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Firms size and directed technological change

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Abstract The analysis of the characteristics of firms helps to understand the causes and consequences of the direction of technological change. Firms differ substantially with respect to the type of technological knowledge they can generate and exploit through technological innovations. This in turn has major effects on the direction of technological change they are able to introduce. Large firms able to command the recombinant generation of codified knowledge with a strong scientific base are more likely to introduce neutral technological changes that consist in a shift effect of production functions. Small firms that rely more on tacit and external knowledge are more likely to rely on technologies directed toward the most intensive use of locally abundant production factors. The effects of this difference in terms of the resulting total factor productivity growth are important and can be grasped only when the changes in output elasticity of production factors in growth accounting are properly appreciated. The empirical evidence for a sample of 6,600 Italian firms observed between 1996 and 2005 confirms that large firms introduced mainly neutral technological changes while small firms with lower levels of profitability introduced biased technological changes.

Keywords Directed technological change · Types of innovation processes · Size of firms · Growth accounting

JEL Classifications O30 · L26

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1 Introduction

The direction of technological change has recently attracted much interest after years of neglect (Hall and Jones 1999; Caselli and Coleman 2006; Jerzmanowski 2007). A large literature has blossomed investigating the effects of biased technological change at the aggregate level with much emphasis on the analysis of labor markets (Acemoglu 1998, 2002, 2003, 2010). The literature on biased technological change has paid lesser attention to the effects of the introduction of directed technological change on the overall efficiency of the production process at the firm level. The poor understanding of these effects has limited the grasping incentives to the introduction of biased technological change at the firm level.

According to the notion of technological congruence, i.e., the analysis of the matching between the levels of output elasticity and the relative price of inputs, output and total factor productivity (TFP) levels are larger when the output elasticity of the cheaper input is larger. It follows that the bias of technological change has major effects upon the actual levels of efficiency of the production process. These effects on the levels of the efficiency of the production process, both positive and negative, according to the type of bias, can be assessed when the changes along time of the output elasticity of production factors are properly appreciated in growth accounting. The decomposition of TFP growth into its two key components, i.e. the shift and the bias effect, stemming from the introduction of innovations that change, respectively, just the position of the map of isoquants and their shape, enables to identify them and hence to better grasp the incentives and determinants of their introduction (Antonelli 2002, 2003, 2012).

Building upon the notion of technological congruence and the decomposition of TFP in bias and shift effect, it is possible to analyze the relation between the type of technological change introduced by a firm (whether neutral or biased), the underlying variety of innovation processes at work, and the key company's characteristics, with a particular focus on the role of the size of firms.

In this paper, we perform an empirical analysis for a large panel of 6,600 Italian manufacturing firms that aims at identifying the presence of significant correlations through time between the shift and biased components of firm-level TFP and firms' characteristics in terms of size, profitability, and organization of the knowledge generation process. In the paper, we also illustrate and discuss a methodology to derive the firm-level biased component of TFP based on the financial accounting data. Such methodological approach is based on the computation of firm-specific time-varying factor shares rather than on the estimation of related parameters of production functions. This stems from the acknowledgment of the significant within-sector heterogeneity of firms' characteristics with respect to both their stock of knowledge and technological competences and to their managerial conducts. We claim that both the shift and the bias effects of the technological changes introduced by firms are the result of a strategic and idiosyncratic decisions implemented at the firm level. As a consequence, the output elasticity of the inputs in the production function of each firm is specific to each firm and should be recognized as an individual attribute.

The rest of the paper is structured as follows. Section 2 implements the theoretical analysis with an application of the new economics of knowledge to appreciating the role of firms' characteristics, including size, in shaping the type of innovation activities and the ensuing direction of technological change whether biased or neutral. The analytical framework enables to articulate the basic hypothesis: the introduction of new biased technologies is the result of the typical innovation activity carried out by small firms to take advantage of the local abundance of production factors. This contrasts the typical innovation process carried out by large corporations based upon the introduction of radical innovations that generate major shift effects. Section 3 illustrates the methodology adopted to compute firm-level TFP and its decomposition. This section also provides a description the dataset. Section 4 reports and discusses the econometric evidence. The conclusions summarize the main findings and put them in perspective.

2 The analytical framework and the hypotheses

The standard theory of production tells that all changes in the production function are the product of the change in technology and all changes in technology do change the specification of the production function. Directed technological change affects congruence efficiency. Changes in the output elasticity of inputs reflect the introduction of biased technological change. The increase in the output elasticity of the input that is locally cheaper increases the levels of technological congruence of a production process and hence, for a given amount of total costs, with no changes in the unit costs of production factors, it increases output. Neutral technological change instead yields only shift effects. Technological change can include both shift and bias that yield a mix of shift and congruence effects. The decomposition of TFP growth into the shift and the bias components enables to better grasp the variety of innovation processes at work and their determinants.

It is interesting to note that shift and bias effects may be contradictory. The introduction of a new technology with a strong and positive shift effect may have negative congruence effects if its mix of output elasticities does not match the local endowments. In this case, the shift effect may be larger than the total effect: the bias effects are negative. This happens when innovators privilege the shift effect without taking care of the constraints and opportunities of technological congruence. When, on the opposite, the shift effect is smaller than the total effect, it is clear that the bias effect is positive and reflects the introduction of biased technological changes that praise the positive effects of technological congruence.

This section articulates the hypothesis that the direction of technological change—whether neutral or directed—is the result of the intrinsic variety of innovation processes at work across firms. It seems possible to build upon the large literature that has investigated the differences across small and large firms with respect to the (1) generation of technological knowledge; (2) the exploration of external sources of knowledge; (3) its exploitation, (4) innovation strategies, (5) access to funds to innovate, to explore the matching with the types of technological change being introduced whether mainly neutral or biased according to the size of firms (Acs and Audretsch 1988, 1990; March 1991; Rothwell and Dodgson 1994; Scherer 1984).

With respect to the generation of technological knowledge, small- and medium-size firms rely primarily upon tacit knowledge acquired by means of repeated learning activities of skilled craftsmen that are highly idiosyncratic with respect to the limited range of techniques that each firm has been able to practice in the past. Research activities are seldom identified, and rarely formal R&D laboratories with clear assignment of scientific tasks can be found. New technological knowledge is the product of informal activities, although it relies upon the wide and deep participation of a variety of functional activities implemented within the firm by expert practitioners ranging from production to procurement and especially marketing (Stoneman 2010).

The access to external knowledge available within industrial clusters is a major source of technological knowledge and provides substantial inputs to the innovation process of small firms (Rogers 2004; Beaudry and Swann 2009). For these firms, the search for efficiency cannot rely upon major shift effects for the limited depth of their competence and the limited access to codified technological knowledge generated by means of formal R&D activities. Localized abundance of production factors pushes firms, co-localized in the same factor markets, to share the same directionality in the generation of technological knowledge and in the eventual introduction of technological change. The collective directionality has positive effects in terms of creation of localized knowledge commons that are factor and region-specific to which small firms can access to support their knowledge generating processes reinforcing the collective directionality (Arvanitis 1997).

Small firms are much more exposed to the external conditions of the single-factor market into which they are embedded. As a consequence, they are more likely to appreciate the positive effects of the congruence of their production process with the local abundance of inputs. Pecuniary externalities yield a powerful mechanism of direction of technological change to which small firms are much more sensitive than large corporations.

Small firms excel in the generation of innovations that stem from the processes of creative adoption and incremental imitation of process innovations introduced by competitors and upstream vendors and in their eventual adaptation to the conditions of local factor and product markets. Creative adoption and imitation enables small firms to adapt existing innovations so as to increase their congruence to the conditions of local factor markets (Antonelli 2003, 2012).

With respect to knowledge exploitation, small firms can take much less advantage of intellectual property rights to increase the appropriability of the rents stemming from the localized introduction of new technologies based upon tacit knowledge. The application to patent offices is quite expensive, and the screening process, based upon the search for originality and priority of the technological content, does not favor them. Small and medium firms can better appropriate the rents stemming from the introduction of innovations as long as they are able to direct technological change toward the intensive use of locally abundant production factors. This incentive mechanism is all the stronger the larger is the difference in the costs, and the more specific and idiosyncratic are the local inputs with respect to the factor markets of competitors. The selection of biased technologies, characterized by higher levels of output elasticity of inputs that are locally abundant, becomes an effective source of barriers to entry and to imitation for other firms based on the regions with different factor markets. A large literature confirms that smaller firms are mainly engaged in markets characterized by price competition where the reduction in costs is the main competitive strategy (Scherer 1984).

With respect to knowledge generation, large firms are able to complement the competence acquired by means of learning process with formal R&D activities performed intra-muros and clearly identified with explicit procedures and protocols. Research activities are conducted by highly qualified personnel with formal training. Knowledge exploration includes systematic relations with the academic community so as to generate new technological knowledge that enables to introduce a flow of discoveries and original applications that can be successfully embodied in new products (Arvanitis 1997). Large firms can introduce technological knowledge that has a wide scope of application and can feed the introduction of such a wide array of innovations that it often leads to the diversification of firms and creation of new industries (Vaona and Pianta 2008).

With respect to knowledge exploitation, large corporations and new science-based firms can rely upon the credible enforcement of intellectual property rights and specifically upon patents to increase the appropriability of the rents stemming from the introduction of their technological innovations because of their strong content in terms of originality and priority. Large firms, protected by intellectual property right regimes, can afford the risks of introduction of major innovations that enable them to move along the original isoclines. Corporations are involved in oligopolistic rivalry that typically pays lesser attention to the price of inputs and relies on the continual introduction of new products (Piva et al. 2005, 2006).

Large firms have a global reach and are active in many heterogeneous factor markets. This variety of factor markets reduces the incentives to focus one single structure of endowments and pushes global firms to concentrate on the introduction of new technologies with strong positive shift effects and possibly minor negative bias effects. Small firms on the opposite are mainly active on domestic factor markets with homogeneous characteristics. The identification of abundant inputs with low unit costs is much easier, and consequently, the incentives to take into account the effects of technological congruence are stronger. Technological changes introduced by smaller firms are more likely to focus on the introduction of directed technological changes with minor shift effects but positive bias effects (Castellani and Zanfei 2006, 2007).

Financial factors play a major role in shaping innovation strategies and hence the incentives to direct technological change at the firm level. Small firms have limited access to equity markets and rely mainly if not exclusively on cash flow to fund the introduction of new technologies (Hall and Lerner 2009). Financial constraints due to credit rationing induce small firms to focus on incremental technological changes that can enhance the technological congruence of their production processes with local factor markets. Large firms, on the opposite, can rely upon internal financial markets where the extra-profits gained with the previous innovations provide the resources to fund new innovations. Large firms, moreover, can access the equity markets and raise additional capital. Corporations can plan long-term research strategies that privilege the introduction of radical technologies with strong shift effects (Scellato 2007; Ughetto 2008; Magri 2009).

In conclusion, the analysis of the range of characteristics of knowledge generation and exploitation, and of the types of innovation and market competition across firms, suggests that the introduction of biased technological change directed toward the increase in the output elasticity of the locally abundant inputs can be considered as the result of the typical innovation process of firms:

- with small size that limits the access to managerial skills and hence the foresight of broader technological opportunities;
- with low profitability that limits the possibility for the internal funding of research and development activities that may extend the ray of technological exploration;
- with high levels of debt that limits the possibility to access financial markets to fund extensive research activities;
- with high levels of tacit competence based upon learning processes implemented by dedicated workforce;

- mainly engaged in price competition based upon the introduction of innovations aimed at reducing production costs;
- with low levels of R&D expenditures and intangible capital.

3 Methodology and dataset

This section presents the empirical methodology followed to decompose firm-level TFP and to identify the correlations between the bias component of TFP and firms' characteristics together with the introduction to the empirical evidence with the description of the dataset.

3.1 The decomposition of total factor productivity

In order to single out a decomposition methodology of the differential effects on TFP growth of the direction of technological change, we elaborate upon the standard procedures of the calculation of TFP, based upon the Cobb–Douglas approach, and derive a new index based upon the assumption that only a constant share of inputs on income can measure properly all the changes in output that are not engendered by changes in inputs (Antonelli 2002, 2003, 2006; Antonelli and Quatraro 2010). As it is well known, the measure of TFP is given by the difference between the actual output and the theoretical one, i.e., the output that should have been produced taking into account only the changes in input (Ruttan 2001). The methods to measure the theoretical output differ widely with respect to the timing of the variables considered and the source of data. A huge literature has addressed the problems raised by the correct measurement of inputs. Much less attention has been paid to the effects of the changes in the output elasticities.

The levels of the output elasticities of inputs reflect directly the technology: a two-way relationship exists between the production function and the state of technology. All changes in one imply a change in the other and vice versa. Hence, their changes should be considered as the effect of a specific form of technological change. A variety of approaches have been considered in the literature (Van Biesebroeck 2007). Translog production functions instead use data for wages and capital service costs that change yearly (Jorgenson and Griliches 1967). In other approaches, the output elasticities of capital and labor are not measured by means of income's shares, but measured by means of econometric estimates of inter-temporal production functions so that the output elasticity is given a single estimated value that reflects the full set of values of each year (Diliberto et al. 2008). Microeconomic investigations of the dynamics of TFP at the firm level apply the same methodology and rely on econometric estimates at the sectoral level to measure the output elasticity of inputs. They apply such sectoral levels to each firm, assuming that such common levels solve noise and adjustment problems at the firm level (Olley and Pakes 1996).

In our approach, the changes in output elasticity of production factors are the clue to assess the effects of the introduction of biased technological changes and explore the individual changes in output elasticity, at the firm level, as vectors of reliable information about the actual features of the technological innovations being introduced, rather than a source of noise and adjustment problems. The analysis of the changes in the output elasticity of inputs as measured by their respective shares on output, applying Euler's theorem to output like Solow did with value added, yields an effective methodology to decompose the productivity-enhancing effects of the introduction of technological changes according to its direction (See Antonelli 2002, 2003; Antonelli 2006; more recently, Bailey et al. 2004 applied the same methodology).

The decomposition methodology in fact enables to identify the shift effects of neutral technological changes and the congruence effects of directed technological change. Let us recall here the main passages. The output Y of each firm i at time t is produced from aggregate factor inputs, consisting of capital (K), labor (L) proxied in this analysis by total worked hours, and input materials (M). TFP (A) is defined as the Hicks-neutral (Ruttan 2001) augmentation of the aggregate inputs:

$$Y_{i,t} = A_{i,t}(K_{i,t}, L_{i,t}, M_{i,t}) \tag{1}$$

Using a standard Cobb–Douglas specification, we can measure the TFP of firm i at time $t_0 + n$ as follows:

$$\mathrm{AS}_{i,t_0+n} = \frac{Y^*_{i,t_0+n}}{K^{\alpha(i,t_0+n)}_{i,t_0+n} L^{\beta(i,t_0+n)}_{i,t_0+n} M^{\gamma(i,t_0+n)}_{i,t_0+n}} \tag{2}$$

where Y^* is the actual output at time $t_0 + n$, K, L, and M are, respectively, the inputs of capital services, labor services, and materials at time $t_0 + n$, and α, β

and γ are their output elasticities, with the standard assumption of constant returns to scale $\alpha = 1 - \beta - \gamma$. The variable AS measures the TFP as Solow did, i.e., allowing the yearly change in output elasticities.

Such a measure accounts for "any kind of shift in the production function" (Solow 1957: 312), and it can be considered a rough proxy of technical change. By means of it, Solow meant to propose a way to "segregating shifts of the production function from movements along it." But the change in the technology of the production function is made up of two elements. Besides the shift effect, one should account for the congruence effect, i.e., the direction of technological change.

The shift effects measure only one of the two effects of technological change: the consequences on TFP levels of the introduction of neutral technological changes that do not alter the factor intensity of production factor for given and constant levels of factor costs. When technological change is not fully and exclusively neutral, but has a directionality, its introduction exerts a second effect: the congruence effect. For this purpose, we elaborate a measure of the TFP that accounts for both the shift and congruence effects (for this reason, we call it total TFP, ATOT in the following equation), by assuming output elasticities unchanged with respect to a reference year t_0:

$$\mathrm{ATOT}_{i,t_0+n} = \frac{Y^{*}_{i,t_0+n}}{K^{\alpha(i,t_0)}_{i,t_0+n} L^{\beta(i,t_0)}_{i,t_0+n} M^{\gamma(i,t_0)}_{i,t_0+n}} \tag{3}$$

Here, clearly the output elasticity of each production factor does not change every year, as in Solow (1957), but remains fixed at the value of the first year of observation. Now, it is clear that the theoretical output is actually measured as if no changes in the technology had been made. Neither the position, nor the slope of the isoquants has changed. Hence, the difference between the real output Y^* and the theoretical one now accounts for both forms of technological change. The position and the slope of the new map of isoquants are now allowed to exert their effects (Antonelli 2012). Next, we get the measure for the bias effect as the difference between the two indexes we introduced above:

$$\mathrm{ABIAS}_{i,t_0+n} = \mathrm{ATOT}_{i,t_0+n} - \mathrm{AS}_{i,t_0+n} \tag{4}$$

This amounts to measure ABIAS as the difference between a theoretical output calculated with the output elasticities kept fixed at time t_0 and a theoretical output calculated with the new output elasticities at time $t_0 + n$. The bias effect measures the changes in the congruence efficiency, as determined by the matching between the ratio of input costs and the slope of the isoquant. Congruence efficiency will increase when biased technological changes make possible to make a more intensive use of the input that is locally most abundant.

The methodology implemented so far has important implications for the empirical analysis not only at the aggregate level but also at the firm level. Firms differ on many counts: they differ in terms of size, profitability, liquidity, stock of knowledge, and competencies. These differences affect the characteristics of their knowledge generation process and have a direct bearing on the direction of their innovation processes. Technological innovations in turn differ in terms of their shift and bias content. As a consequence, the production function of each firm within an industry is different and this difference applies to both components of the total efficiency.

According to our theoretical analysis, in fact, both the shift and the bias effects of the technological changes introduced by firms are the result of a strategic and idiosyncratic decision implemented by each firm. As a consequence, the levels of the output elasticity of the production factors in the production function of each firm are specific to each firm and should be recognized as an individual attribute as much as the traditional index of TFP is generally recognized as the attribute of individual firms. Our analysis contrasts the underlying assumptions of the standard approach according to which the firms operating in the same "market" must have an identical production function. In order to grasp such differences, the use of the individual data for the output elasticity of production factors is necessary. The proposed procedure allows to measure the changing levels of total efficiency as determined both by changes in shift and congruence efficiency. Only in this case, in fact, the actual labor share on output of each firm is equal to the respective output elasticity as determined by the introduction of biased technological change that is specific to that firm (Jaumandreu and Doraszelski 2010).

3.2 Dataset and variables

The dataset includes financial accounting data for a large sample of manufacturing companies, observed along years 1996–2005. The data have been extracted from the AIDA database provided by Bureau Van Dick, which reports accounting information for public and private Italian firms. The companies included in the analysis have been founded before year 1996, they are registered in a manufacturing sector according to the Italian ATECO classification, and they are still active by the end of year 2005 and have at least 15 employees at the end of fiscal year 1996. In order to drop outliers due to possible errors in the data source, we computed a set of financial ratios and yearly growth rates of employees, sales, and fixed capital stock and we then dropped evident cases of outliers due to errors in the data source.[1] The final dataset is a panel of 6,600 firms for which we have been able to collect all required financial accounting data. Financial data have been deflated according to a sectoral two-digit deflator using year 2000 basic prices. For each firm included in the sample, fixed capital stock has been computed using a perpetual inventory technique according to which the first year accounting data are used as actual replacement values. The subsequent yearly values of fixed capital are computed using a depreciation parameter δ, assumed equal to 6.5 %, and adding deflated yearly investments. The investment parameter ($I_{i,t}$) has been computed as the yearly variation in net fixed capital in companies' balance sheets plus yearly amortizations. Hence, the time series of fixed capital is defined as follows:

$$K_{i,t} = (1 - \delta)K_{i,t-1} + I_{i,t}/p_t \tag{5}$$

In order to account for the effects of the changing levels of utilization, the yearly values of capital stock obtained with the perpetual inventory procedure have been multiplied by the industrial coefficient of capital utilization (Basu 1996; Burnside et al. 1995; Shapiro 1996).[2] Firm-level factor shares of labor and input materials have been computed for each year, respectively, as the ratio of total labor costs to revenues and total costs of input materials to revenues. Under the standard assumption of constant returns to scale, capital factor shares have been computed as the complement to one of the labor and input materials factor shares. The variables $\mathrm{AS}_{i,t}$ and $\mathrm{ATOT}_{i,t}$ for firm i in year t are computed for each firm[3] according to specification reported in Eqs. 2 and 3. In particular, we have adopted a time lag of 3 years ($n = 3$ in the above equation, e.g., the value of ATOT in year 2001 is computed using factor shares of year 1998). We have then defined the variable $\mathrm{SHIFT}_{i,t}$ that is given by the ratio of $\mathrm{AS}_{i,t}$ to $\mathrm{ATOT}_{i,t}$ and will be used in the econometric analysis.

Values of the SHIFT variables larger than one indicate that the technological change introduced had a positive shift effect partly reduced by a negative bias effect. This amounts to saying that the new technology was characterized by an increase in the output elasticity of inputs that were less abundant than others in the local factor markets. As anticipated, a shift effect larger than the total effect and hence a negative bias effects are likely to take place when firms do not direct the new technology so as to increase their technological congruence. This in turn is likely to take place when the new technology is characterized by "fixed coefficients" that do not match with the local factor markets. According to this framework, the higher is the value of the SHIFT variable, the higher is the likelihood that the new technology exerts shift effects rather than biased ones.

$$\mathrm{SHIFT}_{i,t} = \mathrm{AS}_{i,t}/\mathrm{ATOT}_{i,t} \tag{6}$$

The econometric analyses investigate the relationship between the levels of the SHIFT variable and a number of firm-level time-varying characteristics. In particular, building on the hypothesis developed in Sect. 2, we will test whether the shift component is more likely to outweigh the congruence component for firms that are larger, show a better past performance, are relatively less indebted and a higher incidence of intangible assets. Firms size is measured through the log of total assets (SIZE). Profitability is defined as the ratio of earnings before interests depreciations and taxes to total assets (PROF). Financial leverage is defined as the ratio of liabilities to total

[1] We have computed a set of financial ratios and yearly growth rates of assets and employees. We have then manually screened the top and bottom centile of the related distributions. The manual procedure led to the exclusion of 35 firms.

[2] The coefficient is computed at sector-year level by the Italian statistical agency and is based on the survey data from a representative sample of Italian firms.

[3] Note that consistently with our approach the standard procedure to measure TFP at the firm level that relies upon sectoral estimates of the relevant output elasticities seems inappropriate because of our emphasis upon the intra-industrial variance stemming from the localized introduction of idiosyncratic and biased innovations.

Table 1 Definition of variables and summary statistics

Variables	Mean	SD	5 %	Median	95 %
SIZE: log (fixed capital stock)	14.362	1.35	11.944	14.322	16.509
PROF: Ebitda/ total assets	0.058	0.062	−0.019	0.0476	0.175
LEV: Debt/ total assets	0.676	0.206	0.284	0.719	0.941
INTANG: ratio of book value of intangible assets to total assets	0.155	0.154	0	0.072	0.540
SHIFT: ratio AS/ATOT	1.010	0.101	0.857	1.004	1.184

Table 2 Firm size distribution and intensity of intangible assets by size class

	Incidence in the sample	Intangibles intensity
Small firms (<50 employees)	38.45 %	0.141
Medium firms (between 50 and 500 employees)	54.37 %	0.166
Large firms (more than 500 employees)	5.07 %	0.185

assets (LEV). The variable INTANG provides a measure of investments in intangible capital and is equal to the ratio of the book value of intangible assets to total assets. In the following tables, we show the summary statistics of the variables used in the econometric analyses and a description of the dimensional distribution of firms in the sample (Tables 1, 2).

4 Econometric analysis

The econometric analyses test whether the firm-level dynamics of the SHIFT parameter are correlated to specific firms' characteristics. More specifically, we investigate the role of the size of the company, its profitability, the capability to access external financial sources, and the intensity of investment in intangible assets. We initially run a set of conditional fixed effect logit models using a dichotomous-dependent variable that takes a value equal to one for those firms showing a value of the SHIFT variable larger than one in a specific year. We then implemented a set of OLS fixed effect models that use SHIFT as the dependent variable. Finally, we have run a set of dynamic models using a system GMM approach. The latter set of models allows us to control for the potential endogeneity of firm-level covariates and to analyze the presence of persistence in time of the values of the SHIFT variable. In all model specifications, we use 1-year lagged firm-level repressors in order to limit potential spurious correlations.

Table 3 reports the estimates of the conditional fixed effect logit models. The results indicate a positive correlation between size and the shift component of the TFP. Small firms are more likely to introduce biased technological changes that enhance their congruence efficiency based upon the more intensive use of locally abundant inputs. Large firms, on the opposite, are more likely to introduce innovations with major shift effects, but less sensitive to the conditions of local factor markets. The positive sign estimated for the variable capturing the past profitability of firms (PROF) is in line with our theoretical expectations: low profitability limits the possibility for the internal funding of research and development activities that may extend technological exploration capabilities. Higher levels of liabilities relative to total assets (LEV) reduce the possibilities to access financial markets to fund additional research and development activities required for the introduction of more radical innovations eventually leading to significant shift effects in the productivity. As expected, the past intensity of intangible assets (INTANG) shows a positive and significant correlation to the subsequent likelihood that a firm has a SHIFT value larger than one. Intangible assets include not only patents and registered trademarks but also capitalized R&D expenditures. Hence, the variable INTANG captures the intensity of technical and scientific know-how of the firm.

Table 4 reports the results obtained for OLS fixed effects models (I–II) and one-step system GMM (III–V). The GMM set of models allows us to control for the potential endogeneity of firm-level covariates. The OLS models confirm the structure of correlations presented so far. In model II, we have introduced also the lagged dependent variable in order to have a first evidence of the presence of persistence in time of the SHIFT variable. For this model that does not account

Table 3 Determinants of the shift component of TFP

Models	I	II
SIZE t − 1	0.184***	0.202***
	(0.029)	(0.030)
PROF t − 1		0.555*
		(0.298)
LEV t – 1		−1.231***
		(0.101)
INTANG t − 1		0.679***
		(0.136)
Year dummies	Yes	Yes
Observations	45,515	45,515
Pseudo R^2	0.052	0.055
Log lik	−17,074.5	−16,985.7
LR χ^2	1,818.3***	1,995.9***

Conditional fixed effect logit models. Dependent variable equals 1 if the variable SHIFT is larger that 1

SEs are in parenthesis

*** Significant at the 1 % level, ** significant at the 5 % level, * significant at the 10 % level

for endogeneity of regressors, we still find a positive correlation between firms' size and the SHIFT variable and a positive impact of the lagged values of the dependent variable. However, the latter impact of the lagged dependent variable is not confirmed in the GMM model (model III). For the GMM models, Table 4 reports the p values of the autocorrelation tests and for the Sargan test of over identifying restrictions.[4] The econometric results fully confirm the set of hypotheses concerning the positive role of the size of firms, their profitability, liquidity, and stock of intangible assets in explaining the share of shift effects. Table 4 presents also two important robustness checks provided by the application of the GMM models to restricted samples. In particular, we limit the analysis to those firms operating in low–mid tech sectors[5] (model IV) and to medium–large companies (model V). Results reveal that the correlation patterns obtained for the full sample are present also in these subsamples, with the exception of past profitability (PROF) for larger companies.[6] This might indicate that, all else equal, the availability of internal funds to invest in technological solutions that lead to a shift effect is a more binding constraint for smaller companies.[7] In sum, the econometric evidence confirms the set of hypotheses and sheds new lights on the different types of technological change introduced, respectively, by small and large firms. Small size of firms, low levels of their profitability, high levels of financial leverage, lower stock of intangible assets are associated with the introduction of new incremental technologies directed to enhance the technological congruence of production processes with local factor markets. The decomposition of TFP into shift and bias effects is an important tool that provides useful insight into the determinants of the direction of technological change at the firm level.

5 Conclusions

The analysis of the effects and causes of the direction of technological change, after years of neglect, plays again a major role in the current debates on innovation and growth. Much attention has been paid to the identification of the determinants of the introduction of biased technological change at the aggregate level. Much less work has been made to assess its determinants and effects at the firm level.

The implementation of a specific methodology of decomposition of TFP and the identification of the notion of technological congruence have enabled to identify and distinguish the effects of neutral technological change from the effects on biased technological change. The introduction of technological changes that engender shift effects leaves specific tracks in growth accountability, well distinct from the congruence effects of the introduction of biased technological changes as defined in terms of the matching between the output elasticity of inputs and their relative abundance on local factor markets.

[4] The GMM models have been run using the xtabond2 routine for STATA 12 (see Roodman, 2006). One-step models. All available lags are used as instruments for the transformed equation, and the contemporaneous first differences are used as instruments in the levels equation. Model run using the "small" options that allows the use of F statistics of overall model fit.

[5] The selected sectors include food and beverages, textiles, garments and leather products, furniture, construction of metal products (except machinery).

[6] Note that for this model specification the autocorrelation test AR2 turns to be weak (p value = 0.07).

[7] Such evidence is in line with a vast literature on financial constraints and innovation investments (Hall and Lerner 2009).

Table 4 Determinants of the shift component of TFP

Models	OLS fixed effect		One-step system GMM		
Samples	Full	Full	Full	Low/mid tech	Medium–large companies
Models	I	II	III	IV	V
SHIFT t − 1		0.173***	−0.581	0.094	−0.630
		(0.006)	(0.658)	(0.614)	(0.882)
SIZE t − 1	0.043***	0.035***	0.373***	0.276**	0.319**
	(0.007)	(0.008)	(0.125)	(0.129)	(0.144)
PROF t − 1	0.112*	0.997***	1.334***	1.571***	0.278
	(0.067)	(0.070)	(0.430)	(0.595)	(0.427)
LEV t − 1	−0.261***	−0.209***	−2.107***	−1.924**	−2.131**
	(0.028)	(0.029)	(0.683)	(0.868)	(0.976)
INTANG t − 1	0.141***	0.144***	17.472***	14.521**	16.248**
	(0.033)	(0.034)	(5.583)	(6.476)	(6.909)
Constant	0.113	−0.041	−4.701**	−3.711*	−3.848*
	(0.110)	(0.117)	(1.869)	(2.029)	(2.005)
Year dummies	Yes	Yes	Yes	Yes	Yes
Observations	45,515	38,533	38,533	24,268	21,121
R^2	0.050	0.092			
AR (1)			−3.067	−2.214	−2.329
AR (1) *p* value			0.002	0.027	0.020
AR (2)			−1.572	−0.842	–1.811
AR (2) *p* value			0.116	0.400	0.070
Sargan test *p* value			0.116	0.146	0.418
F stat.			6.834***	4.386***	3.976***

Dependent variable SHIFT. OLS fixed effects models (I–II) and system GMM models (III–IV)

Heteroskedasticity robust SEs in parenthesis clustered at individual level

*** Significant at the 1 % level, ** significant at the 5 % level, * significant at the 10 % level

This paper has applied these tools to explore the microeconomic foundations of the determinants and effects of the direction of technological change. The analysis of the characteristics of the processes of generation and exploitation of knowledge and of the variety of innovation processes and strategies has provided useful hints to grasp the variance in the characteristics of technological changes, including its direction, at the firm level.

At each point in time, there is not a single innovation process at work but a variety of them. Firms differ widely both for their economic and managerial characteristics and with respect to the organization of the generation, exploration, exploitation of technological knowledge, and the types of innovations. These characteristics have a direct bearing upon the direction of technological change.

Large firms are better able to command the systematic generation and exploitation of codified technological change with a strong scientific content. The characteristics of the processes of generation and exploitation of technological knowledge and of the innovation process push large firms toward the introduction of technological change represented by a change in the position of the isoquants and hence characterized by a major shift component that keeps them closer to the original factor intensity. The search for superior efficiency is based upon the overall reduction in inputs.

Small firms are more likely to introduce biased technological changes based upon creative adoption and imitation and eventual adaptation of existing processes to the conditions of local product and factor markets. The importance of these "soft innovations" is much larger than currently assumed. Their identification however requires careful analyses. Small firms in fact carry out major innovation activities that are characterized by strong idiosyncratic features. They command a generation of knowledge mainly based upon learning processes and the capitalization of tacit competence. External tacit knowledge is a major input into their knowledge generation processes. Their exploitation strategies rely upon secrecy and time lags based upon the strong tacit component of their knowledge base. As a consequence, small firms specialize in a localized search for higher efficiency that leads mainly to a meta-substitution that enhances the technological congruence of their production processes with the local factor markets by means of the localized introduction of technologies that can be found and exploited within the proximity of existing techniques.

These results are important both to enrich the microeconomics of technological change with an important area of investigation such as the analysis of the causes and consequences of the direction of technological change and also for the economics of growth at the aggregate level as they enable to grasp how the microeconomic characteristics of an economic system such as the composition of the industrial system and the average size of firms exert direct effects on the direction of technological change at the aggregate level.

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