Price Stickiness and Contractionary Technology Shocks*

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Abstract

We derive a measure of technological change from a dynamic cost minimization model that controls for imperfect competition, increasing returns and unobserved factor utilization. We estimate this measure using highly detailed panel data of a representative sample of Italian manufacturing firms in the period 1984-1997. Our key finding is that technological shocks result in a contraction of labor and other inputs on impact. This result is hard to reconcile with the transmission mechanism of flexible-price models. However, given the characterization of Italian monetary policy in the period considered, it is consistent with the predictions of a sticky-price model. 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* D24, E32)

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1 Introduction

Business cycle models are typically evaluated on the basis of their ability to match patterns of comovements observed in the data of selected macroeconomic variables. Recently, attention has been drawn to the correlation between technology shocks and labor input. In particular, Basu et al. (1998) and Galí (1999) have documented for the U.S. and other G7 economies a negative correlation between technology shocks, identified under different assumptions, and several measures of labor and other inputs. They interpret this finding, which is hard to reconcile with the predictions of a flexible-price model, as evidence in favor of sticky-price models. For example, Galí (1999) shows that in a model economy with sticky prices and a money supply less than fully responsive to technological shocks, a technology improvement has a negative short-run effect on hours. The argument is that in the wake of a technology expansion, nominal rigidities prevent prices from falling and thus aggregate demand does not increase; on the other hand, firms produce the same amount of output with a smaller volume of inputs, which have become more productive.

However, a number of subsequent contributions have qualified Galí's claim, showing that within a sticky-price model the pattern of correlation between input growth and technology shocks hinges crucially on the response of the monetary authorities to technology shocks, which depends in turn on the characterization assumed for the systematic part of monetary policy. In particular, in the context of a dynamic stochastic general equilibrium model with staggered price setting, Dotsey (1999a; 1999b) and Galí et al. (2000) show that if the central bank follows the optimal monetary policy or a Taylor (1993) rule or the rule estimated by Clarida et al. (2000), then the effect of technology shocks on employment is no longer negative. Indeed, the monetary policy, by responding to deviations of inflation from target and to deviations of output from its natural level, reduces the policy rate so as to provide full accommodation of the shock. With these specifications of monetary policy, sticky-price and flexible-price models are therefore observationally equivalent with respect to the predicted correlation between technology shocks and labor input, and no inference on the price setting behavior can be drawn on the basis of the pattern observed in the data.

Dotsey (1999a), however, also shows that if the monetary authorities employ a modified Taylor rule, in which the central bank responds to output growth rather than to deviations of output from its potential level, then a sticky-price model predicts a contractionary effect of technology shocks. In this situation, the rule induces the central bank to tighten monetary conditions during an expansion, regardless of any increase in the natural level of output due to a technology improvement. Overall, the response of monetary policy to the technology shock falls short of full accommodation, and the impulse response of labor input is similar to that obtained under a constant money growth rule.

The results summarized above imply that economies where monetary policy is well characterized by money growth pegging or any other rule failing to fully respond to technology shocks provide a good basis for assessing the empirical relevance of flexible- versus sticky-price models. In this regard, we believe that the Italian economy in the second half of the eighties and the first half of the nineties provides a very interesting case. In that period Italy largely pegged its currency to the Deutsche mark, which played the role of nominal anchor. In other words, Italian monetary policy was severely constrained by German monetary policy in order to ensure maintainance of the exchange rate margins (see, e.g., Clarida et al. 1998). In terms of monetary rules, Dornbusch et al. (1998) and Favero et al. (2000) estimate the central bank's reaction function using a modified Taylor rule, in which the Bank of Italy responds to deviation of output growth from the target given by German output growth and to deviation of inflation from the target given by German inflation. This scenario closely resembles the policy behavior underlying the modified Taylor rule discussed by Dotsey (1999a) and illustrated earlier. In particular, the focus on output growth (as deviation from German output growth) rather than on output gap implies that in the wake of a technology shock monetary policy is less accommodative than, for example, under a standard Taylor rule or a Clarida et al. rule.

These considerations motivate our empirical investigation of the relationship between technology shocks and labor inputs in the Italian economy in the period mentioned. For this purpose, we use highly detailed panel data of a representative sample of Italian manufacturing firms for the period 1984-1997. In general, the studies focusing on this issue have been conducted on aggregate or sectoral data. However, in light of the significant heterogeneity across firms, theory calls for an investigation on firm-level data. The use of microeconomic panel data prevents individual idiosyncrasies from being washed out in the aggregation process, thus avoiding a potentially serious bias in the estimates.

Following Basu and Kimball (1997), we derive a measure of technology change from a theoretical model based on a dynamic cost minimization set-up that controls for imperfect competition, increasing returns, and variable intensity in the use of labor and capital. 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 netted out. We study the impact of a technology improvement on labor and other inputs and find that, unambiguously, a negative relationship emerges from our data. Moreover, a notable feature of our data, namely the information on the frequency and size of price revisions of each firm, allows us to investigate the interpretation of this finding based on the existence of nominal rigidity. We find that the negative relationship between input use and technology change is indeed much stronger for firms whose product prices are stickier.

Finally, in order to verify our model-based estimates of firm-level technology, 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 evidence that the innovation process is well captured by our analytical approach.

The remainder of the paper is organized as follows. Section 2 outlines the theoretical framework whereby the measure of technology change is derived. Section 3 presents the data and the methodology used for estimation. In Section 4 we analyze the response of input growth to technological shocks and examine the role of price stickiness. In Section 5 we investigate whether our model-based measures of technology change are sensible. The final section draws some conclusions.

2 The model and the empirical specification

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 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}. M_{it} is the quantity of materials and energy inputs and Z_{it} is an index of technology.

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

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

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 the elasticity to technology is assumed to be equal to one. To simplify, time subscripts and the index i are omitted.

In order to measure output elasticities, we recall the first order condition of a simple firm optimization problem, $P\frac{\partial F}{\partial X} = \mu P_X$, where X is one of the inputs 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, each of the output elasticities can be formulated as $\frac{\partial F}{\partial X}\frac{X}{Y} = \mu\frac{P_x X}{PY} = \mu s_X$, where s_X is the revenue-based share of factor X. Similarly, the output elasticities can also be expressed in terms of the returns-to-scale parameter, γ.[1] In that case, they would be:

$$\frac{\partial F}{\partial \widetilde{L}}\frac{\widetilde{L}}{Y} = \gamma c_L; \qquad \frac{\partial F}{\partial \widetilde{K}}\frac{\widetilde{K}}{Y} = \gamma c_K; \qquad \frac{\partial F}{\partial M}\frac{M}{Y} = \gamma c_M; \tag{3}$$

where c_L, c_K and c_M are the cost-based factor shares.

Inserting expressions (3) in (2) yields an equation that still contains two unobservable variables: the time variation of labor and capital utilization (respectively, de and du). As extensive evidence suggests (see, e.g., Fay and Medoff, 1985), inputs are used more intensively in booms than in recessions.

[1] 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 factor shares is equal to total costs over total revenues: ($Costs/PY$). Using the definition of μ as P/MC, we have: $\gamma c_X = \mu s_X$. Of course, this holds true for all the inputs.

The explanation for this pattern points to the sizeable adjustment costs that prevent firms from instantaneously hiring (laying-off) workers or increasing (decreasing) capital when more (less) of these inputs are required. This induces a form of factor-hoarding, with employment (N) and capital (K) being quasi-fixed factors and the intensity of their use varying over the cycle. Clearly, the increase in factor utilization is also costly for the firm and, hence, the "optimal" degree of 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 with adjustment costs in hiring and investing. The optimization problem is the following:

$$\underset{H,E,A,I,U,M}{Min} \int_0^{\infty} \left[NWG(H,E) + NW\Psi\left(\frac{A}{N}\right) + P_I K J\left(\frac{I}{K}\right) + P_M M \right] e^{-rt} dt \tag{4}$$

$subject \quad to:$

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

$$\overset{\circ}{K} = I - \delta(U)K \quad and \quad \overset{\circ}{N} = A$$

The above expressions introduce some new variables in addition to those defined before. W is the base wage; $WG(H,E)$ is total compensation to each worker and depends both on the number of hours and on the effort supplied. As is argued convincingly by Basu and Kimball (1997), one can assume that the wage payments are governed by implicit contracts, 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. Investment as well 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 the expenditure for capital, where P_I is the price of investment goods. δ is the rate of capital depreciation, which is an increasing function of capital utilization, U. P_M is the price of intermediate inputs.

The first order conditions of the problem are derived in Appendix I. Manipulating these equilibrium relations and combining them with the expressions for marginal products stemming from equation (3) yields an expression for changes in capital utilization:

$$du = \frac{1}{1+\Delta}\left(dp_M + dm - dp_I - dk\right) - \frac{\xi}{1+\Delta}(di - dk), \tag{5}$$

where we have used the fact that in steady-state $(\frac{I}{K})^* = \delta^*$. Two new parameters are introduced in (5). The first represents the elasticity of marginal depreciation with respect to utilization, $\Delta = \frac{U\delta''}{\delta'}$, and captures the degree of convexity of depreciation as a function of capital utilization. The second denotes the elasticity of the marginal cost 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 is useful to define these elasticities in terms of steady-state variables and treat them as constant.[2]

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

$$d\widetilde{l} = dn + dh + de = dn + (1+\zeta)\, dh \tag{6}$$

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

Inserting equations (5) and (6) in (2) and using the expressions in (3) for output elasticities, we obtain our main regression equation:

$$\begin{aligned} dy_{it} \;=\; & \alpha dx_{it} + \beta(c_{L,it} dh_{it}) + \varepsilon \left[c_{K,it} \left(dp_{M,it} + dm_{it} - dp_{I,it} - dk_{it}\right)\right] \\ & + \theta \left[c_{K,it}(di_{it} - dk_{it})\right] + dv_{it}, \end{aligned} \tag{7}$$

where dx_{it} represents the weighted average of changes in the observed component of inputs ($dx_{it} = c_{L,it}(dn_{it} + dh_{it}) + c_{K,it} dk_{it} + c_{M,it} dm_{it}$), 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 earlier, they are part of the definition of de_{it} and du_{it}. The unknown parameters to estimate in (7) are α, β, ε, and θ. α represents the degree of internal returns to scale ($\alpha = \gamma$). The second parameter allows us to trace back the elasticity of effort with respect to hours, ζ ($\beta = \gamma\zeta$); the third parameter, ε, depends on Δ according to the relationship $\epsilon = \frac{\gamma}{1+\Delta}$, while the parameter θ is linked to the elasticity ξ through the

[2] A feature of equation (5) 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 on the ratio between the *current* marginal value product of capital, $\lambda\frac{\partial F}{\partial K}$, and the *future* marginal products of capital, q. Thus, whenever q and, consequently, investment, I, decline, $\frac{\partial\delta}{\partial U}$ increases; in turn, owing to convexity of the depreciation function, an increase of $\frac{\partial\delta}{\partial U}$ mirrors a rise in capital utilization.

relationship: $\theta = -\frac{\gamma\xi}{1+\Delta}$. The last term, dv_{it}, represents technology variation. Estimation of equation (7) 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 of technological change

3.1 Data and the econometric procedure

We rely on firm-level data for a representative sample of Italian manufacturing firms drawn from two main sources: the Bank of Italy's Survey of Investment in Manufacturing (SIM) and the 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 SIM has been carried out at the beginning of each year since 1984. We believe the data to be of unusually high quality, thanks 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 fewer than 300 firms. The survey collects data on a considerable number of economic variables, including factor demand and the value of sales, and information on several firm's characteristics.

The SIM omits 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 comprising the Bank of Italy and a very large number of Italian banks, is the principal source of information on balance sheets and income statements of Italian firms. It collects detailed information drawn from the annual accounts of more than 30,000 companies. Merging the information from the two sources resulted in an unbalanced panel of slightly fewer than 1,000 firms, which was used in the estimation process. Data range from 1984 to 1997 and include about 8,000 observations. 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 to us.

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 man-hours 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_KK, 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, computed according to the Hall-Jorgenson approach (see Appendix II).

Equation (7) in the previous section represents our empirical specification in 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 $t \neq s$. The specification in level also contained a firm-specific effect, which was eliminated by taking first differences.

In estimating equation (7), one has to take into account that unobservable technology variation is likely to be correlated with changes in effective labor and capital services and materials inputs. This would yield a specification error leading to inconsistency in the parameter estimates. In order to account for this endogeneity of regressors, we adopted the generalized method of moments (GMM) estimation procedure developed by Arellano and Bond (1991) for panel data. This method has been shown to be efficient within the class of instrumental variable procedures, as it optimally exploits all linear moment restrictions following 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 truncated 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. We also employed external instruments, presumably uncorrelated with technology variation, that are commonly used in production function regressions (see, for example, Hall, 1988, Burnside, 1996, and Basu et al., 1998). These additional instruments include: the contemporaneous growth rate of materials 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.[3] Throughout the paper we report the estimates obtained using all the instruments mentioned above. However, as a sensitivity inspection, we also estimated equation (7) after excluding from the set of instruments the external instruments, both jointly and 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 (Burnside, 1996) and the empirical specification. Two such tests were 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 the instruments, we examined their correlation with each endogenous regressor (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 was 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.[4] 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 use of gross-output data prevents our empirical framework from being misspecified, as would be the case with value-added data (Basu and Fernald, 1995).

[3]The measure of monetary shock was 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 using 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 the measure of monetary impulse.

[4]For an insightful discussion on the effect of aggregation bias in production function regressions, see Basu and Fernald (1997).

3.2 The measure of technological change

The estimation results of equation (7) are reported in Table 1. Before turning our attention to the measure of technology variation, it is worth examining the parameter estimates, which provide some insights into the functioning of the production process. The first four rows of Table 1 refer to the reduced form parameters (α, β, ε and θ) and the last four report the implied values of the structural parameters (γ, Δ, ξ and ζ). The point estimate of the returns-to-scale parameter is slightly higher than one, but not statistically different from unity. Hence, consistently with most microeconomic evidence reported in the literature (see, e.g., Baily et al., 1992, for U.S. firms), the hypothesis of constant returns to scale is not rejected by our sample. The elasticity of effort to hours, ζ, is estimated to be equal to -.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, increasing hours at the margin would lead to a reduction in effort during the marginal hour. This seems a plausible result in light of the physical fatigue associated with the extension of the daily work schedule.[5] The elasticity of marginal depreciation of capital to utilization, Δ, is estimated to be positive (.811) but not statistically significant; this provides only mild evidence in favor of the convexity of the depreciation function, $\delta(U)$. The marginal installment cost of capital, J', is found to be increasing in the rate of investment, $\frac{I}{K}$ (ξ is estimated to be equal to .118 with a standard error of .066). Finally, the empirical specification includes a vector of control dummy variables (call it $W_{i,t}$), referring to the sector, the year, the firm's size and the occurrence of a corporate operation such as a merger, acquisition or break-up. Table 1 reports the values of the Wald test for the joint significance of different groups of dummy variables.

For our purposes, the most important implication of equation (7) is that it allows us to derive a highly refined measure of technological change. In particular, the time-varying firm-specific measure of technology variation,

[5] By contrast, 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 contrasting evidence lies in the rigidities of the Italian labor market. The latter, presumably, lead Italian firms to overexploit their existing work force during expansions to the point that hourly effort starts to diminish. Corroborative evidence on the matter is provided by Marchetti and Nucci (2001).

dz_{it}, is computed as the sum of regression residuals, dv_{it}, and the parameters associated with the control dummy variables included in the specification, 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). The dummy variables are included in dz_{it} because, given our analytical framework, they capture the sector, the year and the size-specific components of firm's technological growth.[6] In order to implement our model in a sufficiently flexible fashion, we obtained our firm-level measure of technology change, dz_{it}, by estimating (7) separately for durable and non-durable goods and allowing for a sector-specific returns-to-scale parameter, γ, as recommended by Burnside (1996).[7]

In manufacturing industry as a whole, the average of dz_{it} is about .018, that is a yearly technology improvement of more than 1.5 per cent. This is about twice 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, 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 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). In order to shed some light on the cyclical properties of our measure of technology, Table 3 reports the results of simple regressions of dz_{it} 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 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 around fifty per cent (forty 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

[6] To check robustness, we replicated all the empirical investigations presented below with a measure of dz_{it}, net of the control effects, $b'\overline{W}_{i,t}$; the results are basically unaffected.

[7] 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. As a robustness inspection, we also derived dz_{it} from a single equation for all of 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 section continue to hold.

of standard measures of technological shocks.[8]

Although the main focus of this paper is on measures of technology variation at the 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. 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. Interestingly, the probability of technological regress, calculated on this aggregate, is about 15 per cent, much lower than the one calculated at the firm level; this indicates that in most years the firms which experience a positive technological shock outnumber those experiencing a negative one.

4 Technology shocks and labor input

4.1 The contemporaneous relationship

Above we have provided motivation for investigating empirically the correlation between technological change and labor and other inputs. In this section, we present the results obtained by regressing several measures of input on dz_{it}. A critic might argue that, since $dz_{i,t}$ was obtained from equation (7) as a regression residual, it should be orthogonal to input growth. When estimating equation (7), however, a number of instruments were used; 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 precisely this correlation that we seek to investigate in this section.

Since our measure of technological shock is exogenous, we do not need an instrumental variable estimator and can resort to a standard random-effects

[8] The importance of unobserved factor utilization has been largely recognized in real business cycle (RBC) models. When account is taken of this element, the remeasurement of technology impulses in this class of models has yielded more plausible properties, compared with the Solow residuals (see, e.g., Burnside et al., 1993 and King and Rebelo, 1999).

model when estimating the effect of $dz_{i,t}$ on input growth.[9] 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. 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.[10] We also used a measure of total input services, namely the observable component of input growth, dx_{it}. Again, the results indicate a contemporaneous contractionary effect of technology improvements.[11] Finally, we estimated other panel regressions where the dependent variables are the same as before but lags of dz_{it} are added as regressors. While the coefficients 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.[12]

[9] Notice that, as shown by Pagan (1984), the use of unlagged generated residuals as regressors does not affect consistency and efficiency of estimators and the validity of standard inference. On the other hand, when lagged generated residuals are included, standard errors become inaccurate and obtaining the correct ones would be a complex task.

[10] A possible explanation of this finding is that, after the introduction of a technology improvement, the number of hours for training 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 after favourable technology improvements.

[11] We also run regressions with the growth of unobserved labor and capital utilization as dependent variable. This is measured as $c_K du_{it} + c_L de_{it}$, consistently with equations (5), (6) and (7) in Section 2 (intuitively, the sum of du_{it} and de_{it}, weighted by the corresponding cost-share, represents their contribution to output growth). The response to a technology improvement is again negative; interestingly enough, this result shows that unobserved factor utilization behaves similarly to observed inputs, confirming that firms view this variable as another form of primary input.

[12] 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

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. Our evidence dovetails with that recently reported by other contributions. In particular, Basu et al. (1998), using sectoral data spanning the whole U.S. economy, show that after a technology innovation a significant fall in inputs occurs on impact. Galí (1999), fitting a structural VAR model to aggregate data for the U.S. and other G7 countries, 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 also point to a negative and statistically significant relationship between technology shocks and labor inputs.[13] Basu et al. (1998) and Galí (1999) have interpreted their finding as evidence in favor of sticky-price models. The intuition is the following. Consider a framework where the quantity theory determines the demand for money and, in the short run, money supply is fixed and price flexibility imperfect. Hence, real balances (and, thus, aggregate demand) are also fixed in the short run. In the wake of a technology improvement, firms meet their demand by producing the same output as before. However, to produce that amount of output firms need fewer inputs, so that a technology impulse would result in a short-run reduction in workers, total hours and, in general, effective factor services. Of course, as prices start to decline over time, the standard adjustment mechanism comes into play and output and input

error of .022, when sectoral output growth is included).

[13]Shea (1998), also, examines the impact of technology shocks on employment. Using VAR models, he considers the dynamic effects of 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 (see Galí, 1998).

eventually rise.

Because of the important implications for business cycle modeling, the claim by Basu et al. and Galí has stirred an intense debate. In particular, Dotsey (1999a; 1999b) and Galí et al. (2000) have shown that in a sticky-price model the prediction of a negative correlation between technology shocks and labor input hinges crucially on the characterization assumed for the systematic component of monetary policy. By calibrating and simulating a dynamic stochastic model of an economy with price rigidity, Dotsey (1999a) has investigated the implications of four different monetary policy rules, which cover a broad variety of monetary authorities' behavior.[14] If the central bank follows a constant money growth rule, technology improvements do induce a contraction of labor input. If, on the other hand, its behavior is well approximated by a Taylor (1993) rule or a Clarida et al. (2000) rule, then, in the wake of a technology improvement, monetary policy, by fully accommodating the shock, induces a significant increase in output and labor. The explanation of this finding is that, with staggered price setting, a technology improvement decreases firms' real marginal costs and generates a reduction in the aggregate price level that is smaller than that obtained under perfect price flexibility. Consequently, aggregate demand increases, but by less than under price flexibility. This creates a wedge between output and its natural level – i.e. the level achieved when prices fully adjust – and, therefore, the output gap diminishes and so does inflation. A monetary authority that responds to deviations of inflation from target and to deviations of output from its natural level would reduce the policy rate so as to provide full accommodation of the shock. In these situations, the correlation between technology shocks and labor input is positive. However, if the central bank follows a modified Taylor rule, according to which it responds to output growth rather than to deviations of output from its potential level, then the response of labor input to technology shocks is closer to that obtained under a constant money growth rule (Dotsey, 1999a). The reason is that, under this modified rule, monetary policy is less accommodative. In fact, as just illustrated, after a favorable technology shock output increases (although by less than under flexible prices). Hence, if anything, the central bank will tighten policy in response to the output growth and this partly offsets the

[14] Among the contributions examining the implications of technology shocks under price stickiness and specific monetary policies, see also McGrattan (1998), King and Wolman (1999) and Galí (2000).

interest rate reduction induced by lower inflation.

The case of this modified Taylor rule is particularly interesting for our purposes because it closely resembles the monetary regime of Italy in the period considered in this paper. By almost any account, a primary objective of Italian monetary policy in the second half of the eighties and the first half of the nineties was exchange rate stability, with some room for stabilizing domestic inflation and output fluctuations (see, e.g. Clarida et al., 1998). During those years, the monetary policy of a number of European countries, including Italy, was constrained by German monetary policy. Maintainance of the exchange rate margins was the external constraint that shaped the conduct of the Italian central bank. As argued convincingly by Dornbusch et al. (1998) and Favero et al. (2000), monetary policy in Italy in that period is well described by a rule in which the short-term interest rate depends on the German short-term rate plus the difference in inflation between Italy and Germany and the difference in output growth between the two countries.[15]

This empirical evidence lends support to the view that, in that period, given the importance of the external constraint, monetary policy in Italy could not fully respond to domestic shocks. We believe this makes our empirical investigation particularly relevant. In fact, with monetary policy falling short of full accommodation of technology shocks, business cycle models featuring sticky prices or, alternatively, flexible prices yield opposite predictions on the correlation between technology impulses and labor input. Namely, our finding of a negative correlation is in line with the prediction of sticky-price models.

Although this result is hard to reconcile with the predictions of a flexible-price model, there are a few exceptions. One is the time-to-plan model of Christiano and Todd (1996). Suppose that a positive technology shock leads the firm to plan new investment projects, which typically require more than one period to be realized. The resources invested in the initial planning phase are assumed to be relatively small compared with the overall cost of the project. In this context, hours worked do not rise immediately after the shock, but start to increase only when the planning phase is completed. An-

[15]The intuition behind this modified Taylor rule is that, in order to pursue the objective of exchange rate stability, the Italian monetary authorities chose the values of German inflation and output growth as target values for the corresponding domestic variables. Indeed, if one includes the Italian domestic output gap in the specification of the monetary rule of the Bank of Italy, the corresponding coefficient is estimated to be non-significant, as shown by Clarida et al. (1998) and by Favero et al. (2000).

other explanation of contractionary technology shocks consistent with flexible prices is that offered by Cooley (1998), based on vintage-capital models. An investment-specific technology improvement causes a short-run reduction in employment because of the intense labor reallocation from older to newer vintages (see, e.g., Campbell, 1998). In the following section, in order to shed some light on the interpretation of our findings, we investigate the link between price stickiness and the effect of technology shocks.

4.2 Sample splitting based on price stickiness

If price stickiness drives our results, we should observe that, on average, the stickier the prices set by a given firm, the stronger would be the contractionary effect of a technology shock. Despite the crucial role assigned to price stickiness in the macroeconomic debate, empirical evidence on the matter is rather limited; this is due, possibly, to difficulty in gathering firm-level data (two exceptions are Carlton, 1986, and Kashyap, 1995). Very interestingly, the SIM database includes firm-specific information on the frequency and size of price variations. With regard to frequency, in the 1996 survey firms were asked the following question: "How frequently does your firm typically modify selling prices?". The possible responses were five: "Several times a month", "Every month", "Every three months", "Every six months" and "Once a year or less frequently". Answers were provided by 962 firms: the first response was chosen by 63 firms (6.5 percent), the second by 67 (7.0 percent), the third by 155 (16.1 percent), the fourth by 343 (35.7 percent) and the fifth by 334 (34.7 percent). Direct comparison with other evidence must be approached with caution in light of differences in the data. This distribution, however, is broadly consistent with that derived from data on transaction prices of U.S. firms reported in Carlton (1986), while the data of U.S. firms analyzed by Kashyap (1995) feature a somewhat stronger degree of price stickiness.[16]

[16] Carlton (1986, Table 1) considers prices of eleven groups of intermediate goods in the period 1957-1966; for three groups, the average duration of price rigidity spells is around three months (more precisely, it ranges from 3.6 to 4.7), for four it is not far from six months (ranging from 5.4 to 8.7) and for the remaining four it is around twelve months (ranging from 10.2 to 13.0). Kashyap (1995, Table 1) considers twelve branch-specific retail goods over the period 1953-1987; for none of them is the average price rigidity spell shorter than 11 months (the longest spells, however, are disproportionately concentrated in the fifties and sixties).

The information from the SIM database allows us to conduct a test on the effects of technology shocks. We split the overall 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. We report in Table 5 the regression results obtained separately for two sub-samples: the first includes firms that typically modify their prices every three months or more often; the second comprises firms that modify their prices every six months or less often. The evidence largely supports the view that, for firms with stickier prices, technology shocks have a contractionary impact effect on input. 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 -.230; it is .020 in the other (with standard errors equal to .035 and .051, respectively). 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 and statistically significant on impact for firms whose prices are less flexible (with the only exception of regressions with hours per capita growth, dh_{it}, as dependent variable, where the effect is negative but not significant). Conversely, a negative and statistically significant effect of dz_{it} is never found in firms whose prices are more flexible.[17] In order to verify if the results presented above were affected by the threshold value chosen for splitting the sample, we also run separate regressions for each of the five groups of firms corresponding to each of the possible answers to the above question. The results broadly confirm the pattern depicted in Table 5. For example, if we consider changes in total hours, $dn_{ih} + dh_{it}$, as dependent variable, the estimated coefficient of dz_{it} is not statistically significant in the regressions which include firms that modify prices more than once a month, every month or every three months, respectively; the parameter estimates are .03, -.11 and .04, respectively (with standard errors of .12, .11 and .06). On the other hand, the estimate of this parameter is statistically significant and has a negative sign in the regressions

[17] Arguably, specific features of a given market or product may cause, *ceteris paribus*, a higher or lower frequency of price revisions. Hence, we also split the sample according to whether the 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 -.101 in the sample with stickier prices and .025 in the other sample (with standard errors of .046 and .052, respectively).

which include firms that modify their prices every six month or less often; the estimated parameters are equal to, respectively, -.38 (with a standard error of .05) and -.09 (with a standard error of .04).

We also devised an alternative criterion for splitting the sample, based on the size of price revisions. In particular, we used information on annual price variations as reported each year by every firm. We split the sample according to whether a given firm has maintained its selling prices unchanged for one or more years rather than revising them every year. We therefore included in one sub-sample the firms that reported an annual price variation equal to zero for at least one year, and included all other firms in the other sub-sample.[18] Table 6 presents the estimation results from this exercise. The main findings illustrated before are confirmed: the evidence supports a negative and statistically significant impact effect of technology change on input growth only in firms characterized by stickier prices.

5 Are our model-based estimates of technological change 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 and Kimball (1997) – which controls for imperfect competition, increasing returns and unobservable factor utilization – except that in the estimation we use firm-level panel data. While we believe that our procedure provides a valid measure of the time-varying stochastic technological progress, it might be appropriate to compare it with alternative, independent proxies of technological innovation. 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 collected data on expenditure on (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 he uses are R&D spending and patent applications for 19 two-digit U.S. manufacturing industries.

[18] In principle, an annual price variation equal to zero may result from several individual price variations of opposite sign that perfectly offset each other. We believe this situation is very unlikely and is presumably limited to few, if any, observations.

Some caution is necessary when intepreting these direct measures of innovative activities as indicators of technological progress. On the one hand, patenting fluctuations may partly reflect changes in legislation and the procedures of the patent office. On the other, technological innovations may be embodied in new equipment. In addition, such innovations may not be due exclusively to scientific and engineering developments, but may also depend on variations in management techniques, capital organization and other intangible inputs, such as the information capital incorporated in production processes (see Shea, 1998 and references therein). Another problem with R&D spending and patents as measures of 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. Despite these limitations, we explored the link between our model-based measures of technology change 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 by the level of output. The evidence points to 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, i.e. the revenue-based and cost-based Solow residual. While their relationship with the indicators of innovative activity is positive and statistically significant, the corresponding estimated coefficient is generally lower than that associated with dz_{it}. This lends additional support to the view that our measures of technological change are more refined than standard Solow residuals.

6 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. By estimating the model on firm-level panel data we avoid the potentially serious problems caused by aggregation. The effects of departures from constant returns to scale and perfect competition turn out to be negligible for our measure of technology. By contrast, explicitly allowing for variable factor utilization leads to, with respect to the Solow residual, more reasonable properties (e.g. a lower probability of technological regress) and a stronger correlation with firm-level information on innovative activities (e.g. spending on R&D and patent purchases).

We employ our firm-level estimates of technology change to evaluate its impact on labor input growth. We find that a positive technology shock tends to reduce inputs on impact. This evidence is hard to reconcile with the transmission mechanism of flexible-price models. On the other hand, it has been shown to be consistent with the predictions of sticky-price models when the response of the monetary authorities to a technology disturbance is not fully accommodative. This seems to have been the case of Italy in the period under investigation, during which monetary policy was severely constrained by the objective of exchange rate stability. The interpretation of our results based on sticky prices is supported by the evidence that we provide on the link between the degree of price rigidity and the strength of the contractionary effect of technological shocks.

A 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 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 (5) and (6) in equation (2) in the text and use the expressions (3) for output elasticities, the estimating equation (7) is obtained.

A 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_KK, 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 general corporate tax rate and S reflects local and other specific 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.

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Table 1
Baseline model - Equation (7)
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; .670)
Test of 2^{nd} order serial correlation	-.64 (.520)
Wald tests for weak instruments:	
dx_{it}	420.9 (106; .000)
$c_{L,it}dh_{it}$	290.0 (106; .000)
$c_{K,it}(dp_{M,it} + dm_{it} - dp_{I,it} - dk_{it})$	492.8 (106; .000)
$c_{K,it}(di_{it} - dk_{it})$	287.0 (106; .000)
Implied estimates of structural parameters	
$\gamma = \alpha$	1.054 (.056)
$\zeta = \frac{\beta}{\gamma}$	-.384 (.200)
$\Delta = \frac{\gamma-\varepsilon}{\varepsilon}$	.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. The sample period is 1984-1997.

Table 3
The cyclicality of different productivity measures
Panel data estimation of random-effects model

	Dependent variables		
	dz_{it}	Cost-based	Revenue-based
Cyclical indicators		Solow residual	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). The sample period is 1984-1997. Aggregate industrial output is measured by the index of Italian manufacturing output (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
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)
Input growth	-.088 (.023)		
”	-.104 (.029)	.179 (.030)	.051 (.030)

Legend: each row corresponds to a regression. The sample period is 1984-1997. Parameter estimates are reported with standard errors in brackets. Input growth is measured by dx_{it}.

Table 5
Price stickiness, technology shocks and input growth
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	stickier	-.230 (.035)		
”	less sticky	.020 (.051)		
”	stickier	-.227 (.044)	.186 (.045)	.095 (.044)
”	less sticky	.080 (.060)	.081 (.060)	.038 (.062)
Employment growth	stickier	-.207 (.024)		
”	less sticky	-.050 (.036)		
”	stickier	-.193 (.030)	.080 (.032)	.058 (.031)
”	less sticky	-.008 (.045)	.097 (.045)	-.001 (.047)
Hours per capita growth	stickier	-.029 (.026)		
”	less sticky	.052 (.040)		
”	stickier	-.039 (.033)	.099 (.034)	.035 (.033)
”	less sticky	.028 (.027)	-.012 (.027)	-.020 (.028)
Input growth	stickier	-.251 (.035)		
”	less sticky	.001 (.054)		
”	stickier	-.265 (.043)	.273 (.044)	.105 (.043)
”	less sticky	-.005 (.061)	.100 (.062)	-.058 (.064)

Legend: each row corresponds to a regression. The sample period is 1984-1997. Parameter estimates are reported with standard errors in brackets. The sample is split according to the frequency of price changes reported by the SIM Survey: “stickier” is the sample of firms that typically modify selling prices no more than twice a year; “less sticky” is the sample of firms that typically modify prices more than twice a year. Input growth is measured by dx_{it}.

Table 6
Price stickiness, technology shocks and input growth
Sample splitting based on the size of annual price changes
Panel data estimation of random-effects model

Dependent variables	Sample	Regressors		
		dz_{it}	dz_{it-1}	dz_{it-2}
Total hours growth	stickier	-.180 (.037)		
"	less sticky	-.016 (.040)		
"	stickier	-.167 (.044)	.142 (.046)	.080 (.043)
"	less sticky	.037 (.051)	.163 (.054)	.065 (.054)
Employment growth	stickier	-.127 (.026)		
"	less sticky	-.082 (.028)		
"	stickier	-.110 (.031)	.048 (.033)	.010 (.031)
"	less sticky	-.061 (.036)	.074 (.038)	.077 (.038)
Hours per capita growth	stickier	-.056 (.027)		
"	less sticky	.060 (.030)		
"	stickier	-.074 (.032)	.077 (.033)	.052 (.032)
"	less sticky	.098 (.039)	.086 (.041)	-.006 (.041)
Input growth	stickier	-.191 (.039)		
"	less sticky	.058 (.041)		
"	stickier	-.213 (.045)	.184 (.047)	.083 (.045)
"	less sticky	-.008 (.051)	.161 (.054)	.054 (.054)

Legend: each row corresponds to a regression. The sample period is 1984-1997. Parameter estimates are reported with standard errors in brackets. The sample is split according to the size of annual price changes reported by the SIM Survey: "stickier" is the sample of firms that reported an annual price change equal to zero in at least one year; "less sticky" is the sample of firms that reported an annual price change different from zero in all years. 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). The estimation period is 1995. Parameter estimates are reported with standard errors in brackets. Each regressor is divided by the value of firms' production.