Pricing Behavior and the Comovement of Productivity and Labor: Evidence from Firm-Level Data*

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Abstract

Recent contributions have suggested that technology shocks have a negative short-run effect on labor input, contrary to the predictions of standard flexible-price models of the business cycle. Some authors have interpreted this finding as evidence in favor of sticky-price models, while others have either augmented flexible-price models in a number of ways or disputed the empirical finding itself. In this paper we estimate a number of alternative measures of TFP growth for a representative sample of Italian manufacturing firms and find a negative impact of productivity shocks on labor input. Furthermore, by relying on the firm-level reported frequency of price reviews, we find that the contractionary effect is strong for firms with stickier prices, but it is weaker or not significant for firms with more flexible prices, consistently with the prediction of sticky-price models.

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1 Introduction

In recent years the comovement between productivity and labor input at business cycle frequencies has come under growing scrutiny. Such comovement is of interest to macroeconomists since it may provide useful insights on the empirical merits of alternative models of economic fluctuations. In a widely cited paper, Galí (1999) reported a negative correlation between technology shocks and labor input, and interpreted it as evidence in favor of sticky-price models. In standard flexible price models the correlation is positive, because, after a positive technology shock, prices fall, aggregate demand increases and hours worked rise (as the substitution effect induced by higher wages more than offsets the corresponding wealth effect). On the other hand, if nominal rigidities prevent prices from falling as much as they would in a flexible-price environment, aggregate demand remains stable or increases only modestly and firms may meet it by employing a smaller volume of now more productive inputs, thus giving rise to a negative correlation between productivity and labor. Later work has emphasized that this occurs unless monetary policy – as described, for example, by Taylor-type rules – fully accommodates technological shocks by lowering interest rates. In that case, aggregate demand would increase and the positive effect of technology improvements on labor input would be preserved (e.g. Dotsey, 1999, and Galí, Lòpez-Salido and Vallès, 2003).

Galí's results have fueled a growing debate in the literature. On the one hand, a number of authors have provided evidence that corroborates, or is consistent with, the finding of a negative correlation between technology shocks and labor input. While Galí (1999) estimated a structural VAR on productivity and hours and identified technology shocks as those having a permanent impact on productivity, Basu, Fernald and Kimball (1998) developed an extended production function framework with proxies for changes in unobserved capital and labor utilization. Francis and Ramey (2002) extended Galí's identification scheme by imposing additional long-run restrictions and considering a wider set of variables. Marchetti and Nucci (2004) applied Basu et al.'s approach to firm-level panel data.[1]

On the other hand, several contributions have either disputed Galí's em-

[1]For earlier evidence on the matter, see Shapiro and Watson (1988); other contributions include Shea (1998), who fitted a VAR model with data on patent applications and R&D spending, and Galí (2004), who uses data for the euro area.

pirical finding or challenged his theoretical interpretation. On empirical grounds, Christiano, Eichenbaum and Vigfusson (2003) have argued that some of the cited results are driven by over-differencing of the hours worked data. In particular, they show that if hours per capita are assumed to be stationary and the level of this variable is considered, a positive effect of technology on hours is found (for a critical discussion of their results, see Francis and Ramey, 2003).[2] A positive effect of productivity shocks on hours is also found by Chang and Hong (2003), who compute the Solow residual of US 4-digit manufacturing sectors, and by Ulhig (2002 and 2004), where productivity shocks are identified in a principal component perspective.[3]

On theoretical grounds, a variety of alternative explanations of Galí's finding are consistent with flexible prices. One class of possible explanations refers to mechanisms through which the adoption of technological progress may divert workers from direct production or somehow disrupt current production, eventually resulting in a decrease in worked hours. For example, reaping the benefits of productivity improvements may require the replacement of existing equipment (Cooper and Haltiwanger, 1993), changes in the labor organization (Hall, 2000), retraining of the firm's labor force (Campbell, 1998) or reallocation of labor across firms (Davies and Haltiwanger, 1990). Another type of explanation, suggested by Francis and Ramey (2002), calls for habit formation in consumption. In models with habit persistence, aggregate demand is largely unaffected by technology shocks (so that firms would employ fewer workers to produce the same amount of output) not because prices are sticky, but because consumers have inertial behavior. Finally, Collard and Dellas (2003) show that, in an open economy framework, if substitutability between domestic and foreign goods is low, a domestic technology improvement drives down the prices of domestic goods relative to those of foreign goods, thus discouraging domestic output and employment growth.

[2] Francis and Ramey use historical data to investigate the implications of alternative assumptions about the time series properties of hours. They argue that the unit root hypothesis yields the most reasonable results for the US post-war economy. These indicate a negative correlation between productivity and labor.

[3] Other contributions to this strand of the literature include Fisher (2002) and Lopez-Salido and Michelacci (2003). Fisher allows for investment-specific technological changes in addition to neutral technological changes, and finds that an increase in hours is associated with a technology improvement. Similarly, Lopez-Salido and Michelacci show that positive shocks to the quality of new capital equipment lead to a rise in employment.

We contribute to this debate by attempting to discriminate between sticky and flexible-price interpretations of the contractionary effect of technology shocks reported in some contributions to the literature. We first document some empirical regularities concerning the pricing behavior of a representative sample of Italian manufacturing firms.[4] Second, coming to the core of this paper, we compute a variety of alternative firm-level TFP measures and investigate if the comovement between labor input and productivity shocks is significantly affected by the degree of stickiness of the firm's prices. We do so by exploiting a highly-detailed panel data set, which suitably combines quantitative and qualitative information. In particular, it combines data on the frequency of price reviews with those on output and inputs.

The firm-level data at hand are especially well-suited to control for the potential impact of monetary policy on the relationship in question. In fact, monetary policy may respond to aggregate technology shocks, not to firm-specific shocks (unless the latter are highly synchronized, which is not the case in our sample). Furthermore, during most of the period considered in this paper (1984-1997), monetary policy in Italy was characterized by the target of maintaining the lira's exchange rate parity vis-à-vis the German mark; hence, domestic technology shocks were very unlikely to be fully accommodated (e.g., Clarida, Galí and Gertler, 1998). The other important advantage of using firm-level data is that they preserve heterogeneity across firms, thus avoiding aggregation bias in the estimates.

The different TFP measures that we use in investigating the comovement of productivity and labor span a large spectrum of theoretical assumptions and models. These measures include the Solow residual, in both its revenue-based and cost-based version, an estimate of productivity change derived from a production function specification augmented with proxies for unobserved capital and labor utilization (Basu and Kimball, 1997), and a measure obtained by controlling for the self-selection in the data induced by the higher probability that firms endowed with more capital survive after a negative productivity realization (Olley and Pakes, 1996). The TFP measure à la Basu-Kimball has already been used and extensively discussed by us in a previous contribution (Marchetti and Nucci, 2004). The results of that paper

[4] In spite of the renewed popularity of sticky price models in recent years, the studies on the actual degree of price rigidity are not numerous and they have limited coverage, owing mainly to poor data availability. They include Cecchetti (1986), Carlton (1986), Kashyap (1995), Blinder, Canetti, Lebow and Rudd (1998), Hall, Walsh and Yates (2000) and Bils and Klenow (2002); for a review, see Taylor (1999).

have prompted this investigation, which avoids over-dependence on any specific approach to productivity measurement and is aimed at reaching more general conclusions.

The remainder of the paper is organized as follows. Section 2 documents some empirical regularities in firms' pricing behavior. Section 3 discusses the TFP measures used and analyzes the response of labor input growth to productivity innovations across different degrees of price stickiness. Section 4 draws some conclusions.

2 Empirical regularities on price stickiness

2.1 Data

We make use of very comprehensive panel data of a representative sample of Italian manufacturing firms. The main source is the Survey of Italian Manufacturing (SIM), carried out annually by the Bank of Italy. The data are of unusually high quality, being directly collected by interviewers who are officials of the local branches of the Bank of Italy, and often have a long-standing work relationship with the firm's management. Each year since 1984 roughly 1,000 firms have been surveyed; because of entry and exit, the balanced panel consists of almost 300 firms. Sample composition is designed and mantained by the statisticians of the Research Department of the Bank of Italy to ensure representativeness with respect to the whole manufacturing sector in terms of its composition by branch, firm size and geographical location. Data drawn from SIM include figures on employment and hours, labor compensation, investment and capital stock (computed according to the perpetual inventory method), plus qualitative information on a number of variables that are crucial for economic analysis but are hard to find in the existing surveys. These variables include the typical frequency of price reviews, the extent of the firm's market power and the degree of concentration of its main market.

Data on gross production (sales plus inventory change) and purchases of intermediate goods are drawn from the Company Accounts Data Service (CADS), which is the most important source of balance sheet data on Italian firms. It covers about 30,000 firms and is compiled by a consortium that includes the Bank of Italy and all major Italian commercial banks.

Merging the SIM and CADS datasets resulted in an unbalanced panel of almost 1,000 firms and 8,000 observations, ranging from 1984 to 1997. The period considered includes three manufacturing-wide expansions (1985-1990, 1994-1995 and 1997) and two recessions (1991-1993 and 1996). Further details on data sources and the definitions of the variables can be found in Appendix I.

2.2 Evidence on price rigidity

The information on the degree of price stickiness characterizing the individual firms of our sample was provided by the replies to a question included in the 1996 SIM survey. Firms were asked the following question, with reference to their main product: "How frequently does your firm typically review selling prices?". The managers interviewed could choose among five possible responses: "Several times a month", "Every month", "Every three months", "Every six months" and "Once a year or less frequently". The replies obtained from 962 firms are summarized in Table 1, first row. The survey found that 30 per cent of the firms reviewed prices on average every three months or more often, 35 per cent every six months and another 35 per cent of firms once a year or less often. Therefore, the median frequency of price reviews was twice a year, as in the case of the US firms surveyed by Blinder et al. (1998) and somewhat lower than the quarterly frequency reported for UK manufacturing firms by Hall, Walsh and Yates (2000). In principle, for the purposes of this paper, information on the frequency of actual price changes (or, better yet, on the time elapsed between a shock and the corresponding price revision) would be preferable as a measure of price stickiness, since the frequency of price reviews is only one aspect of the pricing behavior, though an important one. Unfortunately, such information is not provided by the 1996 SIM survey. However, Blinder et al. (1998) document a strong positive correlation at the firm level between the frequency of price reviews and that of price changes (see also Hall et al., 2000, Table 1). In fact, the Bank of Italy interviewers who conducted the survey used in this paper reported that the re-examination of prices often coincided with their actual change. Furthermore, the data of a recent survey conducted by the Bank of Italy on a different sample of Italian firms confirm a close relationship at the firm level between the frequency of price reviews and that of actual price changes.[5]

[5] The correlation, measured by the Goodman-Kruskal (1954) gamma statistic, is .63 (with an asymptotic standard error of .09). The Goodman-Kruskal statistic is a measure

The evidence on price reviews reported in this paper is also broadly consistent with that on price changes reported in the literature, which points to an average frequency of 1-2 price changes per year, depending on the country, the sector and the type of product and survey.[6]

In Table 1 we also document the frequency of price reviews disaggregated by category of industrial product and sector of economic activity. Contrary to common assumptions, our data suggest that firms producing consumer goods do not review prices more often than producers of intermediate and investment goods. At sectoral level, food and textiles and apparel are the branches characterized by more frequent price reviews (consistently with the sectoral evidence on price changes reported by Kashyap, 1995, and Bils and Klenow, 2002). On the other hand, price reviews are less frequent, and prices are presumably stickier, among firms producing transportation equipment, nonferrous metals, machinery, electric machinery and chemicals.

We also find that firms operating in more competitive markets review prices more often, as in the case of the UK firms surveyed by Hall et al. (2000) and consistently with the evidence on US price changes reported by Carlton (1986). The intuition is that the consequences (in terms of lower profits) for setting an inappropriate price are more severe in markets where demand is more sensitive to prices and competition is stronger. The degree of market competition and the firm's market power were measured, respectively, by the share of market sales of the largest four firms (so-called four-firm ratio) and by the price elasticity of demand perceived by the firm, the firm's own position in the market (i.e., leader, among the top four firms, among the top ten firms) and a standard measure of the firm's markup (i.e., the ratio of production value minus labor compensation minus nominal cost of materials over production value; see e.g. Domowitz, Hubbard and Peterson, 1986).[7]

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of association relevant for ordinal variables; like the conventional correlation coefficient, it ranges from -1 to 1. The survey is described by Fabiani, Gattulli and Sabbatini (2003).

[6]Earlier contributions such as Carlton (1986), Cecchetti (1986) and Kashyap (1995) indicate average spells of price rigidity equal to approximately one year or more (the latter in the case of magazine prices, reviewed by Cecchetti; see Taylor, 1999, for a comprehensive review). More recent contributions, such as Blinder et al. (1998), Hall et al. (2000) and Bils and Klenow (2002) report, on average, somewhat shorter spells of price rigidity (roughly equal to, respectively, eight, six and five months).

[7]With regard to the four-firm ratio, firms were asked whether the four largest firms' aggregate share of total sales in their domestic market was below 10 per cent, between 10 and 29 per cent, between 30 and 49 per cent, between 50 and 80 per cent, or over 80 per cent.

All measures but the latter one were drawn from firms' replies to specific questions in the 1996 SIM survey. Table 2 reports the main results. In all cases, firms operating in more competitive markets or having a lower degree of market power tended to review prices more often. For example, 33 per cent of firms facing a perceived demand elasticity greater than the mean reviewed prices at least every three months, compared with only 23 per cent of the other firms.

3 The comovement of productivity and labor

3.1 Motivation

We employed the information on the firms' pricing behavior to investigate on empirical grounds whether the transmission mechanism of technology shocks differs depending on the degree of price stickiness. The work by Basu et al. (1998) and Galí (1999), and the debate it has stirred, motivate our investigation. As illustrated before, they show that, after a technology innovation, inputs fall significantly on impact (they use, respectively, US sectoral data and G7 economy-wide data). Their intuition for interpreting this finding as evidence in favor of sticky-price models draws on a set-up where money demand is determined by the quantity theory and both money supply and prices are invariant in the short run. In this framework, aggregate demand would not be affected by a technology shock and, therefore, the same amount of output as before could be produced with fewer inputs, which have become more productive; eventually, once prices start to adjust after the initial sluggishness, output and input rise. A model more in the spirit of the so-called New Neoclassical Synthesis (Goodfrey and King, 1997, and Galí, 2003) would feature a more articulated transmission mechanism, yielding the same result.[8] Subsequent contributions (e.g., Dotsey, 1999 and Galí, Lòpez-Salido and Vallés, 2003) have challenged this view, showing that even in a sticky-price model the prediction of a negative response of labor input to technology

[8] The favorable technology variation induces a reduction of current and future expected marginal costs, which would lead firms to adjust their prices downward. However, the Calvo (1983) mechanism of price staggering implies that only a fraction of firms revise their prices. Hence, the aggregate price level declines, but by less than under perfect price flexibility. Aggregate demand and output rise accordingly, but, again, by less than under price flexibility. Thus, if technological change is greater than output change, input use decreases.

shocks rests on the characterization assumed for monetary policy. In particular, using a dynamic stochastic general equilibrium model of an economy with price rigidity, Dotsey (1999) has investigated the implications of four different monetary policy rules. 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 approximated by a Taylor (1993) rule or a Clarida, Galí and Gertler (2000) rule, then in the wake of a technology improvement monetary policy "mimicks" the expansionary effect of declining prices by fully accommodating the shock, and this induces a significant increase in output and labor.[9]

Importantly, however, Dotsey (1999) shows that if the central bank follows a modified Taylor rule, responding to output growth rather than to deviations of output from its potential level, the response of labor input to technology shocks is closer to that obtained under a constant money growth rule.[10] This latter case has some crucial features in common with the Italian central bank's behavior in the second half of the eighties and the first half of the nineties. During those years, the monetary policy of a number of European countries, including Italy, was constrained by German monetary policy (e.g. Clarida et al., 1998).[11] In that period, domestic productivity shocks in Italy were very unlikely to be fully accomodated by the central bank.

Furthermore, it should be emphasized that our focus on firm-level data significantly plays down the importance of monetary policy in the shock transmission mechanism under investigation. The reason is that monetary policy may accommodate aggregate productivity shocks, but can hardly re-

[9] If aggregate demand increases by less than under price flexibility, output would increase by less than its natural level (namely, the level consistent with flexible prices). Therefore, both the output gap and inflation decrease. 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 fully accommodate the shock. In these situations, the correlation between technology shocks and labor input would be positive.

[10] The intuition is that monetary policy is less accommodative under this modified rule. After a favorable technology shock output increases (although by less than under flexible prices) and monetary authorities will therefore respond with a more restrictive policy. This counterbalances the decrease of interest rate prompted by lower inflation.

[11] Monetary policy in Italy in that period is described by Dornbusch, Favero and Giavazzi (1998) by means of a rule in which the short-term interest rate depends on the German short-term rate plus the difference in inflation and that in output growth between the two countries. This type of rule resembles the modified Taylor rule described above, which assigns zero weight to the domestic output gap.

spond to firm-specific shocks, unless they have a very large common component.[12] These considerations motivate our empirical investigation, to which we now turn.

3.2 Measuring productivity change

We employ alternative measures to estimate total factor productivity (TFP) growth, namely the Solow residual and two model-based measures, proposed respectively by Basu and Kimball (1997) and Olley and Pakes (1996). The Solow residual is the traditional and most popular measure of TFP growth since the pioneering work of Solow (1957). The other measures represent some of the main attempts in the literature to overcome several shortcomings of the Solow residual, either on theoretical or empirical grounds or both. Together they span a wide range of theoretical assumptions, satisfying most desirable properties of an ideal measure of TFP growth. All measures are computed at the firm-level, to avoid the well-known aggregation bias which possibly affects estimates obtained from aggregate data (see, for example, Basu and Fernald, 1997). Furthermore, we consistently adopt a gross-output rather than value-added framework, to avoid potential model mispecification and omitted variable bias (Basu and Fernald, 1995). Below we briefly introduce these approaches to TFP measurement.[13]

Consider a firm's production function subject to a technology disturbance, where gross output, Y, is produced using labor, capital and intermediate inputs:

$$Y = F(L, K, M, Z), \tag{1}$$

[12] See Marchetti and Nucci (2004) for evidence on the high degree of heterogeneity of technology shocks across firms.

[13] An alternative, and quite different, approach to the measurement of productivity shocks is that based on long-run restrictions in a structural VAR model, proposed by Galì (1999) and used, among others, by Francis and Ramey (2002 and 2003) and Christiano et al. (2003). Technology shocks are identified as the only shocks which can have a permanent effect on (labor) productivity. That approach has the advantage, compared with the production-function approach described in this section, that the resulting estimates of productivity shocks are, by construction, orthogonal to demand variables. On the other hand, a disadvantage is that any non-technology shocks with permanent effects on productivity, such as a change in capital income tax, are spuriously labeled as "technology shocks" under this identification scheme. Furthermore, Faust and Leeper (1997) have shown that the results of long-run restrictions are crucially affected by the number of variables included in the VAR and the assumptions on the respective time series properties.

where L is labor input, measured by the product of the number of employees, N, and the number of hours per worker, H, i.e. $L = NH$; K is the capital stock; M is the quantity of materials and energy inputs and Z is an index of technology; time subscripts are omitted for simplicity.

With competitive goods and factor markets, perfect factor mobility and constant returns to scale, profit maximization implies that productivity change can be expressed as:

$$dz = dy - s_L dl - (1 - s_L - s_M)dk - s_M dm, \tag{2}$$

where lower-case letters represent logs, s_X is factor X's share of the firm's revenues and the output elasticity to technology has been normalized to one. Expression (2) is the well-known Solow residual; the estimate used in this paper is henceforth denoted as sr.

The Solow residual has been extensively used in the literature and is still very popular, particularly in its value-added version, because the methodology is simple and the data required for its computation are readily available. However, to the extent that the several underlying assumptions listed above are violated, the Solow residual reflects other economic phenomena besides productivity change, since it is affected by any shock that changes the optimal mix of output and input quantities and prices. In fact, contrary to the predictions of the underlying theory, the Solow residual is typically closely correlated with demand variables, such as military expenditure (Hall, 1988), monetary aggregates (Evans, 1992) and government consumption (Burnside, Eichenbaum and Rebelo, 1993). These considerations have induced Hall (1988 and 1990) and others to allow for market power and increasing returns in the computation of the productivity residual. In particular, if one allows for imperfect competition in the product market, expression (2) becomes:

$$dz = dy - c_L dl - c_K dk - c_M dm, \tag{3}$$

where c_X is the cost-based share of factor X; this is the so-called cost-based Solow residual.[14] A further extension is to allow for increasing returns to

[14]As a robustness check, we also computed this measure of TFP growth. It requires estimates of the imputed cost of capital; to this end, we used firm-level estimates of the user cost of capital, obtained by applying Auerbach's (1983) version of the Hall-Jorgenson approach to highly-detailed data (see Appendix 1 for details). The results obtained using

scale, by estimating the scale elasticity parameter γ in the following regression:

$$dy = \gamma(c_L dl + c_K dk + c_M dm) + dz, \tag{4}$$

where dz is the regression residual.

Although an estimate of productivity change obtained by using Hall's approach or estimating equation (4) constitutes an important refinement with respect to the traditional Solow residual, it may still incorporate significant measurement errors in labor and capital inputs. In particular, if there are adjustment costs in hiring and firing and in capital accumulation, the unobserved rate of utilization of labor and capital is likely to fluctuate over time as a consequence of the less-than-optimal adjustment of employment and capital. This is the well-known phenomenon of factor hoarding; to control for it, the production function in equation (1) is modified as:

$$Y = F(NHE, UK, M, Z) \tag{5}$$

where E and U are the rate of utilization of, respectively, labor (i.e., hourly effort) and capital. Since both are typically unobserved, in the empirical analysis one needs to express them as a function of observables, by adding structure to the model and exploring the equilibrium relationships that link factor utilization to the firm's observable inputs. For this purpose, Basu and Kimball (1997) assume that cost-minimizing firms face adjustment costs in labor and capital, the employee is remunerated for his effort along with the number of worked hours, and capital depreciates at a rate which depends on its utilization (see Appendix 2 for details). After the appropriate substitutions, one obtains the Basu and Kimball's regression equation, which is an augmented version of (4):

$$\begin{aligned} dy &= \gamma dx + \beta(c_L dh_{it}) + \eta \left[c_K \left(dp_M + dm - dp_I - dk\right)\right] \\ &\quad + \theta \left[c_K (di - dk)\right] + dz, \end{aligned} \tag{6}$$

the cost-based version of the Solow residual were not substantially different from those obtained with the revenue-based version, sr, and described in the following sections; they are not reported in the paper for the sake of simplicity of presentation and are available from the authors upon request.

where dx represents the weighted average of changes in the observed inputs (i.e. $dx = c_L(dn+dh)+c_K dk+c_M dm$); di is investment growth, dp_I and dp_M are the rate of growth of the price of, respectively, capital and intermediate goods; dz is, again, the regression residual, which corresponds to a very refined measure of productivity growth.[15] Following Basu et al. (1998), the measure used in this paper was obtained by estimating equation (6) separately for durables and non-durables sectors and allowing for sector-specific returns-to-scale parameters, γ (see Appendix 2); henceforth, it is referred to as bk.

A different approach to the measurement of productivity has been taken by Olley and Pakes (1996). In their analysis of the US telecommunications equipment industry, they propose a three-step algorithm to explicitly address two different problems. The first one is the traditional simultaneity bias, which arises in production function regressions because the unobserved (to the econometrician) productivity shock is typically correlated with factor demand. The second problem is the selection bias that arises because firms' shutdown decisions may be endogenously affected by productivity.[16] Olley and Pakes propose a multi-step procedure that does not require instrumental variables. In the first step, the simultaneity bias is taken care of by including, among the regressors of a production function specification, proxies of the unobservable productivity term, derived from a structural model of firm's optimizing behavior (mainly, investment and capital). In the second step, firms' survival probability is estimated using the theoretically-relevant variables and information is extracted on expected productivity and its relationship with capital accumulation. This information is used in the third step to control for the effect of expected productivity on the capital coefficient. Productivity growth can then be computed as:

$$dz = dy - \widehat{\beta}_L dl - \widehat{\beta}_K dk - \widehat{\beta}_M dm \tag{7}$$

[15] For a discussion of Basu et al. (1998)'s approach, see Bils (1998). He argues that unobserved labor and capital utilization are identified using proxies with a degree of procyclicality that is higher than that commonly conjectured for those unobserved variables; in principle, this might contribute to generate Basu et al.'s finding of a countercyclical technology shocks.

[16] For example, a larger capital stock is associated, *ceteris paribus*, with larger profits and this may increase firm's ability to survive after a low productivity realization, thus affecting sample composition and the observed relationship between capital endowments and productivity realizations.

where $\widehat{\beta}_L$ and $\widehat{\beta}_M$ are consistently estimated in the first step and $\widehat{\beta}_K$ in the third step (see Appendix 3 for details). In the rest of this paper, the TFP measure computed according to equation (7) is denominated *op*.[17]

The main descriptive statistics and some cyclical properties of sr, bk and op are summarized in Table 3. A notable feature displayed in the table is the similarity in the distribution of the alternative measures, despite the different underlying assumptions and models. The respective median values of TFP growth range from .7 to 1 per cent per annum, whereas the 25-th and the 75-th percentiles are all around, respectively, -2.5 e 4 per cent. Unsurprisingly, the Solow residual is the most procyclical measure, as suggested by the coefficients estimated by regressing the several TFP growth measures on GDP. Procyclicality is significantly reduced — by at least one half according to this criterion — by controlling for unobservable factor utilization as suggested by Basu and Kimball. It is further reduced and basically disappears if productivity is measured following the method of Olley and Pakes.[18] Further insight on the comparison between the alternative productivity measures is provided by the cross-correlation pattern shown in Table 4. Interestingly, and perhaps surprisingly given the quite different underlying assumptions and identification schemes, all measures are highly correlated, with correlation coefficients

[17] Some questions about the Olley-Pakes approach have been raised by Syverson (1999). He argues that when demand conditions have a significant idiosyncratic component, they may affect investment decisions as well as productivity. In this case, the Olley-Pakes algorithm may provide inconsistent parameter estimates and productivity measures that are a mixture of demand and technology components. Syverson argues that this potential problem is more severe in imperfectly competitive markets, where the degree of specificity of firms' demand is likely to be higher. To tackle this issue as a sensitivity inspection, we re-applied the Olley-Pakes approach only to firms with lower market power, i.e. those reporting a price elasticity of demand lower than the median (-4.0). We replicated all the empirical investigations of this paper focusing on this sub-sample only, for which the Syverson critique applies to a minor extent. Overall, the results obtained were qualitatively unchanged.

[18] The coefficient estimated by regressing *op* on GDP growth remains positive, but has no statistical significance. On the one hand, this result might suggest that, after properly controlling for both the simultaneity and selection biases, much, if not all, of the procyclicality of measured productivity vanishes. Alternatively, one might argue that the proxy suggested by Olley and Pakes fails to capture cyclical fluctuations of productivity adequately (see Levinsohn and Petrin, 2003, for reasons why this might happen). We followed Levinsohn and Petrin's insight and used intermediate inputs as a proxy for unobserved productivity. However, the performance of the modified Olley-Pakes model was not satisfactory, as the estimates of the main parameters fail to converge if polynomials of reasonably low degree are used.

ranging from .85 to .91.

The combined evidence of Tables 3 and 4 suggests that, on the one hand, the bulk of the underlying dynamics of productivity is captured by all TFP measures and, on the other, that each measure captures some (cyclically relevant) components of productivity which are missed by the other measures (and, symmetrically, is free of some noise or measurement error possibly included in other measures). There are no clear grounds for preferring any given measure to the others. Which one is the most appropriate will ultimately depend, for each observation, on the appropriateness of the respective assumptions and the accuracy of the relevant data for the firm and period being considered. For this reason, and for the sake of robustness, throughout the remainder of the paper we report the results obtained with all the above measures.

3.3 Empirical results

We begin this section by documenting for the entire sample the response of labor input to productivity shocks. Following Basu et al. (1998) and Marchetti and Nucci (2004), we first obtain the innovations $\varepsilon(.)$ by estimating an AR(2) process for each of our series of productivity change (i.e. sr, op and bk). Table 5 presents the results obtained from regressing labor input, as measured, respectively, by total hours and employment change, on these innovations.

The empirical findings document a very robust negative contemporaneous relationship between productivity shocks and labor input growth. When total hours, $dn + dh$, are considered, the effect is always negative and statistically significant. This is also true when employment, dn, is the dependent variable (except that with the Olley-Pakes measure the effect is negative but not statistically significant). If, for example, employment change is regressed on the Basu-Kimball productivity impulse, $\varepsilon(bk)$, the estimated coefficient is -.100 with a standard error of .021. With total hours as dependent variable, the estimated effect tends to be larger when the innovations to the Solow residual, $\varepsilon(sr)$, is used: the estimated parameter is -.315 (with a standard error of .031) while it is -.137 (s.e. of .041) for the Olley-Pakes measure, $\varepsilon(op)$, and -.122 (s.e. of .032) for the Basu-Kimball measure, $\varepsilon(bk)$.

All the results reported in Table 5 and the following ones refer to regressions which include, in the right-hand side, control variables such as year, industry and size dummies.[19] As a sensitivity inspection, we also estimated all the regressions without these groups of dummies; the results remained virtually unchanged. Moreover, in order to verify that the results of Table 5 are not simply due to omitted variable bias, we also estimated regressions where some proxies of the firm's demand and supply conditions, such as the firm's sales growth or sectoral output growth, are included in the specification. Again, the results were qualitatively unchanged.[20]

In sections (b1) to (b3) of Table 5, by adding lags of productivity innovations as regressors, we broadly document that the negative response of labor input is limited to the first period only, with a recovery of labor occurring over time, presumably as the frictions and rigidities responsible for the contractionary effect disappear.

Overall, Table 5 provides a picture that points to a short-run negative response of labor input to productivity innovations. Thus, our evidence seems to reinforce a similar finding obtained in other contributions. However, as explained above, the interpretation of this result is problematic. While Basu et al. (1998) and Galí (1999) interpret it as evidence in favor of price stickiness, other researchers have proposed a number of alternative explanations which are consistent with flexible prices. These range from retraining, reorganization and reallocation effects (see Campbell, 1998, and Cooley, 1998) to habit persistence in consumption (Francis and Ramey, 2002) and open economy considerations (Collard and Dellas, 2003).

The available empirical evidence typically does not allow discrimination between flexible- and sticky-price interpretations of Galí's finding. To address this issue, we exploit the information on the frequency of price reviews at the firm level. If the sticky-price explanation is correct, the observed relationship at the firm level between productivity impulses and labor input should differ depending on the slowness of the firm's price adjustments. Under the sticky-price interpretation, we would expect a stronger negative response of labor input to technology the less frequent the price reviews (and, presumably, changes) at the firm level. Eventually, the response should turn positive if

[19] The estimated parameters for these dummies and the results of the tests for their joint significance, not reported, are available from the authors upon request.

[20] In our panel regressions we use generated regressors, since the productivity measures in the right-hand side are generally obtained as residuals of production function estimation. However, if one includes unlagged generated residuals in a regression, consistency and efficiency of the estimators are preserved and the validity of standard inference is unaffected (see Pagan, 1984).

price reviews (and, therefore, changes) are frequent enough, i.e. prices are sufficiently flexible.

Table 6 documents the regression results obtained separately from two sub-samples: the first consists of firms that typically review their prices every three months or more often; the second comprises firms that typically review their prices every six months or less often.[21] The results lend support to the sticky-price hypothesis. Firms with stickier pricing behavior (i.e., less frequent price reviews) experience a sharper decline in labor input associated with a productivity improvement. On the other hand, for firms that review their prices more frequently, overall the negative effect is not found on data, and the estimated coefficients are in general not statistically significant. For example, the effect of $\varepsilon(bk)$ on manhours growth, $dn + dh$, is estimated to be equal to -.154 (with a standard error of .054) for firms with stickier prices and -.007 for the other firms (with a s.e. of .075). Similarly, the estimated effect of the Olley-Pakes technological shock, $\varepsilon(op)$, on employment change, dn, is equal to -.083 (with a s.e. of .045) in the sub-sample of firms with less frequent price reviews and is not statistically different from zero in the other sub-sample (.080 with s.e. .057). In the case of firms with more flexible prices, even when the effect is negative and statistically significant (this occurs only when total hours growth is regressed on distributed lags of $\varepsilon(sr_{it})$), its absolute value is much lower than that of the sample of firms with stickier prices.[22] While part (a) of Table 6 focuses on the contemporaneous effect

[21] In principle, it might be misleading to assess the degree of price stickiness of a given firm based on the frequency of price reviews (or, for that matter, price changes), since such frequency is clearly affected also by that of relevant cost and demand shocks, which in turn depends on the specific market and production process characteristics. In order to control for this potential source of bias, we replicated the analysis described in this section by using as splitting criterion the fact that a given firm reviews prices more or less frequently than the median firm in the same sector. Results remained substantially unchanged.

[22] As previously indicated, the results refer to regressions where the year, the sector and the size-specific dummies are included as controls. Again, in the case of Table 6 the results are qualitatively unchanged if the dummies are removed or if demand-side control variables are included (e.g. firm-level real sales growth). As mentioned, we also run regressions using innovations to the cost-based Solow residual as measure of productivity shock. With $dn + dh$ as dependent variable, the effect is -.084 (with s.e. of .046) in the sub-sample of firms with stickier prices and .073 (with s.e. of .067) in the other. With employment change as dependent variable, again the estimated effect is negative only in the sub-sample of firms with stickier prices (-.027 versus .059 in the other sub-sample); in both cases, however, the effect is not significant.

only, parts (b1) to (b3) consider a distributed lag of productivity impulses. Again, the effect of technology innovations on labor input at impact is always negative and in general statistically significant for firms with stickier pricing behavior, with a recovery of labor over time in all cases. By contrast, the effect of productivity shocks for firms with more frequent price reviews is positive (and statistically significant) or not statistically different from zero. For example, when total hours growth is regressed on distributed lags of the innovations to the Olley-Pakes measure, the contemporaneous effect is -.220 in the sample of firms with stickier prices and .194 in the other sample (with s.e. of, respectively, .077 and .117). For robustness, we also employed another sample-splitting criterior and considered five different sub-samples, one for each possible answer to the survey question on the frequency of price reviews. The results broadly confirm the general picture.[23] We also verified that our finding is not driven by low elasticity of demand.[24]

As noted, the interpretation of the result that technology shocks lead to a decline in labor input is controversial and a variety of alternative explanations have been proposed in the literature. While we provide evidence that lends support to the sticky-price interpretation, recent contributions by Altig et al. (2002) and Christiano et al. (2003) have challenged the finding itself. Their argument is that the contractionary effect of a positive tech-

[23]The first sub-sample refers to firms reviewing prices several times a month, the fifth to firms reviewing prices once a year or less frequently. If, for example, total hours growth is regressed on the innovations to the Solow residual, $\varepsilon(sr)$, the effect is .004 in the first sub-sample (with standard error of .187) and -.150 in the second sub-sample (with s.e. of .144). By contrast, the estimated effect is -.217 (with s.e. of .093) in the third sub-sample and -.553 and -.164 in the fourth and fifth sub-samples (with s.e. of, respectively, .068 and .072).

[24]Even if prices are fully flexible, an inelastic demand may cause output to increase modestly after the price decline induced by a productivity improvement. Accordingly, labor input may decline if demand elasticity is low. In Section 2, we documented that price stickiness is associated with higher market power. Hence, a critic might argue that the reported different response of labor input to productivity shocks may depend in fact on market power and demand elasticity rather than on price rigidity. To tackle this issue, we split the sub-sample of firms with stickier pricing behavior into two groups: one comprising firms with a high price elasticity of demand and the other firms with a low elasticity (the threshold value being equal to the sample mean, -4.0). If the explanation based on price elasticity is the relevant one, we should observe that the contractionary effect of a technology improvement is found only in firms with more inelastic demand. To the contrary, the contractionary effect was also found in firms with higher demand elasticity.

nology shock is a figment of a specification error due to over-differencing of hours worked. Because hours per capita is a stationary variable, its level should be considered in the empirical analysis rather than its first difference. Given the importance of this recent debate, we also address the issue of stationarity in hours in our sample. Following Francis and Ramey (2003) and Fisher (2002), we alternatively assume that hours per capita are difference stationary, level stationary, stationary around a linear trend and stationary around a quadratic trend. In Table 7 we document the response of hours per capita to technology shocks under these alternative assumptions on the dependent variable (the measures of technology shocks are the same as before). Overall, the results in Table 7 suggest that technology innovations have a contractionary impact on hours per capita (with the partial exception of $\varepsilon(bk)$, whose estimated effect is negative but not statistically significant). Again, while this result holds in the entire sample and, more strongly, in the subsample of firms with stickier pricing behavior, it disappears in the subsample of firms with more frequent price reviews.

4 Conclusions

Recent contributions have suggested on empirical grounds that technology shocks have a negative short run effect on labor input, contrary to the predictions of standard flexible-price models of the business cycle. This finding is currently under debate; some studies confirm it, others reject it. Its interpretation is controversial, too. Some authors interpret it as evidence in favor of sticky-price models, while others have augmented flexible-prices models in a number of ways, in order to generate predictions consistent with the evidence. The mechanisms suggested include retooling and reorganization effects and habit persistence in consumption.

In this paper, we document a negative impact of productivity shocks on labor input in a representative panel of Italian manufacturing firms. Furthermore, and more interestingly, by combining information on pricing behavior with time-series of output and inputs, we shed some light on the empirical merits of sticky vs. flexible-price explanations of the finding. Given the complexity of productivity measurement, we do not rely on one specific estimate but, rather, derive a variety of TFP measures spanning a wide range of theoretical assumptions and empirical approaches, generalizing the results reported in a previous contribution of ours (Marchetti and Nucci, 2004). While our evidence does not rule out per se the relevance of mechanisms such as retraining and reallocation or habit formation, it indicates that price stickiness does count in driving the short-run contractionary effect of technology shocks reported in some contributions to the literature.

A Appendix 1: Data sources and description of variables

Data Sources. Data are primarily drawn from two sources: the Bank of Italy Survey of Investment in Manufacturing (SIM) and the Company Accounts Data Service (CADS). The SIM data have been collected since 1984. At the beginning of each year the firms included in the sample receive the questionnaire with questions referring to the year ended. In order to ensure data consistency over time, the questions also refer to the previous year. Officials of the Bank of Italy conduct the interviews and it is their responsibility to verify the accuracy of the information collected. Sample stratification is based on sector of economic activity (three-digit Ateco-91 level), firm size and geographical location. Size refers to the number of employees and four classes are considered: 50-99, 100-199, 200-999, 1000+ employees; firms with fewer than fifty employees are not included in the SIM sample because high quality in their data collection is more difficult to ensure. Firm location refers to the Italian regions (nineteen). Appropriate statistical techniques have been used in order to deal with outliers and missing data within the sample. CADS (*Centrale dei Bilanci*), a data service established by the Bank of Italy and a consortium of banks which are interested in pooling information about their clients, contains detailed financial statement data on around 30,000 Italian firms. The data have been collected since 1982 and are reclassified to ensure comparability across firms.

Industry classification. The industry detail considered in the analysis (for example, for the estimation of sectoral coefficients or the computation of sectoral means) refers to thirteen manufacturing branches: food and tobacco products; textiles and clothing; leather and footwear; wood and furniture; paper and publishing; chemicals; rubber and plastic products; non metallic minerals; metal products; machinery for industry and agriculture; electrical machinery (including computers and office equipment); transportation equipment and other manufactures.

Variable description. Gross output is measured as the value of firm-level production (source: SIM) deflated by the sectoral output deflator computed by ISTAT. Employment is the firm-level average number of employees over the year (source: SIM); firm-level manhours include overtime hours (source: SIM). Intermediate inputs are measured as firm-level net purchases of intermediate goods of energy, materials and business services (source: SIM), deflated by the corresponding industry deflator computed by ISTAT. Investment is firm-level total fixed investment in buildings, machinery and equipment and vehicles (source: SIM), deflated by the industry's ISTAT investment deflator. Capital is the beginning-of-period stock of capital equipment and non-residential buildings at 1997 prices. To compute it, we applied backwards the perpetual inventory method by using firm-level investment data from SIM and industry depreciation rates from ISTAT. The benchmark information is that on the capital stock in 1997 (valued at replacement cost), which was collected by a special section of the SIM Survey conducted for that year. The capital deflator is the industry capital deflator computed by ISTAT.

The series of the required payment to capital, rP_KK $-$ used for the estimation of bk $-$ was constructed using 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 data drawn from both SIM and CADS. An additional statistical source for this variable is the Credit Register (CR) data, which are collected by a special unit of the Bank of Italy (*Centrale dei Rischi*) and contain detailed information on firms' bank borrowing. De Mitri et al. (1998) adopted the Auerbach's (1983) version of the Hall-Jorgenson approach, which is specific to firms that are financed through both equity and debt. The expression for the user cost of capital is the following:

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

τ is the general corporate tax rate. S refers to 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-level ratio of financial debt over total liabilities (source: CR); i is the average debt interest rate paid by the firm (source: CR); e is the required return to equity (i.e., the opportunity cost associated with holding part of the firm's equity). It is approximated by the average yield of Italian Treasury bonds (BTPs), on the ground that the Italian equity premium has usually been estimated to be negligible, or even negative, during most of the period considered; π is the industry-specific expected increase of capital goods prices (source: SIM) and δ is the industry rate of capital depreciation (source: ISTAT).

For more detail on the sample structure and descriptive statistics, see the Data Appendix in Marchetti and Nucci (2004).

B Appendix 2: Measuring productivity change à la Basu-Kimball (1997)

Basu and Kimball (1997) formulate the following firm's cost minimization problem:

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

subject to

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

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

where W is the base wage; $WG(H,E)$ is total compensation to each worker, which depends on both the number of hours and the effort supplied and $NW\Psi\left(\frac{A}{N}\right)$ measures the adjustment cost of varying the number of workers; investment 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 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.

First-order conditions for this problem are reported in Basu and Kimball (1997). Exploiting the resulting equilibrium relationships yields expressions for labor utilization as a function of hours per capita and for capital utilization as a function of investment, intermediate goods and their respective prices. After appropriate substitutions, one obtains the regression model (6) reported in the text:

$$\begin{aligned} dy &= \gamma dx + \beta(c_L dh) + \eta\left[c_K\left(dp_M + dm - dp_I - dk\right)\right] \\ &\quad +\theta\left[c_K(di - dk)\right] + dz. \end{aligned} \tag{A.2}$$

Following Basu et al. (1998) and Marchetti and Nucci (2004), we estimated equation (A.2) separately for durables and non-durables industries, and allowed for sector-specific returns-to-scale parameters, as suggested by Burnside (1996). We also included dummies in the specification to control for time, sector, size and the occurrence of mergers and acquisitions. The estimation was conducted using the Arellano and Bond's (1991) generalized method of moments (GMM) procedure, in order to take into account the correlation between input demand and the productivity residual. The instruments used were the lagged values of the endogenous explanatory variables, dated period t-2 and t-3.[25] We also used external, demand-side instruments, which appear relevant on economic grounds and have been utilized in the literature (see, e.g., Hall, 1988, Burnside, 1996, and Basu et al., 1998). These additional instruments are the rate of growth of sectoral materials prices, the rate of growth of the real exchange rate, the change in sectoral order-book levels (from the business surveys of ISAE, Italy's public Institute for Economic Research) and a measure of unanticipated monetary shock based on a vector autoregression (VAR) model.[26] The results are reported in Table A.1. The measure of technology variation bk used throughout the paper was obtained from these estimates; in particular, it was computed as the sum of regression residuals and the parameters associated with the year, sector and size dummy variables. The latter were included in bk because, given our analytical framework, they capture the sector, the year and the size-specific components of firm's technological growth.

Returns to scale (i.e. parameter γ in equation A.2) were found to be constant in a majority of sectors (seven out of thirteen); estimates range from 0.86 in Other manufacturing to 1.14 in Chemicals. The other coefficients reported in the table can be manipulated to derive the sectoral estimates of the structural parameters implied by the theoretical framework, available from the authors upon request (see also Marchetti and Nucci, 2004). In all sectors the elasticity of effort with respect to hours per capita, ζ, was found to be negative, while the elasticity of marginal depreciation of capital to utilization, Δ, was found to be positive, supporting the view that the depreciation function is convex. The marginal installment cost of capital was found to be not increasing in the rate of investment.

Instruments' validity was assessed through the Sargan statistic of over-identifying restrictions. It is worth noting that the results proved robust to

[25] We truncated the set of these instruments at the third lag to attenuate the potential bias arising when all the available linear orthogonality conditions are exploited (Ziliak, 1997).

[26] The measure of monetary shock is obtained from a monthly recursive VAR model estimated over the period 1975-1997 by Dedola and Lippi (2000). The specification includes the industrial production index, the CPI, an index of commodity prices, the three-month interbank rate, the nominal effective exchange rate and M2.

the choice of instrument. As a sensitivity inspection, we ran equation (A.2) after excluding the external instruments, either together or singly, from the set of instruments; the results remained qualitatively unchanged.[27]

[27]In addition, since we deflate nominal output at the firm-level using sectoral price indices, our estimates are potentially affected by the "omitted price bias" pointed out by Klette and Griliches (1996). We addressed this issue by using their correction and by following Muendler's (2001) insight, i.e. to add sectoral output growth as regressor and include in the measure of bk the deviation of sectoral output growth from its time average, weighted by the sectoral price elasticity of demand (see Muendler, 2001, for details). While the estimates of returns to scale were considerably higher, as expected, the pattern of the comovement of the innovations to bk and labor was qualitatively unchanged (see Marchetti and Nucci, 2004).

Table A.1

Estimating results of equation (A.2): the Basu-Kimball Model

Specification:	Non-durables sectors	Durables sectors
dx (returns-to-scale parameter γ):		
Food and tobacco products	.974** (.017)	-
Textiles and clothing	.904** (.023)	-
Leather and footwear	1.034** (.068)	-
Paper and publishing	.865** (.032)	-
Chemicals	1.140** (.030)	-
Rubber and plastic products	1.135** (.030)	-
Wood and furniture	-	1.020** (.190)
Non metallic mineral products	-	.940** (.034)
Basic metals	-	1.008** (.034)
Machinery for industry and agriculture	-	1.004** (.022)
Electrical machinery	-	.996** (.039)
Transportation equipment	-	1.054** (.025)
Other Manufacturing	-	.861** (.032)
$c_L dh$	-.202**(.083)	-.420** (.070)
$c_K\left(dp_M + dm - dp_I - dk\right)$	.722** (.070)	.822** (.057)
$c_K(dhdh - dk)$	.025**(.010)	.027** (.010)
Sargan test of over-identifying restrictions	193.15 (192; .463)	218.48 (212; .365)
Wald test for weak instruments	707.16 (396; .000)	1041.16 (400; .000)

Legend: sample period 1984-1997; GMM estimation. Heteroschedasticity-consistent s.e. for parameter estimates are shown in brackets. The instrument set includes: lagged values of the endogenous explanatory variables at time t-2 and t-3; growth rate of intermediate input prices; rate of growth of the real exchange rate; variation of sectoral order-book levels drawn from the ISAE business survey; a VAR-based measure of monetary shock. For the Sargan test, degrees of freedom and p-values are reported in brackets. The specifications include time, sectoral, size and major corporate operations dummies; Wald test results (not reported) indicate that the dummies of each group are found to be jointly statistically significant.

**Significant at the 5-percent level.

C Appendix 3: Measuring productivity change à la Olley-Pakes (1996)

This appendix closely follows Olley and Pakes (1996). In measuring productivity, they address the issue of simultaneity and selection bias. To do this, they first approximate unobserved productivity semiparametrically and get consistent estimates of the part of the production function unaffected by it; then, they estimate the exit behavior of firms to extract information on the relationship between expected productivity and capital accumulation. Finally, by controlling for this effect, they obtain consistent estimates of the capital coefficient.

The Olley-Pakes model is slightly modified here to fit the case in which firm's production is measured as gross output, rather than valued added, and intermediate inputs are therefore included in the production function, in addition to capital and labor. Firms are assumed to use the following Cobb-Douglas technology (analogous to equation (1) in the text):

$$y = \beta_0 + \beta_A a_t + \beta_L l_t + \beta_K k_t + \beta_M m_t + \omega_t + \eta_t, \tag{A.3}$$

where a is the firm's age, ω and η are unobservable productivity disturbances.While ω is known to the firm when it decides how much labor to use (i.e. it is a state variable in the firm's optimization problem), η is not known.[28] In each period firms decide whether to stay in business or shut down; in the first case, they also choose the amount of variable factors (labor and intermediate inputs) and the level of investment.

Firms optimize by comparing the sell-off value they would receive if they sell their plants with the expected discounted value of future net cash flows attainable if they continue operations. The equilibrium is characterized by an exit rule $\chi_t(a_t, k_t) = \{0, 1\}$ and by an investment rule $i_t = i(a_t, k_t, \omega_t)$. The exit rule is such that firms continue operations (i.e., $\chi = 1$) if $\omega_t \geq \underline{\omega}(a_t, k_t)$. If the profit function π is increasing in capital, then $\underline{\omega}$ is decreasing in capital. The intuition is that firms with larger capital stocks are likely to generate larger profit flows, *ceteris paribus*, and are thus better equipped to survive after a low productivity realization. This generates a selection bias, which leads to an over-estimation of the capital coefficient in (A.3).

[28] An alternative interpretation of η is measurement error.

Provided that $i > 0$, the investment rule can be inverted, leading to an expression for unobservable productivity, ω_t, as a function of observables, i.e.

$$\omega_t = h(i_t, a_t, k_t). \tag{A.4}$$

This allows us to control, at least partially, for simultaneity bias in the estimation of equation (A.2); in particular, by substituting (A.4) into (A.3) one obtains:

$$y_t = \beta_L l_t + \beta_M m_t + \phi(i_t, a_t, k_t) + \eta_t \tag{A.5}$$

where

$$\phi(i_t, a_t, k_t) = \beta_0 + \beta_A a_t + \beta_K k_t + h(i_t, a_t, k_t). \tag{A.6}$$

Equation (A.5) can be estimated by approximating ϕ with a polynomial in (i, a, k); this is the first step of the Olley-Pakes procedure. In our estimation, we followed Olley and Pakes (1996) and used a fourth-order polynomial, after verifying that there was no significant change in the estimates going from a third to a fourth-order polynomial. The estimation of equation (A.5) provides consistent estimates of β_L and β_M; however, β_A and β_K remain unidentified. In order to identify them, one may use estimates of the survival probabilities:

$$P = \Pr\left\{\chi = 1 \mid \underline{\omega}_{t+1}, J\right\} = \varphi(i_t, a_t, k_t). \tag{A.7}$$

The probit estimation of equation (A.7) is the second step of the Olley-Pakes algorithm. We estimated the survival probability $\widehat{P}$ by approximating φ with a fourth-order polynomial in (i, a, k); as before, there was no significant change in the overall fit of the model going from the third to the fourth-order approximation. Like Olley and Pakes, we allowed for changes over time of the exit behavior by including dummies for three different periods: 1985-1990 (continuing expansion throughout manufacturing industry), 1991-1993 (recession) and 1994-1995 (recovery).

The estimate of the survival probability yields information on the relationship between expected productivity and capital accumulation that generates the downward bias in the estimates of β_K. It can be shown that the conditional expectation of ω_{t+1}, which roughly represents the "bias" in the capital coefficient, can be expressed as a function of P_t and h_t, i.e. $g(P_t, h_t)$. We thus obtain the third-stage regression of the Olley-Pakes's approach:

$$y_{t+1} - \widehat{\beta_L} l_{t+1} - \widehat{\beta_M} m_{t+1} = \beta_A a_{t+1} + \beta_K k_{t+1} + g(\widehat{P}_t, \widehat{\phi}_t - \beta_A a_t + \beta_K k_t) + \eta_{t+1} \tag{A.8}$$

In estimating equation (A.8), which is nonlinear, we used a third-order polynomial approximation of $g(P, h)$. Since estimates of the parameters of interest did not change significantly going from the second to the third order and proved to be robust to the choice of the starting values, the approximation is deemed to be accurate enough.

The main results of the whole estimating procedure are reported in Table A.2, where the first column refers to a simple regression of output on inputs (i.e., equation A.3), the second column refers to the Olley-Pakes first-stage regression (i.e., equation A.5) and the third column refers to the Olley-Pakes third-stage regression (i.e., equation A.8), where the coefficients on labor and intermediate inputs are derived from the first stage and imposed. The results show that in our sample the simultaneity bias has a negligible effect on the estimate of the labor and materials coefficients, whereas the downward effect of selection bias on the capital coefficient is more pronounced. This is broadly consistent with the pattern reported by Olley and Pakes for US telecommunications equipment firms.

Table A.2
Olley-Pakes Procedure: equations (A.3), (A.5) and (A.8)

Specification:	Regression of output on all inputs (Equation A.3)	First-stage regression (Equation A.5)	Third-stage regression (Equation A.8)
l	.171** (.004)	.170** (.005)	.170** (.005)
m	.792** (.004)	.790** (.004)	.790** (.004)
k	.038** (.004)	-	.045** (.001)
a	.001** (.000)	-	.001** (.000)
Other variables	-	Third order polynomial in (i, a, k)	Third order polynomial in P and h

Note: Panel data estimation, sample period 1984-1997. Heteroschedasticity-consistent s.e. are shown in brackets. Labor and materials coefficients in third-stage regression (third column) are derived from the first-stage regression (second column) and imposed. **Significant at the 5-percent level.

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Table 1
Frequency of price changes
by sector of economic activity

Category of firms	Average spell of price rigidity (percent share of firms)					Number of firms
	Less than 1 month	1 month	3 months	6 months	1 year or more	
Whole sample	6.7	6.9	16.0	35.4	35.0	962
Consumer goods	3.2	3.2	13.8	41.2	38.6	311
Interm. and inv.goods	8.3	8.6	16.8	32.7	33.5	636
Food	16.9	11.3	22.5	22.5	26.8	71
Textiles and apparel	5.4	3.6	17.3	60.1	13.7	168
Wood and furniture	14.3	14.3	7.1	35.7	28.6	14
Paper and printing	23.8	4.8	28.6	16.7	26.2	42
Chemicals	5.2	15.5	17.2	19.0	43.1	58
Rubber and plastic	10.3	3.4	17.2	37.9	31.0	29
Non ferrous ores	.0	11.5	15.4	28.8	44.2	52
Metals and metal prod.	6.9	20.7	13.8	25.9	32.8	58
Machinery	4.3	2.6	12.0	37.6	43.6	117
Electric machinery	5.9	3.9	9.8	37.3	43.1	51
Transportation equip.	.0	2.4	17.1	29.3	51.2	41
Other manufacturing	3.3	6.7	10.0	26.7	53.3	30

Table 2
Frequency of price changes,
concentration and market power

Category of firms	Average spell of price rigidity (percent share of firms)					Number of firms
	Less than 1 month	1 month	3 months	6 months	1 year or more	
Whole sample	6.7	6.9	16.0	35.4	35.0	962
Operating in markets:						
- highly concentrated	5.7	3.8	14.5	29.6	46.5	159
- less concentrated	8.2	7.4	16.3	36.4	31.7	571
Firm's position in the market:						
- leader	4.1	7.9	15.7	29.3	43.0	242
- among top four firms	8.0	5.6	17.0	33.3	36.1	324
- among top ten firms	7.5	5.3	17.1	44.4	25.7	187
Price elasticity of demand:						
(absolute value)						
- lower than or equal to 4	2.5	6.8	14.1	38.1	38.4	354
- greater than 4	10.1	6.2	17.1	35.4	31.2	356
Markup:						
(over labor and materials)						
- greater than 9 per cent	6.5	6.0	15.0	33.8	38.7	367
- lower than 9 per cent	7.7	8.8	17.1	38.6	27.8	363

Note: highly concentrated markets are defined as those where the four largest firms' aggregate share of total sales exceeds 80 per cent.

Table 3
Alternative measures of TFP growth:
Main statistical and cyclical properties

Measure of productivity growth	Median	25-th perc.	75-th perc.	Coefficient estimate from regressions on GDP growth
Solow Residual (sr)	.007	-.023	.039	.29 (.07)
Measure à la Olley-Pakes (op)	.007	-.024	.038	.05 (.08)
Measure à la Basu-Kimball (bk)	.010	-.023	.043	.14 (.07)

Note: Sample period 1984-1997.

Table 4
Alternative measures of TFP growth:
Cross-correlation

Measure of productivity growth	Solow Residual (sr)	Measure à la Olley-Pakes (op)	Measure à la Basu-Kimball (bk)
Solow Residual (sr)	1	.85	.91
Measure à la Olley-Pakes (op)	.85	1	.89
Measure à la Basu-Kimball (bk)	.91	.89	1

Note: Sample period 1984-1997.

Table 5
Comovement of productivity innovations and labor input

(a) Dependent variable	Alternative measures of productivity impulses $\varepsilon(sr)_t$	$\varepsilon(op)_t$	$\varepsilon(bk)_t$
$dn_t + dh_t$	-.315** (.031)	-.137** (.041)	-.122** (.032)
dn_t	-.069** (.020)	-.034 (.027)	-.100** (.021)

(b1) Dependent variable	Distributed lags of $\varepsilon(sr)_t$: $\varepsilon(sr)_t$	$\varepsilon(sr)_{t-1}$	$\varepsilon(sr)_{t-2}$
$dn_t + dh_t$	-.208** (.041)	.328** (.043)	.154** (.043)
dn_t	-.051* (.027)	.133** (.028)	.075** (.028)

(b2) Dependent variable	Distributed lags of $\varepsilon(op)_t$: $\varepsilon(op)_t$	$\varepsilon(op)_{t-1}$	$\varepsilon(op)_{t-2}$
$dn_t + dh_t$	-.000 (.059)	.286** (.060)	.063 (.059)
dn_t	.024 (.039)	.148** (.040)	.044 (.039)

(b3) Dependent variable	Distributed lags of $\varepsilon(bk)_t$: $\varepsilon(bk)_t$	$\varepsilon(bk)_{t-1}$	$\varepsilon(bk)_{t-2}$
$dn_t + dh_t$	-.006 (.042)	.288** (.045)	.155** (.045)
dn_t	-.069** (.028)	.137** (.029)	.075** (.029)

Note: Panel data estimation on the entire sample. In part (a) of the table each cell corresponds to a regression; in parts (b1) to (b4) each row corresponds to a regression. Sample period is 1984-1997. Fixed effects or random effects estimator is used, according to the results of the Hausman test. Parameter estimates are reported with standard errors in brackets. Regressions include year, size and sectoral dummies.

*Significant at the 10-percent level; **significant at the 5-percent level.

Table 6

Price rigidity and the comovement of productivity innovations and labor

(a) Dependent variable	Samples	Alternative measures of productivity impulses $\varepsilon(sr)_t$	$\varepsilon(op)_t$	$\varepsilon(bk)_t$
$dn_t + dh_t$	more rigid	-.380** (.049)	-.304** (.069)	-.154** (.054)
$dn_t + dh_t$	less rigid	-.164** (.075)	-.008 (.081)	-.007 (.075)
dn_t	more rigid	-.113** (.034)	-.083* (.045)	-.136** (.034)
dn_t	less rigid	-.020 (.048)	.080 (.057)	-.064 (.048)

(b1) Dependent variable	Samples	Distributed lags of $\varepsilon(sr)_t$: $\varepsilon(sr)_t$	$\varepsilon(sr)_{t-1}$	$\varepsilon(sr)_{t-2}$
$dn_t + dh_t$	more rigid	-.323** (.067)	.396** (.066)	.196** (.067)
$dn_t + dh_t$	less rigid	-.079 (.088)	.214** (.083)	.050 (.083)
dn_t	more rigid	-.118** (.044)	.130** (.043)	.081* (.044)
dn_t	less rigid	.033 (.060)	.185** (.057)	.095* (.057)

(b2) Dependent variable	Samples	Distributed lags of $\varepsilon(op)_t$: $\varepsilon(op)_t$	$\varepsilon(op)_{t-1}$	$\varepsilon(op)_{t-2}$
$dn_t + dh_t$	more rigid	-.220** (.077)	.376** (.079)	.012 (.077)
$dn_t + dh_t$	less rigid	.194* (.117)	.170 (.113)	.124 (.118)
dn_t	more rigid	-.041 (.058)	.120** (.059)	.073 (.057)
dn_t	less rigid	.135* (.076)	.247** (.075)	.076 (.079)

(b3) Dependent variable	Samples	Distributed lags of $\varepsilon(bk)_t$: $\varepsilon(bk)_t$	$\varepsilon(bk)_{t-1}$	$\varepsilon(bk)_{t-2}$
$dn_t + dh_t$	more rigid	-.141** (.063)	.333** (.063)	.185** (.063)
$dn_t + dh_t$	less rigid	.159* (.088)	.168** (.083)	.104 (.083)
dn_t	more rigid	-.128** (.045)	.137** (.045)	.126** (.045)
dn_t	less rigid	.039 (.061)	.192** (.058)	.099* (.058)

Note: Panel data estimation. In part (a) of the table each cell corresponds to a regression; in parts (b1) to (b3) each row corresponds to a regression. Sample period is 1984-1997. Fixed effects or random effects estimator is used, according to the results of the Hausman test. Parameter estimates are reported with standard errors in brackets. The sample is split according to the frequency of price reviews reported by the SIM Survey: "more rigid" indicates the sample of firms that typically review prices every six months or less often; "less rigid" the sample of firms that typically review prices more than twice a year. Regressions include year, size and sectoral dummies.

*Significant at the 10-percent level; **significant at the 5-percent level.

Table 7
The effect of technology shocks on hours per capita:
Alternative assumptions on stationarity of hours

Dependent variable	Alternative measure of productivity impulses		
(a)	$\varepsilon(sr)$		
Hours per capita	All sample	More rigid	Less rigid
First difference (dh)	-.245** (.026)	-.253** (.044)	-.144** (.061)
Level	-.169** (.025)	-.186** (.044)	-.034 (.056)
Deviation from a linear trend	-.168** (.025)	-.181** (.044)	-.015 (.059)
Deviation from a quadratic trend	-.165** (.025)	-.178** (.044)	-.011 (.059)

(b)	$\varepsilon(op)$		
Hours per capita	All sample	More rigid	Less rigid
First difference (dh)	-.103** (.035)	-.221** (.057)	-.009 (.071)
Level	-.110** (.027)	-.120** (.045)	-.074 (.060)
Deviation from a linear trend	-.077** (.029)	-.167** (.044)	.101 (.063)
Deviation from a quadratic trend	-.103** (.028)	-.166** (.045)	.029 (.061)

(c)	$\varepsilon(bk)$		
Hours per capita	All sample	More rigid	Less rigid
First difference (dh)	-.021 (.027)	-.018 (.044)	.057 (.061)
Level	-.029 (.025)	-.045 (.043)	.078 (.055)
Deviation from a linear trend	-.028 (.026)	-.037 (.043)	.101* (.058)
Deviation from a quadratic trend	-.023 (.026)	-.037 (.044)	.100* (.058)

Note: Panel data estimation. Each cell in the table corresponds to a regression. Sample period is 1984-1997. Fixed effects or random effects estimator is used, according to the results of the Hausman test. Parameter estimates are reported with standard errors in brackets. The sample is split according to the frequency of price reviews reported by the SIM Survey: "more rigid" indicates the sample of firms that typically review prices every six months or less often; "less rigid" the sample of firms that typically review prices more than twice a year. Regressions include year, size and sectoral dummies.

*Significant at the 10-percent level; **significant at the 5-percent level.