlines the theoretical model underlying the empirical framework. Section three presents the data and the methodology used for estimation. In section four we report the econometric results of the baseline model, briefly examining the structural parameters; we also derive our refined measure of technological change and discuss its cyclical properties. In section five we analyze the relationship between estimated technology change and input growth and examine the role of price stickiness. In Section six we investigate whether our model-based measures of technology variation and factor utilization are sensible. The final section draws some conclusions.

2. Theoretical framework

We consider a production function subject to a technology disturbance, where gross output of firm i is produced from effective units of labor and capital and from intermediate inputs:

$$Y_{it} = F(\widetilde{L}_{it}, \widetilde{K}_{it}, M_{it}, Z_{it}). \tag{1}$$

Y_{it} denotes gross output. $\widetilde{L}_{it}$ is effective labor services and has three dimensions: the number of employees, N_{it}, the number of hours per worker, H_{it}, and the hourly effort, E_{it}, so that $\widetilde{L}_{it} = N_{it}H_{it}E_{it}$. Effective capital services ($\widetilde{K}_{it} = K_{it}U_{it}$) combines the installed capital stock, K_{it}, and its rate of utilization, U_{it}. The variable U_{it} represents the speed of operation or the number of hours the capital is used. M_{it} is the quantity of materials and energy input and Z_{it} is an index of technology.

Taking logs of both sides of (1) and differentiating with respect to time yields:

$$(2) \qquad dy = \frac{\partial F}{\partial \widetilde{L}} \frac{\widetilde{L}}{Y} (dn + dh + de) + \frac{\partial F}{\partial \widetilde{K}} \frac{\widetilde{K}}{Y} (dk + du) + \frac{\partial F}{\partial M} \frac{M}{Y} dm + dz,$$

where lower-case letters represent logs, the rate of growth of each input is weighted by the output elasticity with respect to that input and we assume for simplicity that the elasticity to technology is equal to one. Time subscripts and the index i are omitted for clarity.

In order to measure output elasticities, we recall the first order condition of a simple firm's optimization problem,

$$(3) \qquad P \frac{\partial F}{\partial X} = \mu P_X,$$

where X is one of the factors of production with its price, P_X, and P is the product price charged as a mark-up, μ, over marginal costs. Using the above expression, the output elasticity with respect to each input can be reformulated. For example, in the case of capital services the following relation holds

$$(4) \qquad \frac{\partial F}{\partial \widetilde{K}} \frac{\widetilde{K}}{Y} = \mu \frac{P_K}{PU} \frac{\widetilde{K}}{Y} = \mu s_K,$$

where s_K is the revenue-based capital share. The product of μ, the price-cost margin, measuring the degree of firm's market power, and s_K, the revenue-based capital share, can be expressed in terms of another product: namely, that between the degree of internal returns to scale, γ, and the cost-based capital share, c_K.[5] In this paper, although we allow for imperfect competition, we abstract completely from the analysis of firm's pricing policies. For this reason, we find it more sensible to express output elasticities in terms of the returns to scale parameter:

$$(5) \qquad \frac{\partial F}{\partial \widetilde{L}} \frac{\widetilde{L}}{Y} = \gamma c_L; \qquad \frac{\partial F}{\partial \widetilde{K}} \frac{\widetilde{K}}{Y} = \gamma c_K; \qquad \frac{\partial F}{\partial M} \frac{M}{Y} = \gamma c_M.$$

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[5] To see this, we first recall that γ, the measure of the local degree of returns to scale, can be viewed as the inverse of the cost elasticity to output: $\gamma = \frac{Costs}{Y} \frac{1}{MC}$, where MC is marginal cost (Fernald and Basu, 1999). In addition, the ratio of revenue-based and cost-based capital shares is equal to total costs over total revenues: $(Costs/PY)$. Using the definition of μ as P/MC, we have: $\gamma c_K = \mu s_K$. Of course, this holds true for the other inputs as well.

Inserting expressions (5) in (2) gives us an estimating equation. The latter, however, cannot yet be treated as a regression, because it contains time variations of capital and labor utilization (respectively, du and de) that are not observable. Indeed, a large body of statistical and anecdotal evidence indicates that inputs are used more intensively in booms than in recessions (Shapiro, 1996). Sizeable adjustment costs prevent firms from instantaneously hiring (laying-off) workers or increasing (decreasing) the capital stock when more (less) of these inputs is required. This induces a form of factor-hoarding with the implication that employment (N) and the capital stock (K) are quasi-fixed factors and the intensity of their use varies over the cycle. Of course, the increase in factor utilization also comes at a cost to the firm and the "optimal" input use is set by balancing benefits and costs at the margin.

These considerations suggest adding more structure to the theoretical framework. Following Basu and Kimball (1997), we consider a dynamic cost minimization set-up, where adjustment costs in hiring and capital accumulation provide motivation for factor-hoarding and cyclical variation in factor use. The optimization problem is formulated as follows:

$$(6) \qquad \underset{H,E,A,I,U,M}{Min} \int_0^\infty \left[NWG(H,E) + NW\Psi\left(\frac{A}{N}\right) + P_I K J\left(\frac{I}{K}\right) + P_M M \right] e^{-rt} dt$$

$subject \quad to$

$$Y = F(NHE, UK, M, Z)$$

$$\overset{\circ}{K} = I - \delta(U)K$$

$$\overset{\circ}{N} = A.$$

In addition to the variables defined earlier, the above expressions introduce some new ones. W is the base wage and $WG(H,E)$ is total compensation to each worker, which takes into account both the hours and the effort expended; as argued convincingly by Basu and Kimball (1997) and Fernald and Basu (1999), implicit contracts may govern the wage payment, so that the actual variation of this compensation is not observed. A denotes net hiring and $NW\Psi\left(\frac{A}{N}\right)$ measures the adjustment cost of varying the number of workers. The accumulation process, also, encounters adjustment costs, which are captured by the function $J\left(\frac{I}{K}\right)$; the product of this term and $P_I K$ gives capital expenditure, where P_I is the price of investment goods. P_M is the price of materials input and δ is the rate of capital depreciation that varies with utilization, U. More intensive capital utilization causes depreciation of the capital stock to be faster, because of wear and tear and because time devoted to maintenance is reduced.

The first order conditions with respect to the choice variables are derived in the first Appendix together with the Euler equations for the quasi-fixed factors. As is well known, in the context of a cost-minimization problem the Lagrange multiplier, λ, associated to the production constraint has, intuitively, the economic interpretation of marginal costs. Hence, an expression for the marginal value product of each input can be obtained. In the case of effective capital input, for example, it would be

$$\lambda \frac{\partial F}{\partial \widetilde{K}} = \lambda \gamma c_K \frac{Y}{UK}. \tag{7}$$

Manipulating the equilibrium conditions and combining them with the expressions for marginal products stemming from equations (5) gives a suitable expression for changes in capital utilization:

$$du = \frac{1}{1+\Delta}\left(dp_M + dm - dp_I - dk\right) - \frac{\xi}{1+\Delta}(di - dk), \tag{8}$$

where lower-case letters continue to represent logs and we have used the fact that in steady-state: $(\frac{I}{K})^* = \delta^*$. Two new entities are defined in (8). The first, Δ, represents the elasticity of marginal depreciation with respect to utilization, i.e. $\Delta = \frac{U\delta''}{\delta'}$, and captures the degree of convexity of depreciation as a function of capital utilization.[6] The second, ξ, denotes the elasticity of marginal costs of adjustment with respect to the accumulation rate, $\xi = \frac{\delta J''}{J'}$, and measures the degree of convexity of adjustment costs. As in Basu and Kimball (1997), it can be useful to define these elasticities in terms of steady-state variables and treat them as time-invariant.[7]

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[6] It is customary in the literature to assume a non-negative, increasing and convex depreciation function, $\delta(U)$ (see, e.g., Burnside and Eichembaum, 1996; Greenwood, Hercowitz and Huffman, 1988 and the references therein).

[7] A feature of equation (8) is that capital utilization is negatively related to investment spending. Intuitively, this traces back to the first order condition with respect to capital utilization, U (see eq. A.3 in Appendix I), setting the marginal benefit of increased utilization equal to its marginal user cost. Building on this relationship, eq. A.9 states that the marginal cost in terms of increased capital depreciation, $\frac{\partial \delta}{\partial U}$, depends upon the ratio between the current marginal value product of capital, $\lambda \frac{\partial F}{\partial K}$ (see eq. 7), and the future marginal products of capital, q. Thus, whenever q and, consequently, investment, I, decline, $\frac{\partial \delta}{\partial U}$ increases; in turn, due to the convexity of the

With regard to effective labor input, the following relation holds:

$$d\widetilde{l} = dn + dh + de = dn + (1 + \zeta)\, dh, \tag{9}$$

where ζ defines the elasticity of hourly effort with respect to hours per worker: $\zeta = \frac{de}{dh}$. Thus, the unobserved change in hourly effort, de, can be expressed as the change in hours per workers, dh, times the elasticity ζ.

The elasticities embedded in equations (8) and (9) are interesting *per se* as regards their size; furthermore, they help to make equation (2) an estimating framework, together with the interplay of optimal conditions from cost-minimization. Thus, inserting equations (8) and (9) in (2) and using the expressions in (5) for output elasticities yields the following regression framework

$$\begin{aligned} dy &= \gamma\left[c_L(dn + dh) + c_K dk + c_M dm\right] + \gamma\zeta c_L dh + \\ &\quad + \frac{\gamma}{1+\Delta} c_K\left(dp_M + dm - dp_I - dk\right) - \frac{\gamma\xi}{1+\Delta} c_K (di - dk) + dz. \end{aligned} \tag{10}$$

The unknown parameters to be estimated are $\gamma,\ \zeta,\ \Delta$ and ξ. All other entities, including input shares, are observable. The first term in brackets in the right-hand side is the weighted average of percentage changes in the observed components of inputs; therefore, γ represents the degree of internal returns to scale. The second term refers to change in labor effort ($\zeta dh = de$), while the third and fourth terms reflect change in the intensity of capital utilization. The last term, dz, represents technology variation. Estimation of equation (10) is useful for several purposes. It yields estimates of the structural parameters of the model and, most importantly, it allows us to derive a highly refined measure of technological change.

3. Data and estimation

3.1 *The data*

In the empirical analysis we rely upon firm-level data on a sample of Italian manufacturing firms drawn from two main sources: the Survey of Investment in Manufacturing

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depreciation function, an increase of $\frac{\partial\delta}{\partial U}$ mirrors a rise in capital utilization.

Another prediction of equation (8) is the positive partial correlation between changes in utilization and materials input. This feature seems rather plausible; several authors (for example, Basu 1996) have used materials growth as a measure of unobserved change in utilization.

(SIM) and Company Accounts Data Service reports. A detailed description of these sources and the variables used in the paper is provided in Appendix II, together with some descriptive statistics. The Survey of Investment has been carried out by the Bank of Italy at the beginning of each year since 1984. We believe the data to be of unusually high quality, due to the representativeness of the sample, appropriately stratified by industry classification, firm size and geographical location, and to the professional experience of the interviewers. On average, the number of firms in each annual survey is about 1,000, with the data having a panel structure; because of attrition, however, the balanced panel consists of less than 300 firms. The survey collects both quantitative and qualitative information on each firm. The former refers to a considerable number of economic variables, including factor demand and the value of sales, the latter to a variety of characteristics that help to describe each firm.

The SIM survey does not cover a few of the variables needed for our analysis, such as gross production and purchases of intermediate inputs. Hence, we also employ data from the Company Accounts Data Service. The latter dataset, maintained by a consortium of the Bank of Italy and a very large number of Italian banks, is the principal source of information on the balance sheets and income statements of Italian firms. It collects detailed information drawn from the annual accounts of more than 30,000 firms. Merging the information from the two sources resulted in an unbalanced panel of slightly less than 1,000 firms, which was used in the estimation process. Data range from 1984 to 1997 and include about 8,000 observations overall. The variability of industrial output during the fourteen-year period considered, which includes the 1993 and 1997 industry-wide recessions, plus branch-specific and firm-specific output fluctuations, appears sufficient to convey plenty of microeconomic evidence on the cyclical behavior of the variables of interest.

In the estimation, output is measured as gross output at constant prices; intermediate goods of energy and materials are included among inputs, in addition to manhours and capital stock services. In order to compute the cost-based capital share, c_K, and the other cost-shares, the series for the required payment to capital, $rP_K K$, was constructed. We utilized data on firm-level capital stock at constant prices, K, and the sectoral deflator of capital stock, P_K, as well as firm-level estimates of the user cost of capital, r, as computed by applying the well-known Hall-Jorgenson approach (see Appendix II).

3.2 *Estimation*

The theoretical model developed in section two provides the basis for our empirical framework. In particular, the estimating equation stems from eq. (10) and is specified as follows:

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\begin{aligned}
dy_{it} &= \alpha dx_{it} + \beta(c_{L,it} dh_{it}) + \varepsilon \left[c_{K,it} \left(dp_{M,it} + dm_{it} - dp_{I,it} - dk_{it}\right)\right] \\
&\quad + \theta \left[c_{K,it}(di_{it} - dk_{it})\right] + b^{'} W_{it} + dv_{it}, \qquad (11)
\end{aligned}
$$

where dx_{it} represents the weighted average of the growth of observed inputs - i.e., $dx_{it} = c_{L,it}(dn + dh) + c_{K,it} dk + c_{M,it} dm$ - with $c_{L,it}$, $c_{K,it}$ and $c_{M,it}$ being the cost-based input shares. The terms in brackets are measurable entities and, as illustrated in section two, they are part of the definition of de_{it} and du_{it}, i.e. the intensity of use of labor and capital. W_{it} is a vector of dummy variables referring to, respectively, the SIC two-digit sector of manufacturing industry, the year, the firm's size and the occurrence of a corporate operation such as a merger, an acquisition or a break-up. The specification in level also contained a firm-specific effect, which was eliminated by taking first differences. The error terms in the level equation, v_{it}, are assumed to have finite moments with $E(v_{it}) = E(v_{it} v_{is}) = 0$, for all $t \neq s$.

In estimating eq. (11) one has to take into account that (unobservable) technology variation is likely to be correlated with changes in effective labor and capital services and in materials input. This would yield a specification error inducing inconsistency in the parameter estimates. In order to account for this endogeneity of regressors, we adopt the generalized method of moments (GMM) estimation procedure developed by Arellano and Bond (1991) for panel data. This method was shown to be efficient within the class of instrumental variable procedures, as it optimally exploits all linear moment restrictions deriving from the assumptions made on the error terms. In our estimation the lagged values of the endogenous explanatory variables dated period t-2 and earlier are utilized as instruments. In particular, we truncate the set of these instruments at the third lag because, as was shown by Ziliak (1997), using fewer instruments makes it possible to attenuate the potential bias that arises in the optimal GMM estimator when all the available linear orthogonality conditions are exploited. In addition, we also employ external, demand-side instruments, which appear relevant on economic grounds and have been used extensively in the literature (see, e.g., Hall, 1988, Burnside, 1996, and Basu et al., 1998). These additional instruments are: the contemporaneous growth rate of material input prices and the real exchange rate, the variation of sectoral order-book levels drawn from business surveys conducted by ISAE (Institute for Economic Analyses, a public body providing technical support to the Italian Treasury) and a measure of unanticipated monetary shock based on a vector autoregression (VAR) model.[8] Throughout the paper we report the estimates obtained using all the instruments mentioned above. However, as a sensitivity inspection, we also ran equation (11) after excluding from the set of instruments the external, demand-side instruments, either together or singly; in all cases, the results are qualitatively unchanged.

The optimal method of Arellano and Bond makes it possible to compute standard errors for the estimated parameters that are asymptotically robust with respect to heteroschedasticity. Moreover, a set of diagnostic tests can be derived to assess the validity of both the instruments used (as recommended by Burnside, 1996) and the empirical specification. Two such tests are considered in our analysis: the Sargan statistic of over-identifying restrictions, which verifies the lack of correlation between errors and instruments, and the statistic developed by Arellano and Bond (1991), testing for the absence of second-order serial correlation in the differenced residuals. Moreover, in order to assess the relevance of our instruments, we examined their correlation with each endogenous regressor (e.g. Ziliak, 1997). In all cases, the results of the Wald test point to a strong rejection of the hypothesis that instruments are uncorrelated with the endogenous variables (see Table 1).

Since the estimation is conducted on firm-level data, our results are not subject to the aggregation bias and composition effects that may arise in aggregate data regressions, inducing misleading inference.[9] Furthermore, not only do we avoid failures of aggregation and the ensuing first-order problems in estimating macro-models, but in the presence of imperfect competition potentially characterizing the firm environment the fact that we use gross-output data prevents our empirical framework from being misspecified, as would be the case with value-added data (Basu and Fernald, 1995).

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[8] The measure of monetary shock is obtained from a monthly recursive VAR model estimated at the Bank of Italy over the period 1975-1997 (Dedola and Lippi, 2000). The specification includes the following variables: the industrial production index, the CPI, an index of commodity prices, the three-month interbank rate, the nominal effective exchange rate and M2. The three-month interbank rate is assumed to be the policy variable, determined according to contemporaneous information on the first three series only and to lagged information on all six series. The error term from the fitted policy rule provides our measure of monetary impulse.

[9] A classic reference on aggregation bias is Theil (1954); for an insightful discussion of the effect of aggregation on the estimate of the returns-to-scale parameter, see Basu and Fernald (1997).

4. Results

4.1 *Evidence from the baseline model*

Before turning our attention to the estimated measure of technology variation and its cyclical behavior, it is worth examining the parameter estimates from the regression equation (11). Comparing equations (10) and (11) makes it clear how to use the estimates from (11) to trace back the values of structural parameters γ, ζ, Δ and ξ. The estimation results are summarized in Table 1. While the first four rows of Table 1 refer to the reduced form parameters (α, β, ε and θ), the last four report the implied values of the structural parameters and their associated standard errors (α is exactly equal to γ). First of all, it can be noted that the point estimate of the returns to scale parameter, although slightly higher than one, is not statistically different from unity. Hence, consistently with most microeconomic evidence reported in the literature (see, e.g., Baily, Hulten and Campbell, 1992, for U.S. firms), the hypothesis of constant returns to scale is not rejected by our sample.

Let us examine the results on the other structural parameters. Consider first the coefficient ζ, which represents the elasticity of effort that an employee spends in one hour of work (de) in response to a change in the number of hours devoted to work (dh). The estimated value of ζ is -.38, with a standard error of .20. That is, if hours per worker increase by, say, ten per cent, then hourly effort declines by about four per cent (while effective labor input per employee, $dh + de$, increases by roughly six per cent). In other words, while in our sample hours per worker is a pro-cyclical indicator and effective labor input provided by each employee is also pro-cyclical, hourly effort is not. Thus, increasing hours at the margin would lead to a reduction in the amount of effort spent during the marginal hour. This seems a plausible result, in light of the physical fatigue associated with the extension of the daily work schedule.[10]

The elasticity Δ measures the response of marginal depreciation of capital to an increase in utilization. The estimate of this elasticity is positive (.811), although it is not statistically significant; this provides only mild evidence in favor of the convexity of the depreciation

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[10] A different result, namely a positive elasticity of effort to hours, is reported by Basu and Kimball (1997) for data of U.S. manufacturing sectors. Apart from the difference in the aggregation level of the data, a possible explanation for the diverging evidence lies in the rigidities of the Italian labor market. The latter, presumably, induce Italian firms to overexploit their existing work force during expansions to the point that hourly effort starts to diminish. On the other hand, U.S. firms do not need to stretch the productive capacity of their employees to the same extent, since they can hire new ones more easily.

function, $\delta(U)$.[11] Finally, the elasticity ξ provides information on the degree of convexity of the adjustment costs typical of the accumulation process. Our results indicate that the marginal installment cost of capital, J', is increasing in the rate of investment, $\frac{I}{K}$ (ξ is estimated to be equal to .118 with a standard error of .066).

4.2 *Measuring technology change*

Perhaps the most important implication of equation (11) is that it allows us to derive a highly refined measure of technological shock. In order to implement our model in a sufficiently flexible fashion, we obtain our firm-level measure of technology change, dz_{it}, by estimating eq. (11) separately for durable and non-durable goods and allowing for a sector-specific returns-to-scale parameter, γ, as recommended by Burnside (1996).[12] In particular, dz_{it} is computed as the sum of regression residuals, dv_{it}, and the parameters associated with the control dummy variables, i.e. $dz_{it} = dv_{it} + b_{it}'\overline{W}_{i,t}$ (unlike $W_{i,t}$, the vector $\overline{W}_{i,t}$ excludes corporate operation dummies). We include the dummy variables in our measure of dz_{it} because, given our analytical framework, they capture the sector, the year and the size-specific components of firm's technological growth.[13]

In the manufacturing industry as a whole, the average of dz_{it} across observations is about .018, that is a yearly technology improvement of more than 1.5 per cent. This is about twice as much as the average of cost-based and revenue-based standard Solow residuals, which we also computed on our firm-level data (see Table 2). With respect to the latter two variables, however, the volatility of dz_{it}, as measured by the coefficient of variation, is found to be substantially smaller. The probability of a technological regress, i.e. that dz_{it} is negative, is

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11 Our value for the elasticity Δ is not statistically different from the estimates of Burnside and Eichembaum (1996) and Basu and Kimball (1997), respectively equal to .56 and 1.13; the large standard errors suggest some caution when these elasticities are used for model calibration.

12 Basu et al. (1998) also estimate two separate equations for durables and non-durables and allow the mark-up μ (which corresponds to the returns-to-scale parameter, γ, in our framework) to differ by sector. In the majority of sectors we do not find a significant departure from constant returns to scale. There are exceptions, however. In Chemicals, Rubber and Transport equipment there is some evidence of increasing returns to scale; conversely, in Textiles, Electrical machinery and Other manufacturing returns to scale seem to be diminishing. As a robustness inspection, we also derived dz_{it} from a single equation for the entire manufacturing industry, both restricting and not restricting γ to be equal across sectors. The pattern of dz_{it} remains qualitatively unchanged and all the results in this and the following sections continue to hold.

13 To check robustness, we replicated in the paper with a measure of dz_{it}, net of the control effects, $b'\overline{W}_{i,t}$; the results were substantially unaffected.

about one third and is less than figures obtained with the standard measures of productivity (.43 for both the cost-based and revenue-based Solow residuals).

We begin the investigation of the cyclical properties of dz_{it} by looking at its relationship with some cyclical indicators. In Table 3 we report results of simple regressions of the growth rate of technology on the growth rate of aggregate industrial production, sectoral industrial production and GDP. The key evidence is that, although our refined measure of technological change is positively related with the pro-cyclical indicators, the relationship is indeed weaker than in the case of Solow residuals. For example, if aggregate industrial production is used as indicator, the regression coefficient when dz_{it} is used is 55 per cent (41 per cent) smaller than in the case of the cost-based (revenue-based) Solow residuals. Similar, and stronger, results have been obtained with GDP. This evidence can be interpreted as suggesting that unobservable factor utilization accounts for half or more of the procyclicality of standard measures of technological shocks.

We also attempted to see how much each source of procyclical productivity accounts for the size of the Solow residual, by computing the respective contributions.[14] The effects of departure from constant returns to scale and perfect competition are found to be negligible. By contrast, the role of factor utilization turns out to be of some importance: on average, about 12 per cent of the Solow residual is accounted for by variable intensity in factor use. The predominant component, however, is technology variation, which accounts for the remaining 88 per cent. Taken together, the results of Table 3 and those just mentioned suggest that "pure" technological shocks are the largest component of standard measures of productivity growth; on the other hand, the fraction of the Solow residual attributable to variable factor utilization, whilst relatively small in size, is the most cyclical component.

Although the main focus of this paper is on measures of technology variation at firm-level, we also calculated a weighted average of dz_{it} across firms, in order to examine the main features of aggregate technology shocks. The weights used are the shares of firms' gross output in total output. Admittedly, the limited number of annual observations that we obtained,

[14] More precisely, we subtracted dx_{it} from both sides of eq. (11) and then divided each of them by the term in the left-hand side, which is the cost-based Solow residual $(dy_{it} - dx_{it})$. Thus, each term on the right-hand side represents the contribution of the corresponding variable to the Solow residual and their sum is, of course, equal to one. Each of these contributions varies across firms and over time. If we look at the median (or the mean) of each of these terms we can evaluate the importance of each component synthetically.

due to the fact that the panel covers the period 1984-1997, prevented us from conducting any meaningful regression analysis and drawing conclusive evidence. Yet, some features seem interesting. The time average of the aggregate measure is .016, a figure almost identical to the sample mean of dz_{it}; the standard deviation is reduced to .012. Importantly, also, the probability of technological regress, calculated on this aggregate, is about 15 per cent, much lower than the one calculated at the firm level.[15]

5. Technology shocks and input growth

5.1 *The contemporaneous relationship*

We argued before that it is rather hard to compare the empirical merits of alternative classes of business cycle models on the basis of the pro-cyclical productivity puzzle. The reason is that explanations of the puzzle are not mutually exclusive and they often co-exist in recent theoretical set-ups. However, a new test has been recently proposed in the literature. In particular, the analysis of the impact effect of a technology impulse on input growth can help to ascertain the empirical relevance of alternative macroeconomic models. Indeed, an unambiguous prediction of RBC models is that a favourable technology variation results in a rise in input. This conclusion holds even if the baseline framework is augmented with a number of extensions (King and Rebelo, 2000). By contrast, business cycle models featuring some degree of price stickiness are fully consistent with a contractionary effect of technology improvements (see, e.g., Galì, 1999, and Kimball and Weil, 2000). In particular, following Basu et al. (1998) and Galì (1999), let us consider a framework where the quantity theory determines the demand for money and, in the short run, money supply is fixed and price flexibility is imperfect. Hence, real balances (and, thus, aggregate demand) are also fixed in the short run. When a technology improvement occurs, firms meet their demand by producing the same output as before. However, to produce the unchanged amount of output firms need fewer inputs, so that a technology impulse would result in a short-run reduction in workers,

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[15] This is a reasonable result, indicating that in most years the firms which experience a positive technological shock outnumber those experiencing a negative one.

We also calculated two aggregate measures of the Solow residual: the first was obtained as a weighted average of the firm-level Solow residuals, while the second was computed directly on aggregate data (i.e., subtracting aggregate inputs, weighted by aggregate shares, from aggregate output), as in the case that firm-level information is not available. The probability of regress increases in both cases and their correlation with a pro-cyclical variable (change in aggregate gross-output) is higher than in the case of aggregate dz.

total hours and, in general, effective factor services. Of course, as prices start to decline over time, the standard RBC mechanism enters into play and output and input eventually rise.[16]

We are able to investigate this issue by using our firm-level measure of technology variation. In particular, we examine the effect of technology change on input growth by regressing several measures of input change on dz_{it}. A critic might argue that, since $dz_{i,t}$ was obtained from equation (11) as a regression residual, it should be orthogonal to the input growth variables. For the latter variables, however, a number of instruments were used in that regression; these instruments, which have been shown to be non-weak, are orthogonal to technology shocks, as confirmed by the test of over-identifying restrictions. Therefore, when used in the first stage regressions, the instruments aim to capture the variability of inputs due to technology-unrelated factors. Consequently, if our instrumental choice is appropriate, the residuals of our instrumental variables regression are orthogonal to technology-unrelated components of input growth, but potentially correlated with the remaining components. It is exactly this correlation that we seek to investigate in this and the following sections.

Since our measure of technological shock is exogenous, we do not need an instrumental variable estimator and may resort to a standard random-effects model. Table 4 reports the estimation results. The overall evidence lends strong support to the hypothesis that, on impact, the effect of a technology change on input growth is negative. This result is, in general, largely significant statistically. For example, when we regress total hours growth, $dn_{ih} + dh_{it}$, the regression coefficient is -.086, with a standard error of .022. A similar result is obtained when the dependent variable is the growth in the number of employees, dn_{it}, (-1.0; standard error: .015). On the other hand, when the change of hours per capita, dh_{it}, is considered the coefficient is not statistically significant.[17] We also used other measures of input services: the observable component of input growth, dx_{it}, and the growth of unobserved labor and capital

[16] In Galì's (1999) model, employment declines in response to a technology impulse not only in the case of exogenous monetary policy, but also when the monetary authority responds in a systematic fashion to technology variations. Under a constant money growth rule, Dotsey (1999) shows that output remains roughly unchanged after a technology shock, thus implicitly confirming the finding that inputs decline on impact. In his analysis, however, this effect is reversed when monetary rules are of the Taylor type.

[17] A possible explanation of this finding is that after the introduction of a technology improvement, the firm may find it necessary to devise training programs for employees. In particular, the number of hours for training and for unmeasured human capital activities might increase to let workers catch up with the technological innovations. This increase could partly offset the mechanism of declining hours illustrated earlier, explaining why, overall, hours per worker do not fall significantly after favourable technology improvements.

utilization.[18] Again, the results indicate a contemporaneous contractionary effect of technology improvements; they also show that unobserved factor utilization behaves in the same way as observed inputs, confirming that firms view this variable as another form of primary input. We also estimated other panel regressions where the dependent variables are the same as before but distributed lags of dz_{it} are used as regressors. While the coefficents associated with lags of dz_{it} are generally positive, suggesting a recovery over time in input growth, those associated with the contemporaneous change in technology remain negative and statistically significant in most cases, providing further support for the view that technology shocks are contractionary in the short run.[19]

In addition to the evidence at firm level, we also examined the relationship between aggregate measures of technological variation and input use. Once the firm-level measures of technology and input growth are appropriately aggregated across firms, simple descriptive evidence can be obtained. Again, the limited number of observations prevents us from conducting regression-based tests. Yet, an interesting result is that the correlation coefficients between aggregate measures of technology variation and input growth are generally negative.

All these empirical results point towards models of business fluctuations consistent with a decline in labor use in response to a positive technology shock. Since we use firm-level data, explanations of our finding based on reallocation effects (i.e., technology shocks would reduce aggregate output and input use because of the cost of reallocating resources) or cleansing effects (i.e., recessions would enhance average productivity by eliminating inefficient firms) are ruled out. In general, therefore, our result appears in contrast to a key prediction of the RBC paradigm. On the other hand, it has been shown to be consistent with models characterized by price rigidities. Because our evidence is based on microeconomic data, we believe it reinforces that recently obtained by Basu et al. (1998) and Galì (1999). In particular, Basu et al. (1998),

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[18] The latter variable is measured as $c_K du_{it} + c_L de_{it}$, consistently with equations (8), (9) and (10) in Section Two. Intuitively, the sum of du_{it} and de_{it}, weighted by the corresponding cost-share, represents their contribution to output growth.

[19] Arguably, the negative relationship found between input growth and dz_{it} might be spuriously driven by some relevant economic variable, on either the demand or the supply side, omitted from the analysis. To tackle this issue, we inserted in the regressions a proxy of the firm's economic activity, such as the growth rate of firm's sales or sectoral output. In both cases the results remain substantially unchanged. For example, when the firm's sales growth is included in the regression of growth in total hours on dz_{it}, the coefficient of the latter variable is -.262, with a standard error of .020 (it is -.099, with a standard error of .022, when sectoral output growth is included).

using sectoral data spanning the whole U.S. economy, show that after a technology innovation a significant fall in inputs occurs on impact. Fitting a structural VAR model to aggregate data for the U.S. and other industrialized countries, Galì (1999) estimates the covariance between total factor productivity and employment growth, conditional on technology being the unique source of fluctuations. Identification is achieved through the restriction that only technology shocks have permanent effects on productivity. His results point to a negative and statistically significant relationship between technology shocks and labor inputs.[20]

While Basu et al. (1998) and Galì (1999) provide a theoretical interpretation of their results on the ground of price stickiness, they do not provide direct evidence to support this view. In principle, as emphasized by Cooley (1998), an alternative explanation of contractionary technology shocks can be found in vintage-capital models, where an investment-specific technology improvement may induce a short-run reduction in employment due to an intense labor reallocation from older to newer vintages (see, e.g., Campbell, 1998). In the following section, by exploiting a notable feature of our data, we provide evidence that sheds light on the role of price stickiness, helping to discriminate among these two explanations.

5.2 *Sample splitting based on price stickiness*

We have provided extensive evidence that, on impact, a technology improvement results in a contraction of inputs. We have also discussed two possible explanations, one of which is based on business cycle models with price rigidity. Thus, for an empirical appraisal of such models and a better interpretation of our results, it would be of some interest to investigate the effect of a technology rise on input growth in firms with different degrees of flexibility in price adjustment. If the prediction of sticky price models holds at the empirical level, we should observe that, on average, the stickier transaction prices are, the stronger the contractionary effect of a technology shock would be.

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[20] Shea (1998), also, examines the impact of technology shocks on employment. Using VAR models, he considers the dynamic effects on the economy of shocks to observable indicators of research activities (R&D spending and patent applications). He finds that a positive technology shock increases labor in the short run and decreases it in the long run and that, generally, total factor productivity (TFP) does not respond to technology shocks at any horizon. Apparently, these findings are at odds with the prediction of sticky price models of a contractionary impact effect of technology improvements. However, a consideration is in order: the latter prediction holds only if a technology variation implies a TFP movement. Indeed, in the few VAR models estimated by Shea where a significant short-run variation of TFP is observed after a technology shock, inputs respond in the opposite direction to that of TFP, which is consistent with the predictions of sticky-price models (see Galì, 1998).

Despite the crucial role assigned to price stickiness in the macroeconomic debate, empirical evidence on the degree of price flexibility is rather limited; this is due, probably, to difficulty in gathering firm-level data (an exception is, for example, Kashyap, 1995). Very interestingly, the SIM database includes firm-specific information on the frequency and size of actual price variations. This set of information allows us to conduct a test on the effects of technology shocks that, we believe, is rather powerful. We split the sample according to the frequency of price revisions reported by each firm and examine whether the response of input growth to a change in technology differs across the two samples. In particular, in the 1996 survey firms were asked the following question: "How frequently does the firm typically modify its selling prices?". The possible answers were five: "Several times in a month", "Every month", "Every three months", "Every six months" and "Once in a year or less frequently". In Table 5 we report the regression results obtained separately for two sub-samples: the first is selected by pooling the firms which have chosen one of the first three answers; the second comprises the firms which have chosen one of the last two answers. The evidence largely supports the view that, for firms with stickier prices, technology shocks are contractionary; conversely, for firms whose prices are less sticky the effect is weaker and not statistically significant. For example, if change in total hours, $dn_{ih} + dh_{it}$, is considered, the estimated effect of dz_{it} in the sample of firms with stickier prices is -.23; it is .02 in the other (with standard errors equal, respectively, to .035 and .051). No matter whether current change in technology alone or a distributed lag of it is considered, the effect of dz_{it} on input growth is always negative on impact for firms whose prices are less flexible; conversely, this negative effect is generally not found in firms whose prices are more flexible.[21]

We also devised another split of the sample based on the size of price revisions. In particular, we focused on annual price variations as reported each year by every firm. We computed firm-specific time averages of the annual change of selling prices (taken in absolute value) and used the sample mean of such time averages as a splitting criterion. Table 6 documents the estimation results from this exercise. The main findings illustrated before

[21] Specific features of a given market or product may induce, *ceteris paribus*, a higher or lower frequency of price revisions. Hence, we also split the sample according to whether the extent of price stickiness of each firm, computed from the answer to the SIM question, was greater or smaller than the sectoral median (or mean). The results are very similar to those presented above. For example, when total hours growth is regressed on $dz_{i,t}$, the estimated coefficient is equal to -.101 in the "sticky price" sample and to .025 in the other sample (with standard errors of, respectively, .046 and .052).

are confirmed: the evidence supports a negative impact effect of technology change on input growth only in firms characterized by stickier prices.

6. Are our model-based estimates sensible?

Measuring technological change presents a number of well-known challenges, and several alternatives are possible. In our paper we rely on the production-function approach proposed by Basu et al. (1998) - which controls for imperfect competition, increasing returns and unobservable factor utilization - except that in the estimation we use microeconomic panel data, taking into account the wide heterogeneity across firms. Whilst we believe that our procedure provides a valid measure of the firm-level, time-varying stochastic technological progress, it might be appropriate to compare it with alternative, independent proxies of technological innovation. Interestingly, the SIM data allow us to verify the robustness of our model-based estimates on the basis of independent sample information at the firm-level. In particular, the 1995 survey has collected data on expenditure in (i) R&D, (ii) patent purchases and (iii) design and production of experimental products. Shea (1998) also uses observable indicators of research activities to extract information on technological change; the indicators that he uses are R&D spending and patent applications for 19 two-digit U.S. manufacturing industries.

It is known that some caution is necessary when intepreting these direct measures of innovative activities as indicators of technological progress. On one hand, patenting fluctuations may partly reflect changes in legislation and the procedures of the Patent Office. On the other hand, technological innovations may be embodied in new equipment. In addition, they may not be due exclusively to scientific and engineering developments, but depend also on variations in management techniques, capital organization and other intangible inputs, such as the information capital embodied in production processes (see Shea, 1998 and references therein). Another problem with R&D spending and patents as measures of a technological improvement is that the latter occurs only when actual output is affected and not when the inventive activity begins. Consequently, the lags between the inception of the innovative process and the effects on output might vary from firm to firm, so that it is difficult to ascertain the exact timing of the effects. Despite these limitations, we explored the link between our model-based measures of technology and the information on "tangible" research activities drawn from the sample. In Table 7 we present results from different regressions for 1995 of our measure of technology change, dz_{it}, on, respectively, R&D expenditure, patent purchases and expenditure in new product experimentation. In order to control for scale effects, we divided each explanatory variable in our regressions by the level of output. The evidence indicates that there is a strong relationship across firms between dz_{it} and each indicator of technological activities. We also used the two traditional measures of TFP as dependent variables: the revenue-based and the cost-based Solow residual. While their relationship with the indicators of innovative activity is positive and statistically significant, the size of each estimated coefficient is generally lower than that associated to dz_{it}. This lends additional support to the view that our measures of technological change are more refined than standard Solow residuals.

Another check of robustness for our model-based estimates refers to capital and labor utilization. Again, we examined the link between them and independent information drawn from the sample. Of course, variations in the intensity of capital and labor use are not observed. Yet, firms in the SIM survey are asked each year to appraise their own rate of effective capacity utilization in the past year. We used this information by estimating a panel regression of du_{it}, as derived from eq. (8), on variations of the reported firm-level capacity utilization rate. The relationship was found to be very strong: the coefficient associated to capacity utilization is .150 with a standard error equal to .013.[22]

7. Conclusion

In this paper we use a dynamic cost minimization model, originally proposed by Basu and Kimball (1997), to derive a measure of technology change that is robust to increasing returns, imperfect competition and unobserved factor utilization. Most importantly, by estimating the model on firm-level panel data drawn from two high-quality sources, we take into account the considerable heterogeneity across firms and avoid the potentially serious problems induced by aggregation. We show that while the effects of departures from constant returns to scale and perfect competition on the Solow residual are negligible, the variation in the intensity of input use accounts for a large portion of the cyclicality of standard measures of productivity growth. Also, explicitly considering variable factor utilization and eliminating it from the measure of technology change induce, with respect to the Solow residual, more

[22] The regression includes a number of dummy variables as control factors, referring to different years, sectors, firm size, type of ownership, location and the occurrence of corporate operations.

reasonable properties (for example, a lower probability of technological regress) and a stronger correlation with independent indicators of innovative activities (e.g., spending on R&D and patent purchases).

We employ firm-level estimates of technology change to evaluate its impact on input growth. We provide extensive evidence that positive technology shocks tend to riduce inputs on impact, confirming the finding presented in the literature for aggregate and sectoral U.S. data. We discuss and rule out a number of alternative explanations and interpret our result as evidence in favor of business cycle models with price rigidity. Unlike other recent contributions, we are able to provide direct evidence to support this view. In particular, by using survey information on both the frequency and size of price adjustments, we show that the negative effect of technology shocks on inputs is much stronger for firms with a larger degree of price stickiness.

Appendix I: Optimality conditions

The first-order conditions of the constrained optimization problem (6) in the text are the following (see Basu and Kimball, 1997):

$$H: \quad \lambda \frac{\partial F}{\partial \widetilde{L}} EL = WL \frac{\partial G}{\partial H}; \tag{A.1}$$

$$E: \quad \lambda \frac{\partial F}{\partial \widetilde{L}} HL = WL \frac{\partial G}{\partial E}; \tag{A.2}$$

$$U: \quad \lambda \frac{\partial F}{\partial \widetilde{K}} K = qK \frac{\partial \delta}{\partial U}; \tag{A.3}$$

$$M: \quad \lambda \frac{\partial F}{\partial M} = P_M; \tag{A.4}$$

$$A: \quad \phi = W\Psi'; \tag{A.5}$$

$$I: \quad q = P_I J'; \tag{A.6}$$

where λ, ϕ, and q are the Lagrange multiplier associated, respectively, with the first, second and third constraint. The Euler equations for the quasi-fixed factors are

$$N: \quad \overset{\circ}{\phi} = r\phi - \lambda \frac{\partial F}{\partial \widetilde{L}} EL + WG + W(\Psi - \frac{A}{L}\Psi'); \tag{A.7}$$

$$K: \quad \overset{\circ}{q} = (r+\delta)q - \lambda \frac{\partial F}{\partial \widetilde{K}} U + P_I(J - \frac{I}{K}J'); \tag{A.8}$$

Combining condition (A.3) with the expression for marginal product of capital stemming from equation (4) in the text ($\frac{\partial F}{\partial \widetilde{K}} = \mu s_K \frac{Y}{UK}$) yields

$$U\frac{\partial \delta}{\partial U} = \frac{\lambda}{q} \mu s_K \frac{Y}{K}; \tag{A.9}$$

similarly, joint consideration of condition (A.4) and the expression for marginal product of intermediate inputs gives

$$\lambda \mu = \frac{P_M M}{s_M Y}; \tag{A.10}$$

if we combine the expression for marginal productivity of capital with (A.10), the following relation holds:

$$\lambda \frac{\partial F}{\partial \widetilde{K}} = \frac{s_K}{s_M} \frac{P_M M}{UK}; \tag{A.11}$$

combining (A.9), (A.10) and condition (A.6) yields

$$U \frac{\partial \delta}{\partial U} = \frac{s_K}{s_M} \frac{P_M M}{P_I J K}. \tag{A.12}$$

If we differentiate the above equation with respect to time and divide both sides by $U \frac{\partial \delta}{\partial U}$, we obtain equation (8) in the text for percentage changes in capital utilization. If we insert (8) and (9) in equation (2) in the text and use the expressions (5) for output elasticities, the estimating equation (10) is obtained.

Appendix II: Data sources, definition of variables and descriptive statistics

Data Sources. The two main sources used in the paper, both at the firm-level, are the Bank of Italy Survey of Investment in Manufacturing (SIM) and the Company Accounts Data Service (CADS). The SIM database goes back to 1984. The questionnaire is sent to each enterprise at the beginning of each year and the questions refer to the year just past and the previous year (this allows data consistency to be checked over time). Interviewers are officials of the Bank of Italy, who tend to establish long-run relationships with firms' managers and are also responsible for verifying the accuracy of the information collected. The sample is stratified according to three criteria: sector of economic activity, size and geographical location. With regard to the first, the three-digit Ateco-91 classification of the National Institute of Statistics (ISTAT) is used (fully consistent with the international Standard Industrial Classification). Size refers to the number of employees; four classes are considered: 50-99, 100-199, 200-999, 1000+ employees. Due to difficulties in ensuring high quality in the data collection, small firms, defined as those with fewer than fifty employees, are excluded from the SIM sample. Firm location refers to the regions (nineteen). The presence of outliers and missing data within the sample is dealt with by means of appropriate statistical techniques.

The company accounts report is a data service provided by an institution (*Centrale dei Bilanci*) established by the Bank of Italy and a pool of banks. Information on the annual accounts of around 30,000 Italian firms has been collected since 1982 and data are reclassified to ensure comparability across firms.

Panel structure. Merging the information from the two sources resulted in an unbalanced panel of around 1,000 firms. After taking rates of growth, there is a total of 6,811 observations. The structure of the sample by number of observations per firm is reported in Table A.1.

Table A.1

Sample structure by number of observations per firm

Number of annual observations	3	4	5	6	7	8	9	10	11	12	13
Number of firms	136	130	103	88	80	73	80	96	37	42	85

Source: SIM and CADS.

Sectoral classification. The sectors of economic activity in manufacturing industry are: 1) Food and tobacco products; 2) Textiles and Clothing; 3) Leather and footwear; 4) Wood and furniture; 5) Paper and publishing; 6) Chemicals; 7) Rubber and plastic products; 8) Transformation of non metalliferous minerals; 9) Metals and Metallurgy; 10) Machinery for industry and agriculture; 11) Electrical machinery (including Computers and office equipment); 12) Transport equipment (automobiles, railways, ships, aircraft and other motor vehicles) and 13) Other manufactures.

Variable definitions and sources. Gross output is measured as firm-level production (source: SIM) deflated by the sectoral production deflator computed by ISTAT. Employment is firm-level average employment over the year (source: SIM); manhours are also firm-level and include overtime hours (source: SIM). The use of intermediate inputs is measured as firm-level net purchases of intermediate goods of energy, materials and business services (source: SIM), deflated by the corresponding sectoral deflator computed by ISTAT. Investment is firm-level total fixed investment in buildings, machinery and equipment and vehicles (source: SIM), deflated by the sectoral investment deflator published by ISTAT. Capital stock is measured as the beginning-of-period stock of capital in equipment and non-residential buildings at 1997 prices. It was computed by applying backwards a procedure based on the perpetual inventory method (using firm-level investment figures from SIM and sectoral depreciation rates from ISTAT), using as a benchmark the information on the capital stock in 1997 (valued at replacement cost), collected by a special section of the Bank of Italy Survey conducted for that year. The capital deflator is the sectoral capital deflator computed by ISTAT.

In order to construct the series of required payment to capital, $rP_K K$, we used the firm-level, time-varying estimates of the user cost of capital computed at the Bank of Italy by De Mitri, Marchetti and Staderini (1998) on the basis of the SIM and CADS datasets. A further source is the Credit Register (CR) data, which are collected by a special unit of the Bank of Italy (*Centrale dei Rischi*) and include detailed information on bank-firm contracts. De Mitri et al. (1998) followed the well-known Hall-Jorgenson approach, as developed by Auerbach (1983) for firms that use both equity and debt finance. Thus, the user cost of capital is expressed as follows:

$$r = \frac{(1-S)}{(1-\tau)}\left[gi(1-\tau) + (1-g)e - \pi + \delta\right] \qquad \text{(A. 13)}$$

where τ is the corporate tax rate and S reflects corporate tax rates, investment tax credits, depreciation allowances and any relevant subsidy, all of which are set to the appropriate firm-specific value according to Italian law in the given year and to a number of firms' characteristics; g is the firm-specific ratio of financial debt over total liabilities (source: CR); i is the average borrowing rate payed by the firm (source: CR); e is the required nominal return to equity (i.e., the opportunity cost associated with holding part of the firm's equity), approximated by the average yield of Italian Treasury bonds (BTP), on the ground that the equity premium on the Italian stock market is usually estimated to have been negligible, or even negative, during most of the period considered; π is the sector-specific expected increase of capital good prices (source: SIM) and δ is the sectoral rate of capital depreciation (source: ISTAT).

Descriptive statistics of key variables. See Table A.2.

Table A.2

Descriptive statistics of selected variables (percent)

Variable	25th perc.	50th perc.	75th perc.	Mean
Gross output growth, dy	-6.4	3.0	12.4	2.9
Total hours growth, $(dn + dh)$	-3.3	.2	4.3	.7
Capital stock growth, dk	-3.0	-.5	2.9	.8
Materials growth, dm	-7.6	3.0	13.8	3.0
Labor cost-share, c_L	15.0	20.5	26.9	21.9
Capital cost-share, c_K	7.6	13.1	20.8	15.5
Materials cost-share, c_M	53.4	64.5	73.4	62.9

Source: SIM and CADS.

Table 1

Baseline model - Equation (11)

GMM estimates on firm-level panel data

Dependent variable: dy_{it}	
dx_{it}	1.054 (.056)
$c_{L,it}dh_{it}$	-.404 (.210)
$c_{K,it}(dp_{M,it} + dm_{it} - dp_{I,it} - dk_{it})$	.582 (.190)
$c_{K,it}(di_{it} - dk_{it})$	-.069 (.033)
Wald tests of joint significance:	
year dummies	40.2 (12; .001)
sectoral dummies	33.6 (12; .001)
firm size dummies	8.4 (4; .079)
corporate operat. dummies	11.0 (6; .088)
Sargan test of over-identifying restrictions	62.4 (68; .67)
Test of 2^{nd} order serial correlation	-.64 (.52)
Wald tests for weak instruments:	
dx_{it}	420.9 (106; .00)
$c_{L,it}dh_{it}$	290.0 (106; .00)
$c_{K,it}(dp_{M,it} + dm_{it} - dp_{I,it} - dk_{it})$	492.8 (106; .00)
$c_{K,it}(di_{it} - dk_{it})$	287.0 (106; .00)
Implied estimates of structural parameters	
$\gamma = \alpha$	1.054 (.056)
$\zeta = \frac{\beta}{\gamma}$	-.384 (.20)
$\Delta = \frac{\gamma - \varepsilon}{\varepsilon}$	.811 (.657)
$\xi = -\frac{(1+\Delta)\theta}{\gamma}$	.118 (.066)

Legend: the sample period is 1984-1997. Variables and parameters are defined in the text. Heteroschedasticity-consistent s.e. for parameter estimates are shown in brackets. For each test, degrees of freedom and p-values are reported in brackets; the test for second-order serial correlation is distributed asymptotically as a standard normal. The instrument set includes: lagged values of the endogenous explanatory variables at time t-2 and t-3; contemporaneous growth rate of material input prices and of the real exchange rate; variation of sectoral order-book levels drawn from the ISAE business survey; a VAR-based measure of monetary shock. In the Wald tests for weak instruments the null hypothesis is that instruments jointly explain none of the variation in the endogenous variable. S.e. of structural parameters are not heteroschedasticity-consistent.

Table 2

Alternative measures of productivity change

Descriptive statistics

Variable	Mean	Coefficient of variation	5th percentile	95th percentile
dz_{it}	.018	4.33	-.098	.126
Revenue-based Solow residual	.008	9.50	-.101	.114
Cost-based Solow residual	.007	11.43	-.110	.116

Legend: the statistics reported are computed over all firms and years; dz_{it} is computed as described in the text.

Table 3

The cyclicality of different productivity measures

Panel data estimation of random-effects model

	Dependent variables		
Cyclical indicators	dz_{it}	Cost-based Solow residual	Revenue-based Solow residual
Aggregate industrial output growth	.139 (.030)	.306 (.031)	.234 (.029)
Sectoral industrial output growth	.089 (.019)	.211 (.019)	.173 (.018)
GDP growth	.178 (.068)	.511 (.070)	.325 (.066)

Legend: the results in the table refer to nine different panel regressions, each with one cyclical indicator only as explanatory variables (apart from the constant). Aggregate industrial output is measured by the index of industrial production in total Italian manufacturing (source: ISTAT); sectoral industrial output is measured by the index of industrial production of the SIC two-digit sectors corresponding to each firm. Parameter estimates are reported with standard errors in brackets.

Table 4

The relation between technology shocks and input growth

Panel data estimation of random-effects model

Dependent variables	Regressors		
	dz_{it}	dz_{it-1}	dz_{it-2}
Total hours growth	-.086 (.022)		
”	-.046 (.028)	.132 (.030)	.078 (.029)
Employment growth	-.100 (.015)		
”	-.078 (.020)	.082 (.021)	.064 (.021)
Hours per capita growth	.012 (.017)		
”	.029 (.021)	.048 (.022)	.012 (.022)
Factor utilization growth	-.066 (.006)		
”	-.065 (.007)	.020 (.008)	-.005 (.008)
Input growth	-.088 (.023)		
”	-.104 (.029)	.179 (.030)	.051 (.030)

Legend: each row corresponds to a regression. Parameter estimates are reported with standard errors in brackets. The growth rate of unobserved capital and labor utilization is computed as $c_K du_{it} + c_L de_{it}$; input growth is measured by dx_{it}.

Table 5

Technology shocks, input growth and price stickiness

Sample splitting based on the frequency of price changes

Panel data estimation of random-effects model

Dependent variables	Sample	Regressors		
		dz_{it}	dz_{it-1}	dz_{it-2}
Total hours growth	SP	-.230 (.035)		
”	NSP	.020 (.051)		
”	SP	-.227 (.044)	.186 (.045)	.095 (.044)
”	NSP	.080 (.060)	.081 (.060)	.038 (.062)
Employment growth	SP	-.207 (.024)		
”	NSP	-.050 (.036)		
”	SP	-.193 (.030)	.080 (.032)	.058 (.031)
”	NSP	-.008 (.045)	.097 (.045)	-.001 (.047)
Hours per capita growth	SP	-.029 (.026)		
”	NSP	.052 (.040)		
”	SP	-.039 (.033)	.099 (.034)	.035 (.033)
”	NSP	.028 (.027)	-.012 (.027)	-.020 (.028)
Factor utilization growth	SP	-.106 (.009)		
”	NSP	-.021 (.014)		
”	SP	-.081 (.011)	.029 (.012)	-.003 (.011)
”	NSP	-.038 (.015)	-.000 (.015)	-.021 (.016)
Input growth	SP	-.251 (.035)		
”	NSP	.001 (.054)		
”	SP	-.265 (.043)	.273 (.044)	.105 (.043)
”	NSP	-.005 (.061)	.100 (.062)	-.058 (.064)

Legend: each row corresponds to a regression. Parameter estimates are reported with standard errors in brackets. The sample is split according to the degree of price stickiness as measured by the frequency of price changes reported by the SIM Survey. SP is the sample of firms that modify selling prices no more than twice a year; NSP is the sample of firms that modify prices more than twice a year (see text for more details). The growth rate of unobserved capital and labor utilization is computed as $c_K du_{it} + c_L de_{it}$; input growth is measured by dx_{it}.

Table 6

Technology shocks, input growth and price stickiness

Sample splitting based on the size of price changes

Panel data estimation of random-effects model

Dependent variables	Sample	Regressors		
		dz_{it}	dz_{it-1}	dz_{it-2}
Total hours growth	SP	-.120 (.028)		
”	NSP	-.033 (.035)		
”	SP	-.104 (.036)	.130 (.038)	.126 (.036)
”	NSP	.026 (.045)	.127 (.048)	-.004 (.050)
Employment growth	SP	-.112 (.020)		
”	NSP	-.084 (.024)		
”	SP	-.107 (.026)	.089 (.027)	.082 (.026)
”	NSP	-.038 (.031)	.065 (.034)	.035 (.035)
Hours per capita growth	SP	-.010 (.021)		
”	NSP	.045 (.027)		
”	SP	.004 (.027)	.040 (.028)	.044 (.027)
”	NSP	.058 (.034)	.061 (.037)	-.045 (.038)
Factor utilization growth	SP	-.048 (.008)		
“	NSP	-.091 (.010)		
“	SP	-.063 (.010)	.017 (.010)	-.002 (.010)
“	NSP	-.070 (.012)	.027 (.013)	-.012 (.013)
Input growth	SP	-.131 (.030)		
”	NSP	-.024 (.038)		
”	SP	-.181 (.037)	.175 (.039)	.106 (.037)
”	NSP	-.003 (.045)	.178 (.049)	-.043 (.050)

Legend: each row corresponds to a regression. Parameter estimates are reported with standard errors in brackets. The sample is split according to the degree of price stickiness as measured by the size of price changes reported by the SIM Survey. SP is the sample of firms whose average selling price variation, taken in absolute value, is below the overall sample mean; NSP is the sample of firms whose average selling price variation is above the overall sample mean. The growth rate of unobserved capital and labor utilization is computed as $c_K du_{it} + c_L de_{it}$; input growth is measured by dx_{it}.

Table 7

Model-based measures of technology shocks

and survey data on innovative activities

Dependent variables	Regressors		
	R&D expenditure	Expenditure for patent purchases	Expenditure for experimental products
dz_{it}	.373 (.148)	1.47 (.402)	1.17 (.266)
Revenue-based Solow residual	.280 (.144)	1.13 (.39)	1.21 (.257)
Cost-based Solow residual	.289 (.151)	.99 (.410)	1.11 (.269)

Legend: the results in the table refer to nine different regressions, each with one regressor only (apart from the constant). Parameter estimates are reported with standard errors in brackets. Each regressor is divided by the value of firms' production.

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