Directors' Talent and Firm Productivity*

Audinga Baltrunaite   Giulia Bovini   Sauro Mocetti

Bank of Italy†

May 22, 2019

Abstract

We build a matched firm-director panel dataset for the universe of limited liability companies in Italy, tracking directors across different firms over time. Exploiting cross-sectional variation due to board interlocking and longitudinal variation due to director moves between firms over time, we estimate how much of the variation in firms' productivity can be attributed to director fixed effects (which we name *talent*). We find that, after controlling for firm fixed effects and time-varying characteristics, the board talent explains a significant portion of variation in firm productivity. The impact is higher for firms more exposed to competition, grows with firm size and age, and is lower for family-owned firms. To shed light on what managers do to boost firm productivity, we exploit survey data on a wide set of firm strategies. We find that the increase in TFP is driven by an increase in firm output and by a reduction in the number of low-pay employees. We also show that board talent is associated with the adoption of good managerial practices and of innovations in the production process. Finally, while both board talent and managerial practices positively affect firm productivity, there is evidence of the positive interaction between the two factors, suggesting important complementarities between good managers and good managerial practices.

Keywords: Board of directors, corporate governance, managerial practices, firm productivity.
JEL classification: G34, L20, M10, D24.

*Preliminary and incomplete. Please do not cite.

†The views and opinions expressed in this paper pertain to the authors only and do not represent in any way those of the Bank of Italy.

1 Introduction

The existence of large productivity differences among firms even in the same narrowly defined industries is an acknowledged stylized fact (Melitz, 2003; Syverson, 2011). The magnitude of these differences is huge: in a typical four-digit manufacturing industry in the United States, establishments at the 90th percentile of total factor productivity (TFP) makes almost twice as much output with the same inputs as plants at the 10th percentile Syverson (2004).[1] What affects these productivity differences, however, is still an open issue. Bloom and Van Reenen (2010), Syverson (2011) and Gibbons and Henderson (2013) argue that one possible explanation can be found in the role of management quality, both in terms of people who manage the firm and practices adopted within the firm.

This paper explores the role of management quality in explaining the firm-level variation in productivity. More precisely, we address the following research questions: do (and how much) managers' talent explain firm productivity? For which firms does it matter more? Which are the channels through which managers' talent impacts firm productivity? Are managers and managerial practices complements or substitutes?

We exploit the information on the universe of the limited liability companies in Italy and identities (and personal characteristics) of their directors. The latter are similar to plant managers for firms in our sample, which are primarily non-large (the fraction of micro, small and medium-sized firms is, respectively, 77%, 17% and 5%) and, hence, we interchangeably use the terms *directors* and *managers* throughout the paper. We build a matched firm-director panel dataset over the period 2005-2016, tracking managers across different firms over time. To estimate how much of the unexplained variation in firms' productivity can be attributed to an individual manager, we exploit two sources of variation: cross-sectional variation due to the fact that the same person can sit on the boards of several firms and longitudinal variation due to the fact that the same person can switch from one firm to another over time. We estimate director fixed effects, conditional on firm fixed effects and

[1] See Lotti and Sette (2019) for evidence on Italy.

time-varying firm characteristics, and we interpret this measure as directors' talent (i.e., the individual contribution to the variation of the firms' TFP). The average of the estimated manager fixed effects at the firm level is, therefore, our measure of its board/management talent.

We find that management talent matters as firm productivity sharply increases when a better manager takes charge. The estimated impact is sizable: one standard deviation in management talent leads to nearly one standard deviation variation in the firm performance. Including management talent in a regression of firms' TFP on firm-fixed effects and time-varying firm characteristics increases the the predictive power of the model by 10% (R-squared rises from 0.57 to 0.63). This impact is in the ballpark of the estimates obtained by previous studies (Bertrand and Schoar, 2003; Graham et al., 2011). We also perform a horse race between our measure of management talent and the average schooling of the firms employees, an important determinant of firm productivity differences (Bugamelli et al., 2018). To this end, we restrict the analysis to a subsample of firms for which we observe the fraction of employees with a college degree. We find that both variables are positively and significantly correlated with firms' TFP; management quality has an impact that is more than one half of the effect of the workforce education.

The estimation of managerial talent via a high-dimensional two-way fixed effect model (inspired by the work of Abowd et al., 1999) relies on the assumption that sorting of directors into companies is as good as random, conditional on firm time-invariant characteristics (which are absorbed by firms' fixed effects) and other observed covariates. We test this assumption in a number of ways and conclude that endogenous sorting based on the idiosyncratic value of the match or on the transitory component of firms' productivity does not seem to be relevant in this setting. On the other hand, there is some evidence of sorting based on the trend component of productivity: more (less) talented directors appear to sort into firms whose performance is improving (deteriorating) over time. Because of this, our estimates of the contribution of managerial talent to a firm total factor productivity could be slightly overstated. However, to the extent that the bias introduced by this form of endogenous mobility is similar across different firms (which we show to be a plausible assumption), it should not affect our further set of results that exploit heterogeneous effects of managerial talent across firms and complementarities with other firms' strategies and characteristics.

We further investigate whether the role of management in determining firm outcomes varies across firm types and across different contests in which they operate. First, we find that the effect of board talent grows with firm size and age (and, arguably, the complexity of organizational processes to be managed within the firm). Second, we rely on detailed data on the level of competition different firms face and find that the management talent appears to be more important for those exposed to higher competition. Finally, the role of skillful managers is smaller in family-owned firms. Interestingly, within family-firms, those who move from family to external directors are characterized by an increase in the TFP and in the average talent of the board.

To shed light on what managers do to boost firm productivity, we exploit survey data containing a rich set of variables on production inputs and on firm strategies. We show that an increase in the board talent is associated with an increase in the revenues and higher utilization rate of the physical capital, without any significant variation in the capital stock. Moreover, talented managers reduce the number of less-paid (likely less-skilled) employees, especially among white-collar workers. We also find that talented managers are more likely to introduce innovation in the production process and to adopt good managerial practices. Interestingly, while both board talent and managerial practices positively affect firm productivity, there is evidence of the positive interaction between the two factors, suggesting important complementarities between firm management and its managerial practices. Therefore, while there are some practices that are in principle always better (e.g. not promoting incompetent employees to senior positions, or collecting some information before making decisions), the positive effects of these practices are even larger when there are good managers (e.g. those who decide whether an employee is competent or not, or those who are more capable of reading available information and exploit it to make better decisions).[2] In other

[2]Bender et al. (2018) examine complementarities between managerial practices and employees' abilities.

words, the role of individual directors, our study suggests, appears to extend beyond the sole adoption of the tools boosting firm productivity, shedding light on the importance of "soft" skills in managing those tools.

Our paper is related to a growing literature examining the role of managers. In a seminal paper Bertrand and Schoar (2003) examine top executives (e.g., CEOs, CFOs, Presidents, etc.) who manage at least two firms in their sample period and find that the individual manager fixed effects are significantly correlated with firms' performance.[3] Other studies exploit a similar strategy to identify manager fixed effects within a single firm, as in Lazear et al. (2015) who use data from a large services company and Fenizia (2019) who uses data from Italian Social Security Agency. Other related studies instead of focusing on manager fixed effects, investigate the role of managers and their characteristics on firm performance. Bennedsen et al. (2007) show that family CEOs have a negative causal effect on firm performance. Kaplan et al. (2012) document how differences in CEOs psychological traits explain the performance of the firms they manage. Bandiera et al. (2019) build an individual-level index of behavior by parsing CEOs diaries and find that "leaders" are more likely to manage more productive and profitable firms.[4]

Another strand of literature has emphasized the role of managerial practices. In a seminal paper, Ichniowski et al. (1997) find that the adoption of advanced management practices (e.g. incentive pay and employee participation in problem-solving teams) are significantly correlated with plant-level productivity. The interest in this topic has increased enormously thanks to the surveys managed by Bloom and Van Reenen and their research team, who collect information on managerial practices at the plant level for a wide set of industries and countries. Bloom and Van Reenen (2007 and 2010) contain a comprehensive analysis of

[3]In a similar vein, Lieberman et al. (1990) find that manager fixed effects are significant in explaining productivity variation in the U. S. and Japanese automobile industry. Interestingly, Graham et al. (2011) identify manager fixed effects using both individual-level regressions where the dependent variable is manager compensation and firm-level regressions where the outcomes are different indicators of firm performance as in Bertrand and Schoar (2003). They find that manager fixed effects in compensation are significantly correlated with manager fixed effects estimated in the regression of firm outcomes.

[4]Partly related, Adams et al. (2018) and Bernile et al. (2018) examine the role of skill composition and diversity of the boards on firm performance.

the relationship between management practices and productivity. Bloom et al. (2013) find a large causal role for such management practices in a field experiment with Indian textile plants.

Our paper contributes to the existing literature along three main directions. First, although our paper is close to Bertrand and Schoar (2003) and to the following papers based on a similar two-way fixed effect model, we depart from them by exploiting additional sources of variation. Namely, to identify manager fixed effects we rely both on board interlocking (i.e. the fact that the same person might sit on the board of several firms) and on directors' switching behavior (i.e. the fact that the same person might move from one firm to another over time). This increases the sample size, allowing us to obtain more precise estimates of manager- and firm-fixed effects and to have a larger (and therefore more representative) connected set. Second, the empirical evidence on the importance of managers for firm performance are typically based on small and not representative sample of firms. In particular, Bertrand and Schoar (2003) base their analysis on the sample of 500 CEOs of large publicly traded companies. The focus instead is on a single large firm operating in private or public sector, respectively, in Lazaer et al. (2015) and Fenizia (2019), with the sample size limited to several hundred individuals.[5] The larger sample size allows us to explore the role of managers' quality also for smaller privately-held firms and to examine heterogeneous effects across different categories of firms. Third, we examine a broad set of channels through which management quality affects firms' productivity, shedding light on what good managers do. In particular, we show that managers impact both quantities of productive inputs and choices how to combine them in production process. This also bridges the gap between the literature on manager identity and that on managerial practices, showing significant complementarities between the two.

The structure of the paper is as follows. Section 2 presents the empirical framework.

[5]Similarly, the literature on managerial practices relies on detailed data on a moderate number of firms. For example, Bloom and Van Reenen (2007) explore managerial practices of around 700 firms in the United States, the United Kingdom, France, and Germany, while Bloom and Van Reenen (2010) - of around 6000 large firms in 17 countries worldwide.

Section 3 describes the data and the variables. Section 4 discusses the main findings of the paper. Section 5 examines the channels through which managers' talent may affect TFP. Section 6 concludes.

2 Empirical strategy

In order to estimate whether and how much directors affect the total factor productivity of the firm, we first derive a measure of individual talent by estimating the following high-dimensional two-way fixed effect model on a matched firm-director panel dataset:

$$y_{ijt} = \alpha_i + \beta_j + \gamma_{st} + \lambda_{rt} + \eta_{at} + r_{ijt} \tag{1}$$

y_{ijt} is the total factor productivity of firm j, managed among others by director i, in year t; α_i are individual fixed effects, which we interpret as capturing the portable and time-invariant component of director's talent, and are the coefficients of interest; β_j are firm fixed effects, which account for time-invariant heterogeneity across firms; γ_{st}, λ_{rt} and η_{at} are sector-year, region-year and age of the firm-year fixed effects, which control for possibly different business cycles across sectors, regions and firms of different ages; r_{ijt} is the error term.

Directors' and firms' fixed effects can be estimated separately insofar as there exist directors who hold a seat in multiple firms, either over time or in the same year. In a seminal paper Bertrand and Schoar (2003) estimate a specification similar to (1) on a small sample of top executives (e.g., CEOs, CFOs, Presidents) who serve on at least two U.S. firms over a sample period of 30 years. More recently, other papers (Graham et. al,, 2011; Fenizia, 2019) have estimated managers fixed effects relying on the method pioneered by Abowd et al. (1999) (AKM, henceforth).[6] While Bertrand and Schoar (2003) could estimate executives' fixed effects only for those who managed different companies, the AKM method allows to estimate individual fixed effects for all managers, including those who do not serve on

[6]The AKM method was firstly used to separately estimate the effect of workers' and firms' time invariant characteristics on individual wages. Card et al. (2013) provide a neat and detailed application of the AKM method to explain the drivers of the increasing wage inequality observed in West Germany.

multiple firms during their career, who belong to a set of firms connected via managers' mobility.

During the 2005-2016 period, a non-negligible share of directors served in more than one firm and interlocking directorates (i.e. the practice of directors sitting on the board of multiple firms at the same time) were widespread (see Section 3 for more details). We therefore estimate specification (1) on the largest set of connected firms and we adapt the AKM model to a setting where connections arise not only via directors serving on multiple companies over time, but also via interlocking directorates. Leveraging this additional source of cross-sectional variation, on top of the longitudinal variation provided by directors who switch firms, might help to attenuate the limited mobility bias (Andrews et al., 2008) and to increase the precision of estimates of directors' and firms' fixed effects. Descriptive statistics about firms belonging to the largest connected set are presented in Section 3.

The OLS estimation of equation (1) identifies the parameters of interest (i.e. directors' fixed effects) as long as directors do not systematically sort into firms based on choice variables that are not observed by the econometricians and are thus included into the composite error term r_{ijt}. As specification (1) features firms fixed effects, directors sorting into firms based on companies time-invariant characteristics would not constitute a threat to identification. Following Card et al. (2013) we assume that the composite error term captures three forms of endogenous mobility: first, mobility patterns that depend on the idiosyncratic component of the firm-director match ($\mu_{jI(j,t)}$); second, mobility patterns based on the drift/trend component of firm productivity (ϕ_{ijt}); third, mobility patterns that arise as a response to the transitory component of firm productivity (π_{ijt}).[7] Given this type of structure of the composite error term, we therefore assume that directors do not sort into firms based on their comparative advantage. Moreover, directors should neither systematically leave or join firms whose productivity is declining or increasing over time, nor companies which experience a sharp change in their productivity. In Section 4.2 we present a battery

[7] As in Card et al. (2013), we assume that: $E(\mu_{jI(j,t)}) = 0$ across every director-firm pair (i, j); ϕ_{ijt} follows a unit root process and has mean 0 for every firm j over time; π_{ijt} has mean 0 for every firm j over time.

of validity checks that aim to verify the plausibility of these assumptions.

After estimating individual fixed effects on the firm-director panel dataset, we collapse observations at the firm-year level: if a firm is managed by a single director, managerial talent coincides with the fixed effect estimated for such director; if a firm is managed by a board, managerial talent is represented by the average of fixed effects of directors who serve on the board. We then assess the effect of managerial talent on firms' total factor productivity by estimating the following specification:

$$y_{jt} = \beta_j + \gamma_{st} + \lambda_{rt} + \eta_{at} + q_{it} + \varepsilon_{jt} \tag{2}$$

where q_{it} managerial talent.

3 Data

3.1 Data sources and and variables

The analysis relies on two main datasets. The first one is *Infocamere* database which is based on administrative data on the Italian firms gathered by provincial Chambers of Commerce. It contains information on the registration data of the universe of Italian private non-financial sector firms. Most important, this dataset includes personal information on firms' stockholders, managers and directors, i.e., name, surname and personal identification code. We use this information to derive their age, gender and place of birth. The second data source is the database managed by the *Cerved Group* which gathers balance sheet information of the universe of the Italian limited liability firms. Our sample comprises all the firms included in the intersection of the *Infocamere* and *Cerved* databases for the years from 2005 to 2016 (the longest available panel for both datasets) for which there are available data to compute measures of firm performance.

The main dependent variable is a measure of the total factor productivity *TFP* computed using Levinsohn and Petrin (2003) estimator. Their semi-parametric model uses intermediate inputs to address the simultaneity problem arising from the potential presence of correlation between unobservable productivity shocks and input levels. We also construct indicators of a firm's age, province in which the headquarters are located and primary sector of its economic activity.

To investigate more in depth what talented managers do to successfully direct their companies, we merge our data with the Bank of Italy Survey of Industrial and Service Firms (*Invind*), containing detailed information on firm performance measures and strategies. In particular, it includes measures of a firm's productive inputs, i.e., capital stock, its utilization rate and workforce composition and wages. Moreover, the 2010 wave contains several questions on the adoption of innovation and managerial practices within the firm, which we use to derive measures of firm-level strategies conducive to higher productivity. In particular, we use indicators of the adoption of process innovation, organization and managerial innovation and product innovation. To measure the intensity of the adoption of managerial practices, we extract the principal component (which we name *Managerial practices*) from the information on the presence of team work, performance pay and employees' involvement in the decision-making within the firm.

3.2 Corporate directors labour market

We observe about 900,000 directors of limited liability companies every year. More than one fourth of the directors in our sample is observed in at least two different firms over the period considered in the analysis and we refer to such directors as "movers" in the remainder of the paper. The category of movers comprises individuals who are involved in the management of more than one firm either due to board interlocking (i.e. the same manager sits on the board of several different firms in the same year) or due to switching (i.e. the same manager moves from one firm to another over time). As shown in Figure 1, nearly 15% of the directors sit every year on boards of two different firms (11% in two firms, nearly 4% in three or more firms). Moreover, every year about 11% of the directors exit from or enter to the board of a firm. In our sample period, more than 20% of the directors move at least once (more than 12% at least twice).

Directors tend to move across firms that are "close" from both a geographical and sectoral point of view (Figure 2).[8] On average interlocking and/or switching occur between firms that are less than 50 kilometers away from each other. In particular, 55% of these moves occur within the same municipality, while nearly 90% of the moves occur between firms less than 100 kilometers away. Directors tend to sit also on the boards of firms belonging to the same sector of activity: the likelihood that the two firms belong to the same section (1 digit), division (2 digit) or group (3 digit) of the NACE classification of economic activities are, respectively, around 40%, 30% and 25%. These probabilities are significantly larger than those that would be recorded by observing a random shift from one sector to another.[9]

Table 1 shows the descriptive statistics of the observable characteristics of directors in the universe of the Italian limited liability companies in columns 1-2 and in the largest connected set which is used for the estimation of manager fixed effects in columns 4-5. The averages are presented separately for directors in movers and non-movers sample, and columns 3 and 6 test the significance of the difference between the two. Among all Italian directors, more than 75% are male. Men, in fact, appear to be more often involved in management of more than one firm: while female directors reach nearly 30% in the non-mover sample, they only correspond to about 18% among movers. Furthermore, directors in the movers sample appear to be more often native Italians, born outside the province in which the firm is located and older by roughly two years.

Our largest connected set includes 21% of the universe of the firms and 31% of the universe of directors. The differences between mover and non-mover directors are similar as

[8]To construct measures of geographical or sectoral distance we need the manager to be present in at least two firms, one of origin and one of destination, simultaneously (as in the case of interlocking) or sequentially (as in the case of switching). To simplify the analysis we have considered all the cases with interlocking equal to two (for the cross-sectional component) and all the cases in which the administrator leaves a company and, in the following year, enters another (for the longitudinal component).

[9]An alternative way to capture sectoral proximity is to examine if the move of the director takes place between firms belonging to the same production chain. Using the input-output matrices we consider, for each combination of branches of economic activity, the average between the fraction of output of the branch of origin used as input in the branch of destination and the fraction of output of the destination branch used as input in the branch of origin. This figure, that captures how much two branches are integrated in the same production chain, is equal to 9% for the moves that we observe, 5 times larger than the simple average obtained from a random move.

in the main sample, except for the share of local directors who are more often involved in management of several, and likely geographically close, companies.

Table 2, columns 1 and 2 compare observable characteritics of firms in our connected set with other firms, respectively, while column 3 shows the test of statistical significance of the difference between the two samples. Firms in the connected set are larger. Figure 3 illustrates the distribution of firms by their size. The left panel shows that the majority of firms in our connected set are micro and small, representing 77% and 17% of the total, respectively. The right panel, however, shows that the connected set is more representative of the universe for medium-sized and large firms, as it contains 70% and 91% of the total in these categories. Moreover, the descriptive statistics in Table 2 reveals that firms in the connected set are also older and more productive. Interestingly, they are less likely to be located in the Southern Italy, suggesting that firms' networks, defined in terms of their directors' linkages, are seemingly more dense in the Northern and Central Italy. Finally, firms in the connected set are more often managed by the board of directors.

4 Results

4.1 Estimation of directors' talent using a two-way fixed effect model

We estimate the equation 1 using OLS to obtain a set of firms' and directors' fixed effects and depict them in Figure 4. There is a considerable dispersion in directors' talent and firms' efficiency. Table 3 presents raw and conditional correlations of directors fixed effects and their individual characteristics. While there are no significant differences in directors' talent by gender, young, non-local and foreign-born directors seem to be less capable of boosting firms' productivity, possibly due to their lack of experience. Mover directors appear to be less talented, perhaps reflecting that they invest less effort to management of a single firm or that they are more likely to be fired and, hence, switch firms. More talented directors tend to be in more productive firms, as shown in Figure 5. The joint distribution of firms and directors fixed effects, in contrast, highlights the presence of the negative assortative matching, in line with what has been found in other studies examining workers-firms matching processes and possibly due to standard estimation error (Goux and Maurin, 1999; Andrews et al., 2008). Yet, it is worth noting that this is not problematic for the estimation of the managers fixed effects, as the model already absorbs all time-invariant firm characteristics.

We collapse the data on the firm-year level and explore the explanatory power of the model of the total factor productivity on board talent in Table 4. For comparison, the most parsimonious model, including industry, region and firm age time-varying shocks, is reported in column 1 and the model with firm fixed effects - in column 2. The adjusted R^2 of the model remains virtually unchanged once the (average) observable board characteristics (i.e.. gender, age, share of foreign-born and local-born director) are included in column 3, while it jumps substantially once we include our measure of board talent in column 4. In particular, it goes up from 0.57 to 0.63, corresponding to a 10% increase.

To better assess the relative importance of the board talent in affecting firm outcomes, we put this variable in a horserace with another important determinant of firms' productivity: schooling level of its workforce. To this end, we combine our board talent measures to information in the 2010 wave of the Invind survey on the share of firms' employees (total and separately for white-collar and blue-collar workers). Notice that the coefficients are not directly comparable to those reported in Table 4 both because the sample is different and (more importantly) because we exploit variation across firms in a cross-section setting instead of a within-firm variation over time as in a panel setting. Table 5 shows that the relationship between the board talent and firms' productivity is positive, significant and robust to the inclusion of industry, region and firm size fixed effects, and, most important, workforce education level. Both board talent and workforce schooling have a positive and statistically significant effect on productivity, with the relative importance of the board talent being more than a half of that of the workforce schooling variable. Interestingly, columns 3, 4 and 5 reveal that the effect of workfoce schooling is primarily driven by white-collar workers, while education of blue-collar workers has a much smaller and statistically not significant effect.

4.2 Validity checks

As explained in Section 2, the specification postulating that firms' total factor productivity is an additive function of firms' and directors' time-invariant characteristics requires that directors do not systematically sort into companies based on the idiosyncratic component of the match.

If this form of endogenous mobility is not relevant, a fully saturated model that features the interaction between the fixed effects of directors and firms should not have a significantly larger explanatory power than an additive model. To check for this, column 6 in Table 4 estimates a modified version of specification (2), where board talent fixed effects (obtained after discretizing into percentiles the continuous measure of board quality q[10]) and firms' fixed effects are replaced by their interaction. The R^2 of the model improves only marginally (from 0.63 to 0.64), suggesting that match-specific effects should not have a first-order relevance in determining the sorting of directors into companies.

Furthermore, if match-specific effects are not relevant the additive model should not deliver abnormally large residuals. Figure 6 shows mean residuals in each of the 100 cells defined by the interaction of firms' and directors' fixed effects estimated in specification (1): the mean residuals in each cell are small, exceeding the rule-of-thumb of 0.02 in only two occurrences. Therefore we argue that these few departures from the additive separability assumptions of the AKM model should have little effect on our basic conclusions.

Finally, if endogenous mobility based on the match component is not important, we should observe that productivity gains experienced by companies that improve their managerial talent are roughly symmetric to productivity losses undergone as a result of a decline

[10] The model in column 5 estimates the same mode as in column 4, substituting the continous board talent measure with indicators for each centile of the discretized measure. Although the discrete variable has less informative value with respect to the continuous variable, the use of fixed effects allows capturing potential non-linearities between board talent and firm TFP. The explained variance is only marginally affected by the change in the measurement of the board talent.

of similar extent in managerial talent.[11] To check for this, we focus on the balanced sub-set of firms that: change at least one director in a given year t (which we relabel as year-to-event 0); are managed by the old board/director in the two years preceding the switch (years-to-event -1 and -2); are served by the new board/director in the two years following the switch (years-to-event 1 and 2).[12] We classify these companies into 9 groups, based on the terciles of managerial talent of the old board and the new board. Figure 7 plots the evolution of total factor productivity from year-to-event -2 to year-to-event 2 for firms whose old director/board belongs to the bottom or top tercile of managerial talent. The figure shows no change in productivity if changes in the composition of the board do not result in a change in managerial talent (i.e. for transitions of the type 1-1 or 3-3). On the other hand, productivity improves after a more talented director/board takes over and the size of the improvement is larger for firms that move from the bottom to the top tercile of managerial talent than for companies that only move to the middle tercile. Opposite and symmetric patterns in productivity arise when companies experience a decline in directors' quality. Figure 8 plots the overall change in total factor productivity (between year-to-event -2 and year-to-event 2) for downward movers against that of upward movers making the opposite change in managerial talents.[13] Dots are closely aligned to the the -45 degree line, indicating that productivity gains and losses for companies that experience opposite changes in directors' quality are roughly symmetric.

Figure 7 also allows to assess the extent to which endogenous mobility based on the trend or the transitory component of productivity. If sorting based on productivity trends was not important, total factor productivity should display a flat dynamic before a new director joins the firm. Figure 7 shows that the productivity of firms experiencing an improvement in managerial talent had been slightly improving before the change, while the productivity of firms undergoing a decline in directors' quality had been slightly falling. This would

[11]On the other hand, if match effects are relevant, gains would be larger than losses, as directors would systematically sort into companies where they have a better match.

[12]Nearly thirty thousand firms belonging to the largest connected set satisfy these criteria.

[13]This figure also includes transitions from the middle to either the bottom or the top tercile of managerial talent.

imply that more (less) talented directors tend to join companies whose TFP is increasing (decreasing) over time. A consequence of this is that we could be overstating the impact of managerial quality on total firm productivity. However, Figure 7 also shows that the changes in productivity before a new director of different talent joins/leaves the firm are lower than those observed after: the evident change in the slope suggests therefore that managerial talent still has an effect. Stated differently, the kink in the TFP can be attributed to the variation in board talent.

Finally, if sorting based on the transitory component of productivity was important, we should observe dips or spikes in productivity just before the change in the composition of the board. Such patterns do not emerge from Figure 7, suggesting that this type of endogenous mobility is likely not of first-order relevance.

In Figures 9, 10 and 11 we examine whether there are differences in endogenous mobility across different categories of firms; these evidences show that pre-trends in productivity appear roughly similar across firms belonging to different sectors (specifically, manufacturing and services), different size classes (specifically, micro and larger firms) or different geographical areas (namely, Centre-North and South). To the extent that the bias in the estimation of managerial talent due to sorting based on productivity trends is similar across different firms, the conclusions of the following analyses, which focus on the interaction between directors' talent and other firm characteristics, are unlikely to be affected.

4.3 Heterogeneity analysis

Backed by the evidence that the upward bias of board talent is similar across different categories of firms, in this section we explore heterogeneous effects of management talent. Table 6 column 1 shows that board talent has a stronger impact on firms in the Northern Italy, while it decreases as we move to the Central and Southern parts of the country. In line with the idea that more able managers are better at dealing with complex tasks, the effect of board talent increases both with firm size (column 2) and firm age (column 3).

Related to the finding in Bloom and Van Reenen (2010) that product market competition is positively associated with management practices, we examine sectoral differences in the role of managerial talent in column 4. Board talent appears to have a stronger effect on firm productivity in manufacturing sector (more exposed to product competition from abroad) and is considerably weaker in regulated sectors (e.g. professional services, public utilities, retail trade, etc.) that are more protected from competition. Firms in construction sector, instead, are no different compared to those in non-regulated services sectors in the reference group. Similarly, the interaction term between board talent and a continuous measure of a firm's exposure to exports in column 5 is positive and statistically significant[14]. Therefore, similar to managerial practices, managerial talent indeed seems to matter more in competitive environments.

Inherited family-owned firms which choose family members for top management positions are often poorly governed (Bloom and Van Reenen, 2010). Motivated by this finding, we investigate the role of managerial talent in family firms, defined as such if more than 50% of a firm's equity is owned by individuals with the same surname. Column 6, in fact, shows that managers are less able to boost firm productivity when in family firms.

We explore this idea more in depth by analyzing changes in family firms' productivity and board talent due to changes in their management. In Table 7 we first show that the effect of an increase in board talent on firm TFP is positive, althought the estimated coefficient is lower with respect to that found in the whole sample (column 1). Morevoer, we find that if a family firm hires a manager external to the family (based on their surname), a firm's total factory productivity rises (column 2). This is likely due to a boost in the board talent, as shown in column 3.[15]. These results confirm those by Bennedsen et al. (2007), who find that family successions have a large negative causal impact on firm performance. Moreover, we show directly that this effect goes through the quality of the board.

[14]The result is robust to using the Lerner's index as an alternative measure of a firm's exposure to competition.

[15]These results are confirmed if we replicate the regression analysis in the *Invind* sample, with more precise measures of family ownership, management changes and the presence of external managers (although the size of the sample is much smaller). Results are available from the authors upon request.

5 Mechanisms: what managers do

This section analyses the mechanisms through which good managers may influence firm productivity. To this end, we combine our data with detailed information from the *Invind* survey, allowing to draw a detailed picture of managers role in boosting firm productivity.

5.1 Use of production inputs

Positive effects on firm productivity may arise either due to higher sales/larger output produced, or due to more effective use of productive inputs, such as capital or labor. Table 8 investigates the effect of talented managers on each of these items separately. To examine these effects we exploit the combined *Infocamere-Cerved-Invind* sample which includes more than 4,400 firms observed over the period 2005-2016. The firms included in this sample are larger, more productive and older with respect to those considered in the whole connected set in the previous section.

First, we confirm the result of a positive association between board talent and firms productivity also in this sample (column 1). Moreover firms led by talented directors increase their revenues (column 2) while we do not detect any significant changes in the capital stock (column 3). Finally, talented managers seemingly reduce the workforce used by their firms (column 4), overall, producing more with a less labor-intensive technology and higher utilization rate of the existing physical capital (column 5).

Table 9 studies directors' role in managing their workforce more in depth. First, we find that talented managers reduce the firm's labour input primarily by laying-off white-collar workers (column 1), suggesting an increase in the efficiency of middle-management and administration, while the effect is virtually null for the blue-collar workers (column 2), who are all directly involved in the productive process. The literature documents an important role of managerial practices in determining workforce skill-composition. For example, Bender et al. (2018) find that better-managed firms are able to build up a superior stock of employees through selective hiring and attrition, i.e. plants with higher management scores are more likely to recruit higher-ability workers and are less likely to lay off or fire the highest-skilled workers. Similar to their findings, while talented managers reduce the workforce, they seem to retain better paid (and likely more skilled) workers (column 3). This effect is particularly strong for white-collar workers (column 4), suggesting that less able employees, who are not directly involved in output production, are fired. Finally, this so-called "skill-upgrading" is also visible for the blue-collar workers' category (column 5).

Firms' efficiency may rise also due to the improvement in the quality of the use of its productive inputs, for example, due to adoption of innovation or better managerial practices. Furthermore, the effectiveness of the latter factors may be higher if talented managers are better able to exploit them. In the following subsections we examine these issues more in depth.

5.2 Innovation adoption

We first investigate various determinants of the innovation adoption within the firm. In particular, we exploit the 2010 *Invind* survey question on whether over the last three years a firm has adopted innovation in production process, innovation in organizational process and/or product innovation. Table 10 uses the three indicators for each of these categories as dependent variables in columns 1-2, 3-4 and 5-6, respectively. Board talent has a positive effect on the adoption of innovation in production and (although to a lesser extent) organizational processes[16], while it does not influence adoption of product innovation. More in general, firm size, exposure to export competition and workforce schooling are positively related to the innovation adoption.

Table 11 investigates the direct effects (on firm productivity growth) of a variation in board talent and of the three types of innovations, and the existence of potential complementarities. Our results confirm the positive impact of board talent on productivity growth, while there is no evidence of the direct short-term effect of production process, firm organi-

[16]The latter effect is statistically significant only when the share of college educated workers is included in the regression as a control.

zational processes or product innovation on productivity on average (columns 2, 4 and 6). Interestingly, the effect of the board talent is nearly doubled for firms which adopt these types of innovation (columns 3, 5 and 7), suggesting important complementarities between these two factors. In other words, innovation per se does not necessarily leads to higher productivity; the positive effect arises only if it is introduced by better managers.

5.3 Managerial practices

Our analysis documents that managers explain a significant portion of productivity differences. Yet, whether these differences stem purely from their managerial talents or the quality of the managerial practices they implement is still an open issue. Moreover, there is hardly any evidence on whether good managerial practices matter *per se* or whether they are complementary to the talent of those who implement them (Syverson, 2011).

To shed light on this issue, we further exploit the 2010 *Invind* survey wave and use the set of questions on the adoption of managerial practices, i.e., the extent of use of team work, performance-based incentive pay and participation of employees at a lower hierarchical level in the decision-making. We then rely on a principal component analysis to extract information from these three variables: the first principal component explains about 66% of the total variance of the underlying variables and is positively associated, as expected, with each of the input variables (see Table 12). We use the first principal component as the main explanatory variable of interest, as it is well-suited to capture a multidimensional phenomenon such as the quality of managerial practices. Moreover, the large fraction of variance explained by the first component is reassuring about the informational content of this variable. Nevertheless, for the easier interpretation of the results, we also replicate the analysis using the three single items separately.

Table 13 shows a positive association between our composite index of goodness of managerial practices and several firms' characteristics. Namely, more talented boards, larger firms and those more exposed to international competition have significantly higher management scores, while family-owned firms are significantly lagging behind. Moreover, unsurprisingly, we also find that highly-educated workforce of the firm is positively associated with higher managerial practices scores. These results are largely reassuring about the information content of our index of managerial practices as they are consistent with the findings in Bloom and Van Reenen (2007 and 2010).[17] Specifically, board talent is positively associated to each practice separately (although the coefficient is statistically significant only for the use of team work and for the involment of lower hierarchical level in decision making).

Table 14 investigates the role of the board talent and the adoption of managerial practices in determining firms' total factor productivity. Columns 1 and 2 shows that managerial practices and schooling of the workforce both contribute positively to firms' efficiency, on average. Interestingly, the positive effect of the board talent doubles once the regression model includes its interaction with the adoption of good managerial practices. Most important, managerial practices and management quality appear as complements, as it appears that the effect of the former matters for firm productivity only if these practices are adopted by talented bosses. Column 4 shows a similar complementarity with the education level of the workforce. Finally, columns 5, 6 and 7 confirm that the positive interaction effects are robust to using each type of the managerial practices separately.

6 Concluding remarks

We build a matched firm-director panel dataset for the universe of limited liability companies in Italy, tracking directors across different firms over time. Exploiting cross-sectional variation due to board interlocking and longitudinal variation due to director moves between firms over time, we estimate how much of the variation in firms' productivity can be attributed to director fixed effects. We find that, after controlling for firm fixed effects and time-varying characteristics, the board talent explains a significant portion of variation in firm productivity. The estimated impact is sizable: including management talent in a re-

[17] In a similar vein, Bender et al. (2018) show that the skills (measured as the individual fixed effects in a two-way fixed effects model) of the top quartile of employees at a plant a group that they interpret as the managers is positively correlated with plant-level productivity and with higher management practice scores.

gression of firms' TFP on firm-fixed effects and time-varying firm characteristics increases the the predictive power of the model by one tenth. The horse race between our measure of management talent and the average schooling of the firms employees show that management quality has an impact on firms' TFP that is more than one half of the effect of the workforce education. The impact is higher for firms more exposed to competition, grows with firm size and age, and is lower for family-owned firms.

To shed light on what managers do to boost firm productivity, we exploit survey data on a wide set of firm strategies. We find that the increase in TFP is driven by an increase in the level of activity and by a reduction of less-skilled employees, especially among white-collar workers. We also show that board talent is associated to the adoption of good managerial practices and by innovations in the production process. Finally, we show that while both board talent and managerial practices positively affect firm productivity, there is evidence of the positive interaction between the two factors, suggesting important complementarities between good managers and good managerial practices. In a similar vein, process innovation has a stronger effect on firm productivity, if adopted by talented managers.

References

Abowd, J., F. Kramarz and D. Margolis (1999), High Wage Workers and High Wage Firms, *Econometrica*, vol. 67, pp. 251-333.

Adams, R.B., A.C. Akyol and P. Verwijmeren (2018), Director Skill Sets, *Journal of Financial Economics*, vol. 130, pp. 641-662.

Andrews, M.J., L. Gill, T. Schank and R. Upward (2008), High-Wage Workers and Low-wage Firms: Negative Assortative Matching or Limited Mobility Bias? *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, vol. 171, pp. 673-697.

Bandiera, O., S. Hansen, A. Prat and R. Sadun (2019), CEO Behavior and Firm Performance, *Journal of Political Economy*, forthcoming.

Bender, S., N. Bloom, D. Card, J. Van Reenen and S. Wolter (2018), Management Practices, Workforce Selection, and Productivity, *Journal of Labor Economics*, vol. 36, pp. 371-409.

Bennedsen, M., K.M. Nielsen, K. M., F. Perez-Gonzalez and D. Wolfenzon (2007), Inside the Family Firm: the Role of Families in Succession Decisions and Performance, *Quarterly Journal of Economics*, vol. 122, pp. 647-691.

Bernile, G., V. Bhagwat and S. Yonker (2018), Board Diversity, Firm Risk, and Corporate policies, *Journal of Financial Economics*, vol. 127, pp. 588-612.

Bertrand, M. and A. Schoar (2003), Managing with Style: the Effect of Managers on Firm Policies, *Quarterly Journal of Economics*, vol. 118, pp. 1169-1208.

Bloom, N. and J. Van Reenen (2007), Measuring and Explaining Management Practices across Firms and Countries, *Quarterly Journal of Economics*, vol. 122, pp. 1351-1408.

Bloom, N. and J. Van Reenen (2010), Why Do Management Practices Differ across Firms and Countries?, *Journal of Economic Perspectives*, vol. 24, pp. 203-224.

Bloom, N., B. Eifert, A. Mahajan, D. McKenzie and J. Roberts (2013), Does Management Matter? Evidence from India. *Quarterly Journal of Economics*, vol. 128, pp. 1-51.

Bugamelli, M., F. Lotti, M. Amici, E. Ciapanna, F. Colonna, F. D'Amuri, S. Giacomelli, A. Linarello, F. Manaresi, G. Palumbo, F. Scoccianti and E. Sette (2018), Productivity Growth in Italy: A Tale of Slow Motion Change, Bank of Italy working paper No. 422.

Card, D., J. Heining and P. Kline (2013), Workplace Heterogeneity and the Rise of West German Inequality, *Quarterly Journal of Economics*, vol. 128, pp. 967-1015.

Gibbons, R. and R. Henderson (2013), What Do Managers Do? Exploring Persistent Performance Differences among Seemingly Similar Enterprises, in R. Gibbons and J. Roberts (eds.) *The Handbook of Organizational Economics*, Princeton University Press.

Fenizia, A. (2019), Managers and Productivity in the Public Sector, working paper.

Graham, J.R., S. Li and J. Qiu (2011), Managerial Attributes and Executive Compensation, *Review of Financial Studies*, vol. 25, pp. 144-186.

Goux, D. and E. Maurin (1999), Persistence of Interindustry Wage Differentials: A Reexamination Using Matched Worker-Firm Panel Data, *Journal of Labor Economics*, vol. 17, pp. 492-533.

Ichniowski, C., K.L. Shaw and G. Prennushi (1997), The Effects of Human Resource Management Practices on Productivity: A Study of Steel Finishing Lines, *American Economic Review*, vol. 87, pp. 291-313.

Kaplan, S.N., M.M. Klebanov and M. Sorensen (2012), Which CEO Characteristics and Abilities Matter? *Journal of Finance*, vol. 67, pp. 973-1007.

Lazear, E.P., K.L. Shaw and C.T. Stanton (2015), The Value of Bosses, *Journal of Labor Economics*, vol. 33, pp. 823-861.

Lieberman, M., L. Lau and M. Williams (1990), Firm-Level Productivity and Management Influence: A Comparison of U. S. and Japanese Automobile Producers, *Management Science*, vol. 36, pp. 1193-1215.

Lotti, F. and E. Sette (2019), Frontier and Superstar Firms in Italy, Bank of Italy Occasional Papers, forthcoming.

Melitz, M. (2003), The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity, *Econometrica*, vol. 17, pp. 1695-1725.

Syverson, C. (2004), Product Substitutability and Productivity Dispersion, *Review of Economics and Statistics*, vol. 86, pp. 534-550.

Syverson, C. (2011), What Determines Productivity? *Journal of Economic Literature*, vol. 49, pp. 326-365.

Tables and figures

Table 1: Descriptive statistics of directors in the full sample and in the *connected* set

	(1)	(2)	(3)	(4)	(5)	(6)
	universe of firms			connected set		
	Non-movers	Movers	Δ	Non-movers	Movers	Δ
Female	0.294	0.176	0.118***	0.250	0.153	0.097***
Foreign-born	0.078	0.050	0.028***	0.097	0.050	0.047***
Age	46.843	48.892	-2.049***	48.999	50.125	-1.127***
Local	0.752	0.741	0.011***	0.698	0.731	-0.034***
Director's talent				-0.003	-0.005	0.001
Share	0.747	0.253		0.560	0.440	
N		2,129,250			551,072	

Notes: Data are drawn from the combined *Infocamere-Cerved* sample. Columns (1) and (2) report mean values for movers and non-movers in the universe of limited companies while columns (4) and (5) report the same figures for the subsample of firms included in the connected set; Δ report the corresponding difference in means; N represents the total number of directors in the period considered.

Table 2: Descriptive statistics of the firms in the *connected* set

	(1)	(2)	(3)
	other firms	connected set	Δ
# employees	3.400	19.416	-16.016***
TFP	-0.090	-0.077	-0.013***
Firm age	8.057	11.947	-3.890***
# directors	1.448	2.364	-0.916***
% manufacturing	0.150	0.156	-0.006***
% South	0.304	0.135	0.168***
Share	0.795	0.205	
N		1,487,293	

Notes: Data are drawn from the combined *Infocamere-Cerved* sample. Columns (1) and (2) report mean values for firms out from the connected set and within the connected set, respectively; Δ report the corresponding difference in means; N represents the total number of firms.

Table 3: Individual characteristics correlated with directors' talent

	(1)	(2)
Female	0.002	0.002
Foreign-born	-0.011***	-0.012***
Age	-0.001**	-0.001*
Age squared	0.000***	0.000**
Local	0.003*	0.003*
Mover	-0.004***	-0.007***
N	472,419	472,419
Firm controls	-	Yes

Notes: Data are drawn from the combined *Infocamere-Cerved* sample. The dependent variable is (estimated) directors' fixed effects. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Board talent and firm productivity: analysis of the variance

Dependent variable:	Total factor productivity					
	(1)	(2)	(3)	(4)	(5)	(6)
Board talent				0.932^{***}		
				(0.003)		
Industry FE × Year	Yes	Yes	Yes	Yes	Yes	Yes
Region FE × Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm age FE × Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes	Yes	Yes	Yes	Yes
Director chars			Yes	Yes	Yes	Yes
Board FE					Yes	Yes
Board FE × Firm FE						Yes
R^2	0.027	0.570	0.570	0.626	0.628	0.641
N	1,702,579	1,702,579	1,702,579	1,702,579	1,702,579	1,702,579

Notes: Data are drawn from the combined *Infocamere-Cerved* sample. Panel with fixed effects. The table shows how much of the variation of firm TFP is explained by the firm fixed effects, the observable characteristics of the board, the board talent, with the latter being measured with a continuous variables (the average of directors fixed effects at the firm-year level) and with FEs corresponding its centiles. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Board talent and workforce schooling

Dependent variable:	Total factor productivity				
	(1)	(2)	(3)	(4)	(5)
Board talent	0.067**	0.074***	0.072**	0.070**	0.072**
	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)
% college	0.085***	0.133***			
	(0.030)	(0.032)			
% college white-collars			0.102***		0.099***
			(0.029)		(0.029)
% college blue-collars				0.039	0.012
				(0.027)	(0.027)
Industry FE		Yes	Yes	Yes	Yes
Region FE		Yes	Yes	Yes	Yes
Size FE		Yes	Yes	Yes	Yes
R^2	0.011	0.080	0.075	0.067	0.075
N	1,484	1,484	1,484	1,484	1,484

Notes: Data are drawn from the combined *Infocamere-Cerved-Invind* sample, using the 2010 wave. OLS cross-section regression. The dependent variable is firm TFP. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Heterogeneous effects

Dependent variable:	Total factor productivity					
	(1)	(2)	(3)	(4)	(5)	(6)
Board talent (BT)	0.956***	0.923***	0.923***	0.937***	0.922***	0.923***
	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
BT × North East	0.052***					
	(0.008)					
BT × Centre	−0.071***					
	(0.007)					
BT × South	−0.095***					
	(0.007)					
BT × small		0.017***				
		(0.003)				
BT × medium		0.065***				
		(0.006)				
BT × large		0.171***				
		(0.015)				
BT × age 5-10			0.003			
			(0.002)			
BT × age 10-20			0.012***			
			(0.003)			
BT × age 20+			0.024***			
			(0.005)			
BT × manufacturing				0.023***		
				(0.008)		
BT × construction				−0.005		
				(0.009)		
BT × regulated services				−0.019***		
				(0.006)		
BT × export					0.002***	
					(0.000)	
BT × family firm						−0.030***
						(0.003)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE × Year	Yes	Yes	Yes	Yes	Yes	Yes
Region FE × Year	Yes	Yes	Yes	Yes	Yes	Yes
Age FE × Year	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.627	0.627	0.626	0.626	0.626	0.620
N	1,702,579	1,702,579	1,702,579	1,702,579	1,702,579	1,510,348

Notes: Data are drawn from the combined *Infocamere-Cerved* sample. Panel with fiexed effects. The dependent variable is firm TFP. Board talent is interacted with firm characteristics. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Management selection in family firms

Dependent variable:	TFP	TFP	Board talent
	(1)	(2)	(3)
Board talent	0.838***		
	(0.005)		
External manager		0.012***	0.005***
		(0.003)	(0.002)
Firm FE	Yes	Yes	Yes
Industry FE × Year	Yes	Yes	Yes
Region FE × Year	Yes	Yes	Yes
Age FE × Year	Yes	Yes	Yes
R^2	0.597	0.561	0.962
N	659,965	659,965	659,965

Notes: Data are drawn from the combined *Infocamere-Cerved* sample. Panel with fiexed effects. The sample is restricted to family-owned firms; *External manager* is a dummy variable equal to 1 if directors do not have the surname of the family owing the firm, and 0 otherwise. The dependent variable is TFP in columns 1 and 2 and board talent in column 3. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Use of productive inputs

Dependent variable:	TFP	Revenues	Capital stock	# employees	Capacity use
	(1)	(2)	(3)	(4)	(5)
Board talent	1.093***	0.133***	0.003	−0.014*	0.035***
	(0.033)	(0.013)	(0.017)	(0.007)	(0.006)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.768	0.976	0.960	0.986	0.577
N	18,564	18,564	18,564	18,564	11,073

Notes: Data are drawn from the combined *Infocamere-Cerved-Invind* sample. Panel with fixed effects. Dependent variables in columns 2-5 are in logarithms. The dependent variable in column 6 is the utilization rate in percentage points of physical capital. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Workforce composition and wages

Dependent variable:			Wages		
	# white collar	# blue collar	per worker	per white collar	per blue collar
	(1)	(2)	(3)	(4)	(5)
Board talent	−0.038***	−0.008	0.015**	0.021***	0.013*
	(0.011)	(0.013)	(0.007)	(0.007)	(0.007)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.959	0.939	0.785	0.721	0.750
N	18,564	18,564	18,564	18,564	18,564

Notes: Data are drawn from the combined *Infocamere-Cerved-Invind* sample. Panel with fixed effects. Dependent variables in all columns are in logarithms. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Determinants of innovation

Innovation in:	Production process		Organization		Product	
	(1)	(2)	(3)	(4)	(5)	(6)
Board talent	0.200***	0.226***	0.110	0.168*	0.011	0.096
	(0.071)	(0.085)	(0.075)	(0.094)	(0.069)	(0.082)
Firm FE	0.055	0.040	0.054	0.044	0.044	0.059
	(0.039)	(0.045)	(0.042)	(0.049)	(0.038)	(0.044)
Log employees	0.077***	0.071***	0.081***	0.061***	0.075***	0.066***
	(0.011)	(0.014)	(0.012)	(0.015)	(0.011)	(0.014)
Export exposure	0.011***	0.012***	0.006***	0.007***	0.017***	0.017***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Family-firm	0.021	0.021	0.030	0.004	0.034	0.047
	(0.037)	(0.047)	(0.038)	(0.047)	(0.036)	(0.045)
% college		0.001		0.003**		0.004***
		(0.001)		(0.001)		(0.001)
R^2	0.122	0.123	0.072	0.070	0.211	0.221
N	928	704	925	702	924	702

Notes: Data are drawn from the combined *Infocamere-Cerved-Invind* sample, using the 2010 wave. OLS cross-section regression. Dependent variables are various dimensions of innovation adoption occurred within the firm in the last three years. Odd columns include the control for the fraction of employees with a college degree, an information that is not available for small firms. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Complementarities between management talent and innovation

Dependent variable:	TFP						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Board talent variation (BT)	0.324***	0.322***	0.249***	0.327***	0.256***	0.328***	0.261***
	(0.034)	(0.034)	(0.041)	(0.036)	(0.043)	(0.036)	(0.045)
production process innovation (I1)		−0.107	−0.112				
		(0.071)	(0.071)				
BT × I1			0.201***				
			(0.066)				
organization innovation (I2)				0.048	0.044		
				(0.061)	(0.060)		
BT × I2					0.177**		
					(0.071)		
product innovation (I3)						−0.003	−0.007
						(0.070)	(0.070)
BT × I3							0.171**
							(0.070)
Firm size	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.124	0.127	0.137	0.124	0.132	0.122	0.129
N	972	956	956	953	953	953	953

Notes: Data are drawn from the combined *Infocamere-Cerved-Invind* sample, using the 2010 wave. OLS cross-section regression. Dependent variable is variation of the TFP in the last three years while the explanatory variables are various dimensions of innovation adoption occurred within the firm in the last three years, interacted with board talent. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Managerial practices: principal component analysis

	(1)	(2)	(3)
	1st component	2nd component	3rd component
Eigenvalue	1.966	0.656	0.656
Proportion	0.551	0.184	0.839
Cumulative	0.483	0.161	1.000
	use of team works	performance-based incentive pay firm	extent of participation in decision-making
Correlation with 1st PC	0.819	0.790	0.819

Notes: Data are drawn from the *Invind* sample, using the 2010 wave. Results of the first principal component analysis. For each managerial practice, the firms is required to answer the extent of the use of each of them (none, poor, moderate, high).

Table 13: Determinants of managerial practices

Dependent variable:	Managerial practices		Team work	Performance-pay	Decision-making
	(1)	(2)	(3)	(4)	(5)
Board talent	0.075*	0.083**	0.071*	0.054	0.078*
	(0.044)	(0.038)	(0.039)	(0.040)	(0.045)
Firm FE	0.242**	0.199**	0.140	0.244***	0.105
	(0.100)	(0.091)	(0.091)	(0.092)	(0.095)
Log employees		0.287***	0.217***	0.340***	0.148***
		(0.030)	(0.032)	(0.028)	(0.033)
Export exposure		0.010***	0.007**	0.009***	0.009***
		(0.003)	(0.003)	(0.003)	(0.003)
family-firm		−0.285***	−0.167*	−0.247***	−0.284***
		(0.083)	(0.090)	(0.077)	(0.094)
% college		0.121***	0.103**	0.147***	0.047
		(0.040)	(0.040)	(0.040)	(0.037)
R^2	0.010	0.189	0.104	0.244	0.072
N	672	672	672	672	672

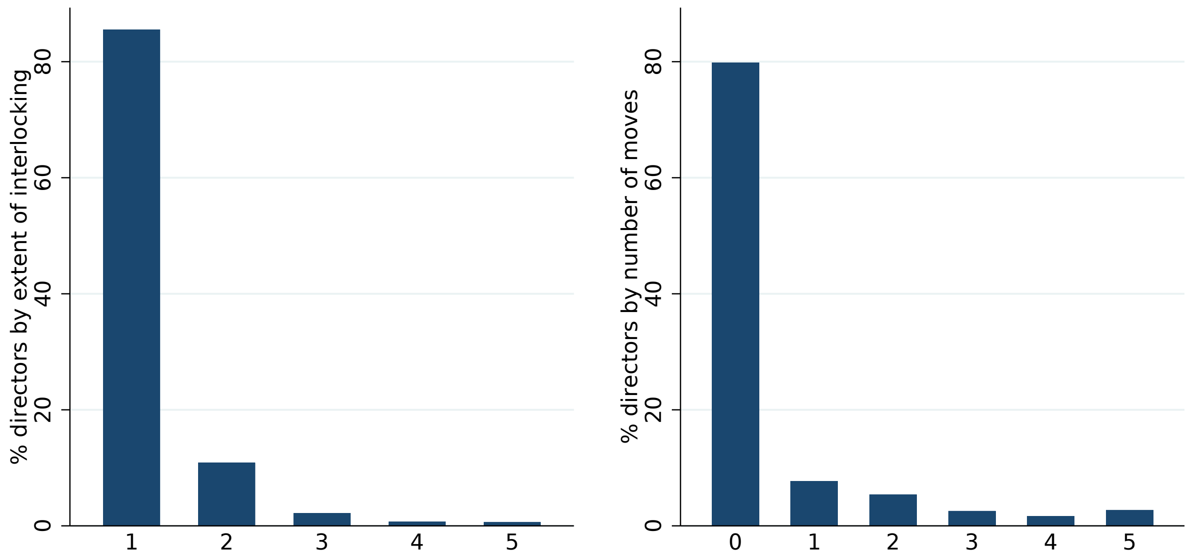
Notes: Data are drawn from the combined *Infocamere-Cerved-Invind* sample, using the 2010 wave. OLS cross-section regression. Dependent variable is the managerial practice score obtained with the principal component analysis (and corresponding to the first component). Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Complementarities between management talent and managerial practices

Dependent variable:	TFP						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Managerial practices (MP)	0.094**	0.074*	0.067	0.062			
	(0.043)	(0.043)	(0.043)	(0.042)			
Board talent (BT)		0.056	0.105**	0.103**	0.081**	0.099*	0.082*
		(0.040)	(0.047)	(0.046)	(0.040)	(0.051)	(0.043)
% college (ED)		0.132***	0.131***	0.125***	0.136***	0.127**	0.137***
		(0.050)	(0.050)	(0.047)	(0.049)	(0.050)	(0.050)
MP × BT			0.111**	0.112**			
			(0.048)	(0.047)			
MP × ED				0.075*			
				(0.042)			
Team work (TW)					0.053		
					(0.042)		
TW × BT					0.066		
					(0.043)		
Performance-pay (PP)						0.106**	
						(0.044)	
PP × BT						0.094*	
						(0.053)	
Decision-making (DM)							0.011
							(0.040)
DM × BT							0.085**
							(0.040)
Firm size	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.058	0.074	0.083	0.088	0.076	0.084	0.077
N	657	657	657	657	657	657	657

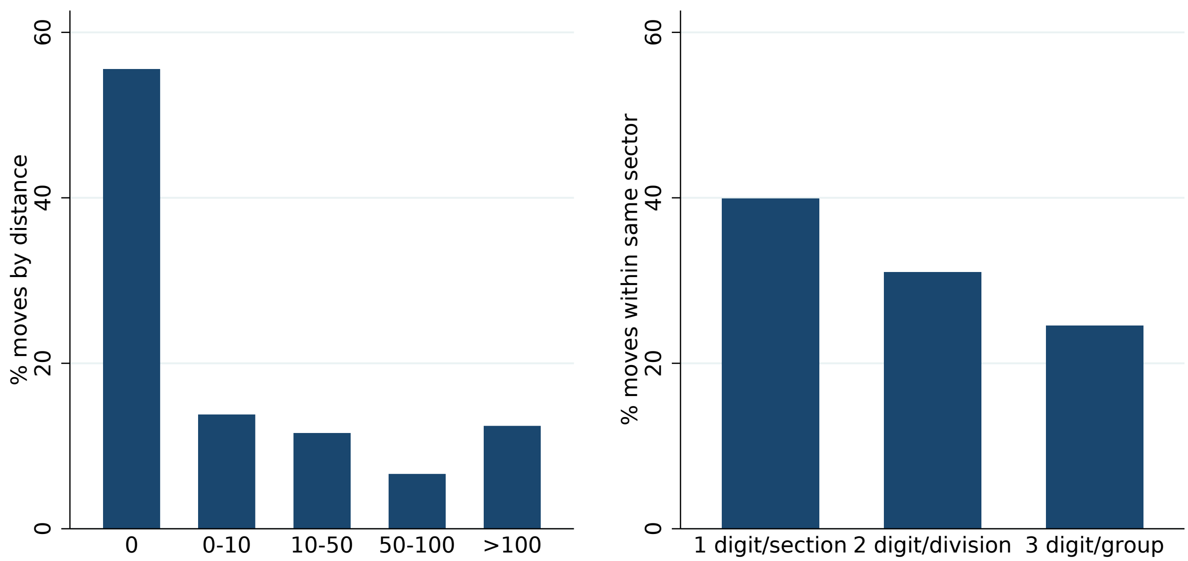
Notes: Data are drawn from the combined *Infocamere-Cerved-Invind* sample, using the 2010 wave. OLS cross-section regression. Dependent variable is firm TFP while the explanatory variables capture various dimensions of managerial practices and their interaction with board talent. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Extent of interlocking and switching among directors



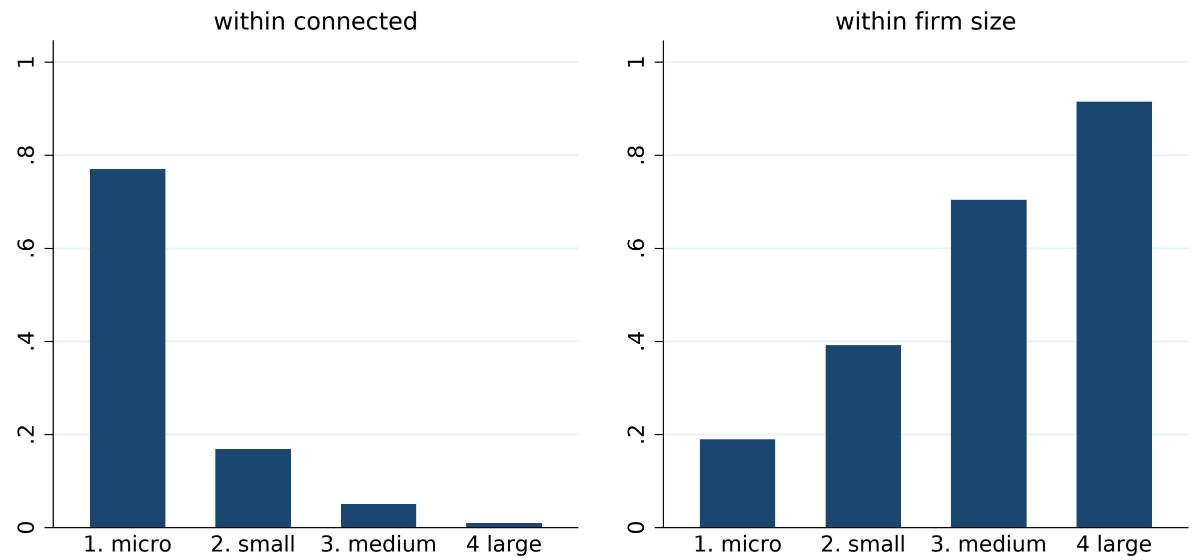
Notes: Data are drawn from the combined *Infocamere-Cerved* sample. The left panel shows the extent of interlocking, i.e. the distribution of directors by the number of boards (of different firms) on which they seat in the same year; the right panel shows the extent of switching, i.e. the distribution of directors by the number of switch (from one firm to another across time) over the period 2005-2016.

Figure 2: Geographical and sectorial distance of "moves" between firms



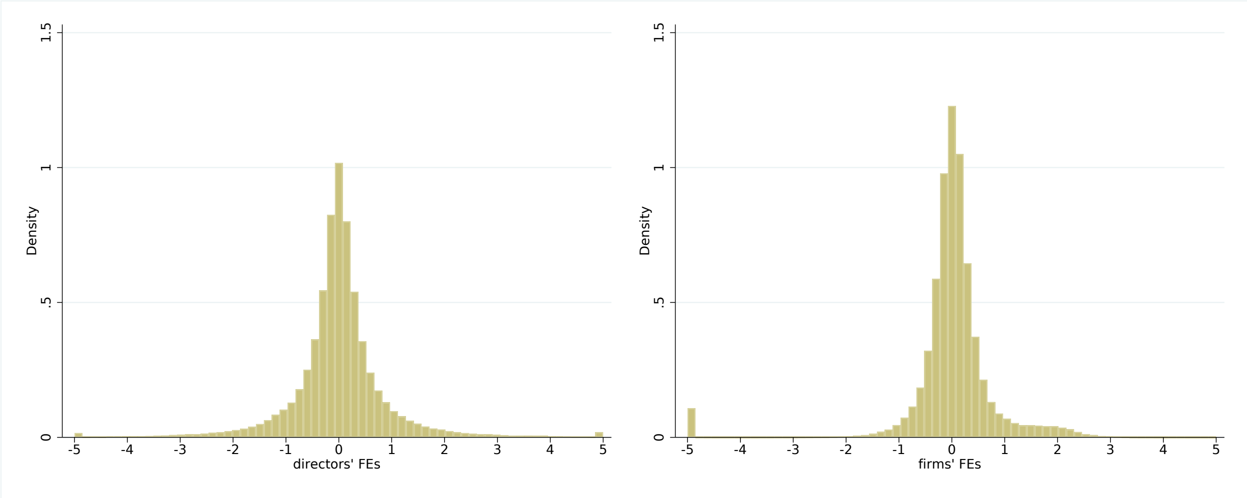
Notes: Data are drawn from the combined *Infocamere-Cerved* sample. We consider as moves both the presence in the board of two different firms in the same year and the switch from one firm to another across time.

Figure 3: Distribution of firms in the connected set by size



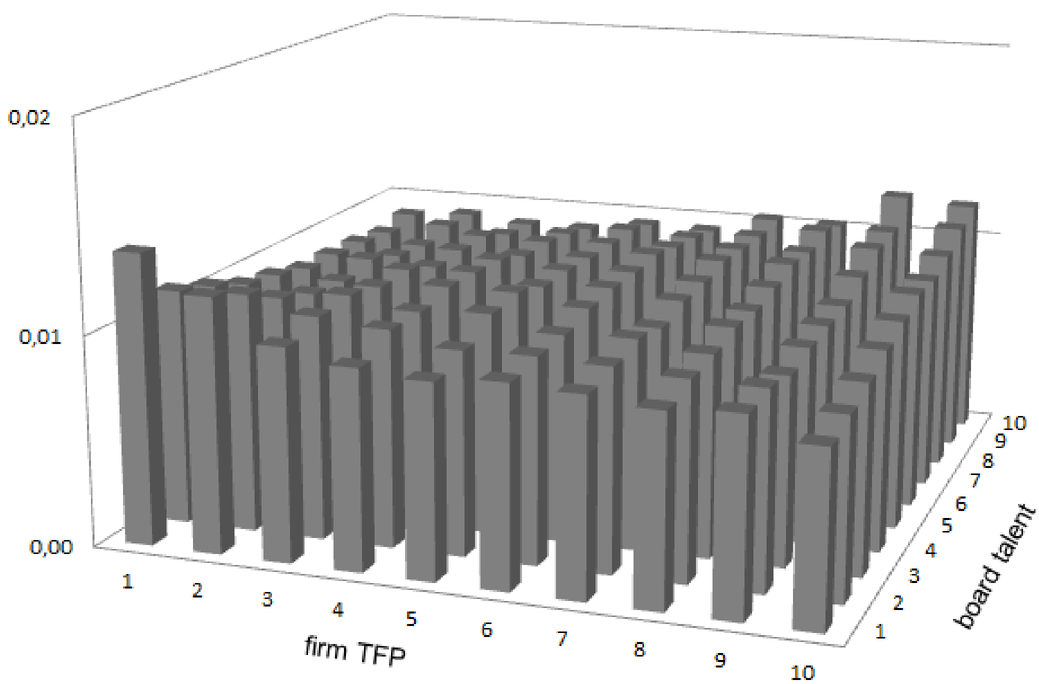
Notes: Data are drawn from the combined *Infocamere-Cerved* sample. The left panel shows the distribution of firms in the connected set by size; the right panel shows the share of firms in the connected set with respect to the universe by size. Following the European Commission classification, micro firms have up to 10 employees, small firms have up to 50 employees, medium-sized firms have up to 250 employees while large firms have more than 250 employees. Micro firms

Figure 4: Distribution of firms' and directors fixed-effects



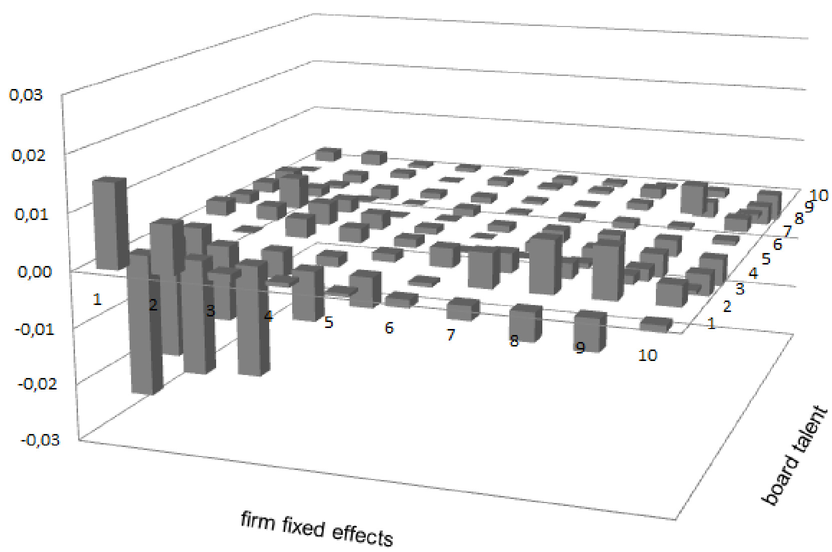
Notes: Data are drawn from the combined *Infocamere-Cerved* sample. Distribution of firms' and directors' fixed effects estimated through the two-way fixed effect model. Both variables are standardized.

Figure 5: Assortative matching



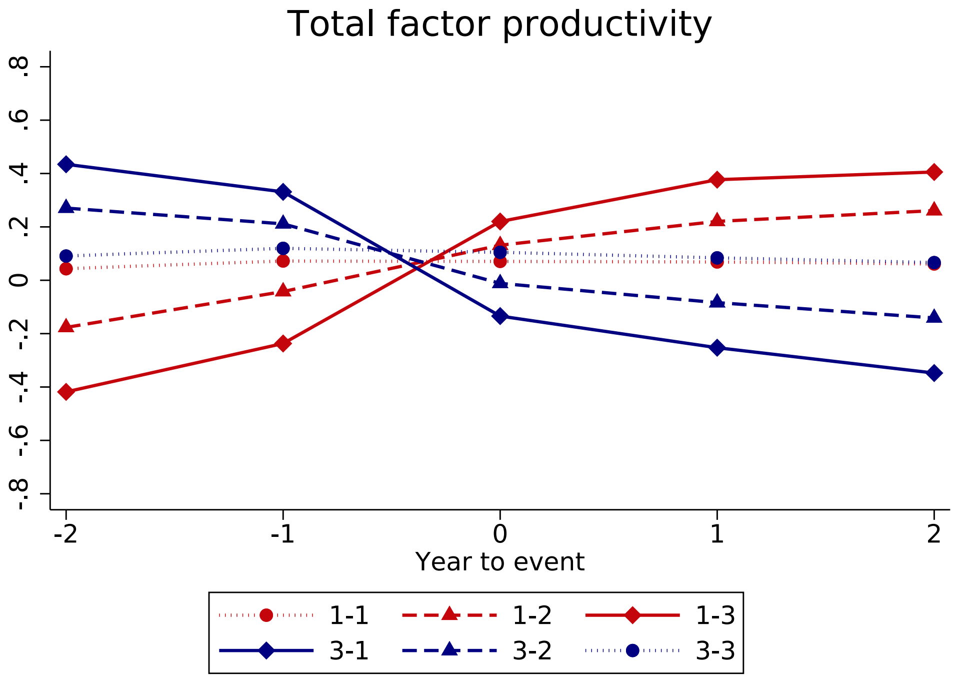
Notes: Data are drawn from the combined *Infocamere-Cerved* sample. Joint distribution of (deciles of) firms' fixed effects and board quality.

Figure 6: Residuals



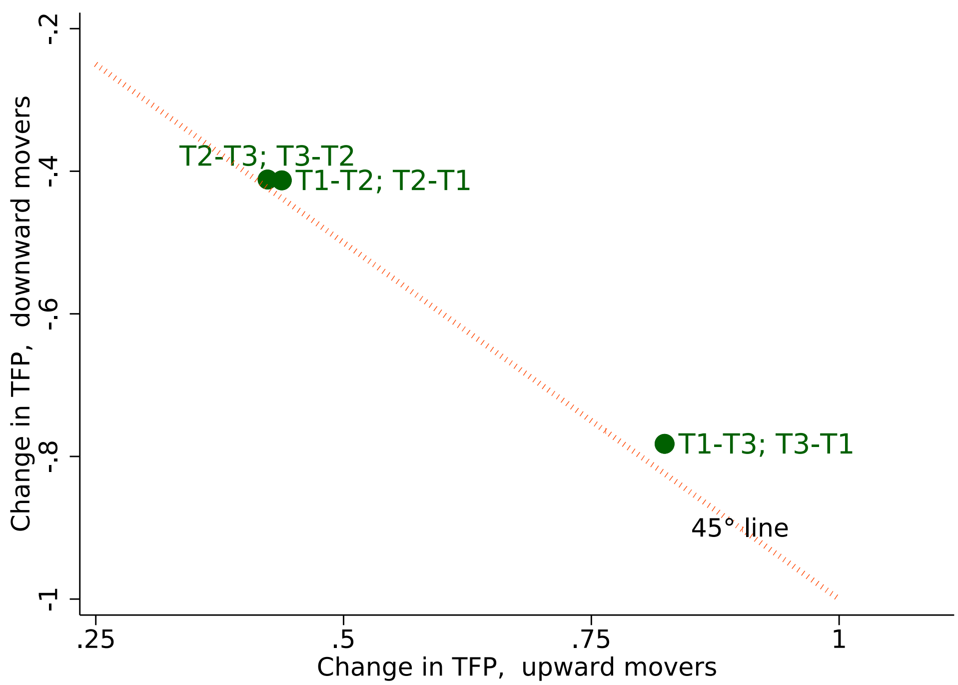
Notes: Data are drawn from the combined *Infocamere-Cerved* sample. Figure shows mean residuals from model (1) on the largest connected set with cells defined by deciles quartiles of board talent, interacted with deciles of estimated firm fixed effects.

Figure 7: Evolution of TFP following a change in directors



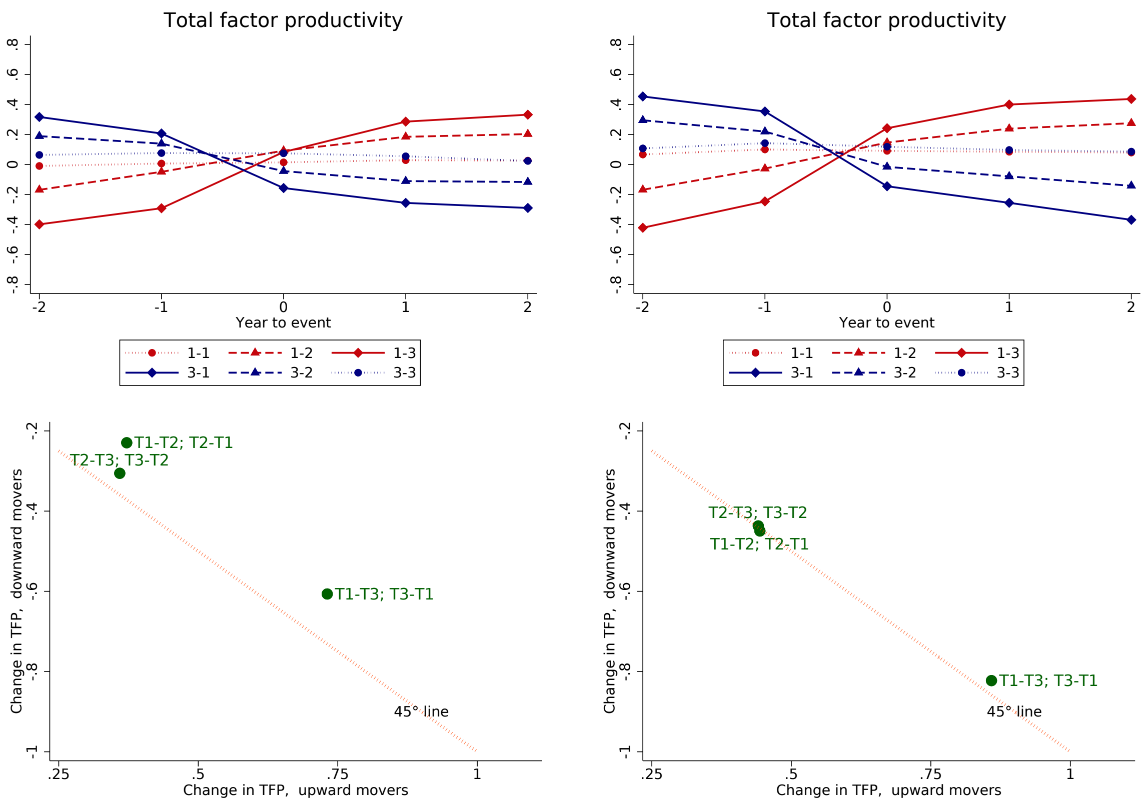
Notes: The figure plots the evolution of TFP from year-to-event -2 to year-to-event 2 on the balanced subset of firms that: change at least one director in year-to-event 0; are observed with the old board/director in the 2 years preceding the change; are observed with the new board/director in the 2 years following the change. Firms are divided into 9 groups based on the terciles of managerial talent of the old and the new board. The figure shows the evolution of TFP for firms whose old board belongs to either the bottom (1) or the top (3) tercile of managerial talent.

Figure 8: Symmetry of gains and losses in TFP following a change in directors



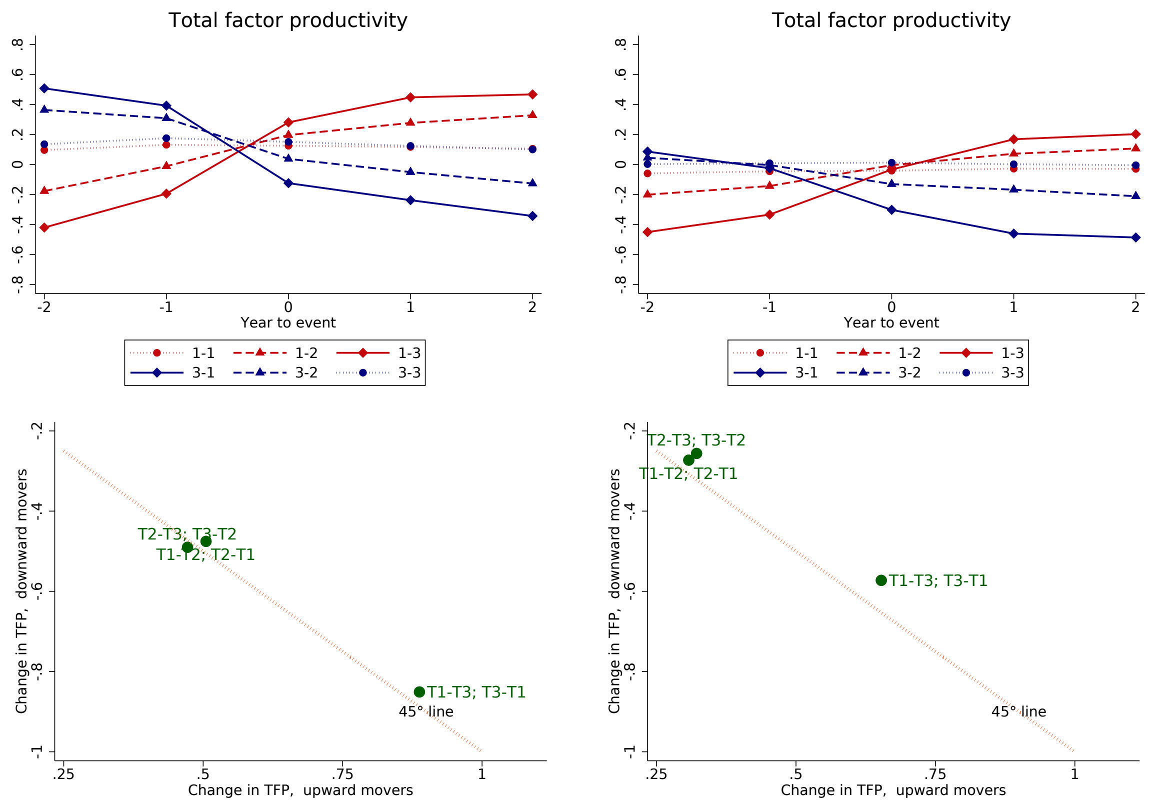
Notes: The figure plots the change in TFP between year-to-event -2 and year-to-event 2 for the balanced subset of firms that, following the change of at least one director in year-to-event 0, experience a reduction in managerial talent (from tercile t_a to tercile t_b, y-axis) against that of companies experiencing a same-intensity improvement in managerial talent (from tercile t_b to tercile t_a, x-axis).

Figure 9: Evolution of TFP and symmetry of gains and losses in TFP following a change in directors, by sector



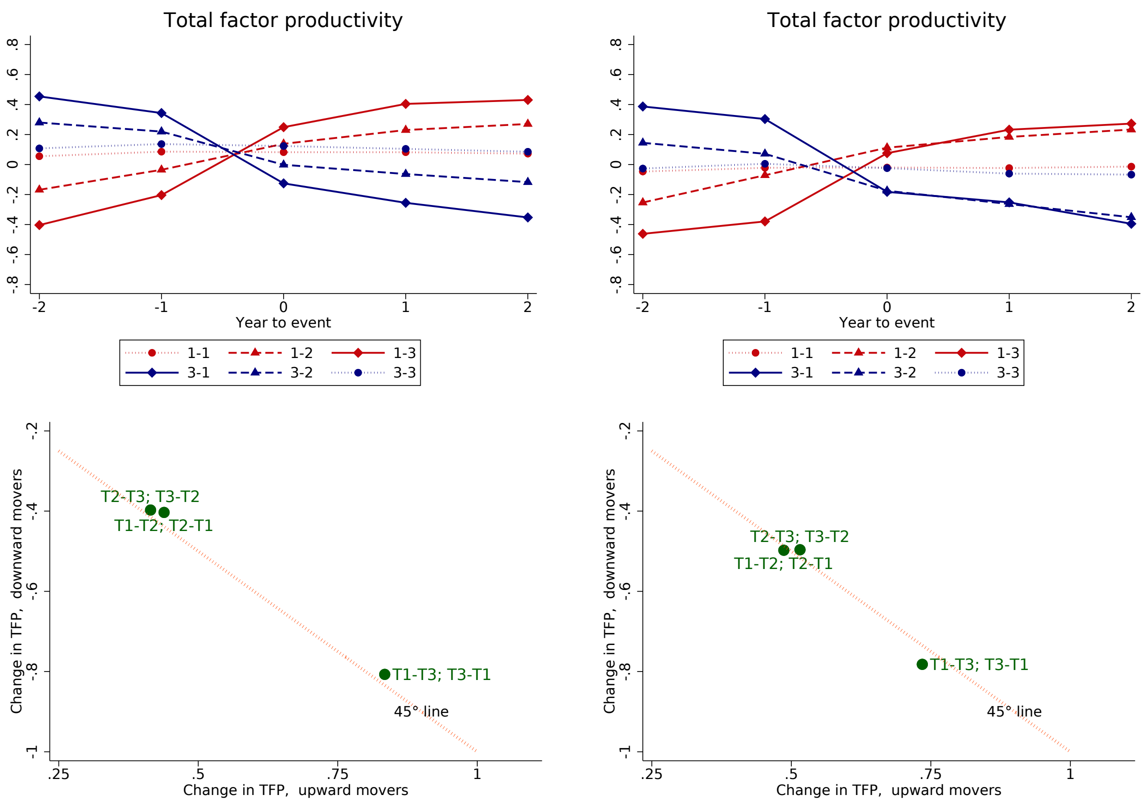
Notes: The figures show the evolution of TFP (see notes to Figure 7) and the change in TFP (see notes to Figure 8) between year-to-event -2 and year-to-event 2, dividing firms based on the sector they belong to in year-to-event -2. Figures in the left column refer to manufatcuring firms, while figures in the right column refer to service firms.

Figure 10: Evolution of TFP and symmetry of gains and losses in TFP following a change in directors'talent, by size



Notes: The figures show the evolution of TFP (see notes to Figure 7) and the change in TFP (see notes to Figure 8) between year-to-event -2 and year-to-event 2, dividing firms based the class size they belong to in year-to-event -2. Figures in the left column refer to micro firms, while figures in the right column refer to small, medium and large firms.

Figure 11: Evolution of TFP and symmetry of gains and losses in TFP following a change in directors'talent, by geographic area



Notes: The figures show the evolution of TFP (see notes to Figure 7) and the change in TFP (see notes to Figure 8) between year-to-event -2 and year-to-event 2, dividing firms based the class size they belong to in year-to-event -2. Figures in the left column refer to firms in the Central and Northern Italy, while figures in the right column refer to firms in the South.